國立臺灣大學工學院土木工程學系

碩士論文

Department of Civil Engineering
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Master’s Thesis

以數據驅動貝葉斯網絡建立鐵道行車風險評估框架

Development of Train Operation Risk Assessment Framework Based on a Data-Driven Bayesian Network

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致謝

研究所的兩年時間是人生學習歷程中，時間最短的一個階段，然而，也是挑戰最多、也讓我最為徬徨的兩年，從大學唸土木，到研究所改成念交通，雖然外面掛的都還是土木系的名字，但學習的內容跟研究的項目卻大不相同，從小就對鐵道有很大的興趣，一直以為來到交通組之後，能夠真正的對一項我所熱愛的事情有更多和更深入的了解，然而過程跟我所想像的有著不小的差距，可能跟我的性格有關，當遇到困難的時候逃避總是我的第一選項，這個缺點變成為我在做研究時最大的阻力。

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摘要

在普悠瑪事故和太魯閣事故接連發生之後，鐵路行車安全的風險管理成為大眾關注的焦點。面對鐵道行車的不確定性，本研究提出了一個結合人因分析與分類系統和貝葉斯網路的六階段步驟，建構鐵道行車風險評估框架，全面檢視風險並提前辨識潛在風險因子。首先，透過事故分析識別和定義潛在風險事件，並進行因果分析，確定導致風險事件的原因。接著，基於過往行車數據構建貝葉斯網路，量化各風險因子之間的關係和影響，並利用貝葉斯推斷計算風險事件的發生機率，進行事故後果分析，評估每個風險事件的潛在影響。在案例分析中，以實際的路線和行車資訊進行路段分析，結果顯示瑞芳到雙溪的風險相對較高，這表明除了人為失誤外，平交道和施工區域造成的風險也必須重視。此結果也說明了本研究提出的框架，能根據每班列車的行車資訊，提前預測路段風險，若能在行車前通知司機員各路段風險差異，使其提前準備，達到事前預防的效果，更可提升鐵道行車的整體安全性

關鍵字：鐵路運輸、行車風險、風險評估、事故分析、風險因子、司機員行為、路段評估

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ABSTRACT

Following the consecutive occurrences of the Puyuma and Taroko accidents, public attention has been drawn to the importance of risk management in train operations. To address operational uncertainties, this research proposes a six-phase approach that integrates the Human Factors Analysis and Classification System with Bayesian networks to develop a risk assessment framework. Initially, potential risk events are identified through accident data, followed by causal analysis. A Bayesian network, constructed from historical data, quantifies relationships and impacts of various risk factors. Bayesian inference calculates the probabilities of risk events and assesses their potential impacts. A case study applying this framework to real routes reveals higher risks between Ruifang and Shuangxi, emphasizing the risk in level crossings and construction areas. The results also demonstrate that the framework proposed in this research can predict section risks in advance based on the train's operational information and all the latest details about the route it travels through. By informing drivers of the varying risks of different sections before their journeys, they can be better prepared, achieving proactive prevention. This approach can possibly enhances the overall safety of train operations.

Keywords: *Rail Transportation, Train operation risk, Risk assessment, Accident analysis, Risk factors, Driving behavior, Section Assessment*

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CHAPTER 1 INTRODUCTION

1.1 Background

In reviewing each major railway accident, operational errors by the drivers often emerge as the primary cause. However, external factors such as environmental conditions, equipment malfunctions, and communication issues with dispatchers can also indirectly contribute to the occurrence of accidents. Therefore, attributing an accident solely to a single cause is inadequate. Organizational changes and the establishment of a risk management system are necessary to address the risks associated with drivers and thoroughly examine all potential factors that may lead to unforeseen events.

Generally speaking, corresponding improvement measures are usually proposed after an accident occurs, but in fact, accidents only account for a small portion of the overall risk. After the Puyuma train derailment accident in 2018, Taiwan Railway (TR, previously known as Taiwan Railway Administration before 2023) proposed numerous improvement plans, targeting not only the trains and routes but also conducting further reviews of the organization. However, two and a half years later, in 2021, the Taroko train collided with a construction vehicle that had intruded onto the tracks, resulting in a derailment accident that caused more severe casualties than the Puyuma accident. A thorough investigation into the causes of these two accidents reveals completely different reasons. Since each accident has different causes, the aim is to identify potential risk factors during daily operations to achieve the goal of preemptive prevention.

To achieve this, it is necessary to shift from lagging indicators, which propose improvement measures after an accident, to leading indicators, which are established before an accident occurs. This way, risks can be predicted before accidents happen and preemptive measures can be taken against potential hazards.

From a risk management perspective, the aviation industry provides valuable

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insights that are highly applicable to railways. Both sectors involve numerous factors that make risk assessment complex. Each phase of a flight—such as takeoff, cruise, and landing—presents different risks, leading to a multi-layered risk management framework. Similarly, in railways, each stage of a journey is influenced by various risk factors, and different sections may present unique risks.

To address these issues, the aviation industry implements various strategies to manage risks. They ensure the proper condition of equipment and utilize risk models to identify events that, although low in probability, could have severe consequences. The Flight Operation Risk Assessment System (FORAS) provides airlines with a method for predicting risks throughout the entire flight process, as depicted in the Figure 1-1. This information can be shared with pilots or dispatchers before takeoff. Beyond just the risk values, FORAS highlights key factors influencing risk, enabling relevant personnel or authorities to make proactive responses. This approach supports the objective of active risk management, enhancing overall flight safety (Cheng et al., 2014).

Normal Warning Alert Data Incomplete Beyond Limits Interrupted Processing

DRV	ALRV	Flt No	A/C No.	Fleet	Dep. Time(TPE)	DEP A/P	ARR A/P	Region	DRV	ALRV
		BR31	B16716	B777	2011/09/23 20:00	ANC	TPE	THM	1.00	1.00
		BR68	B16715	B777	2011/09/23 17:25	BKK	TPE	THM	1.00	1.00
		BR772	B16301	A330	2011/09/23 14:15	TSA	SHA	THM	1.00	1.15
		BR855	B16405	B747	2011/09/23 14:10	TPE	HKG	THM	1.00	1.00
		BR392	B16701	B777	2011/09/23 13:55	SGN	TPE	THM	1.00	1.00
		BR67	B16717	B777	2011/09/23 13:50	BKK	LHR	EUR	1.00	1.00
		BR868	B16410	B747	2011/09/23 13:45	HKG	TPE	THM	1.00	1.22
		BR35	B16711	B777	2011/09/23 13:30	YYZ	TPE	THM	1.22	1.00

Figure 1-1 Flight risk report of FORAS

From this, it can be concluded that a risk assessment system capable of predicting risks in advance is essential. However, another challenge is determining how to conduct such predictions. In the FORAS system, the risk status of each factor is determined by experts based on their experience. Although this method can present risk assessment results through quantitative data, it remains fundamentally qualitative. This approach can be risky, as practitioners and management may mistakenly believe that risks have been

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scientifically assessed, when in fact, the results rely on subjective judgments. If quantitative data sources are unavailable, purely qualitative assessments are acceptable. However, in cases where abundant data sources are available, risks should be quantified using this data, as it represents the truly objective approach to addressing risks.

Returning to the railway context, major accidents are low-frequency, high-consequence events. Due to scarce data, traditional statistical methods cannot provide sufficient support. In the absence of direct data on major accidents, using precursor data has garnered widespread attention. Driver behavior has always been a focus of concern, and accident data show that drivers often are a key cause of accidents (Lin, 2018). In the railway safety concept proposed by Dorrian (2006), railway driver behavior can be analyzed from three aspects: human, vehicle, and environment. If driving behavior errors occur, accidents may result. Preventing violations of railway drivers and fostering good driving habits can significantly reduce railway accidents.

In today's train operations, numerous driving operation data are recorded. Chen (2019) attempted to identify unsafe driver behaviors from these data. By continuing to find more causes of unsafe behaviors from these records and using them as leading indicators, it becomes possible to objectively predict operational risk from the data. Therefore, the railway system requires a risk assessment system that can evaluate various potential factors during driving and objectively handle the uncertainties of risks to enhance system safety.

1.2 Research Objectives

This research aims to establish Train Operation Risk Assessment System (TORAS) inspired by the FORAS. The goal is to enhance the understanding of risks in train operations and build a framework for assessing these risks. This system seeks to define risk events and utilize a comprehensive classification system for risk identification. By

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analyzing operational data, this research aims to explore the causal relationships between risk events and risk factors, ensuring objective risk assessments. The ultimate objective is to thoroughly assess the risk status of all factors before train departures to ensure operational safety. Additionally, the system will provide driving risk assessment, enabling drivers to understand risk differences and key factors for each section. This proactive approach aims to alert drivers in advance of high-risk sections, thereby reducing the occurrence of potential accidents.

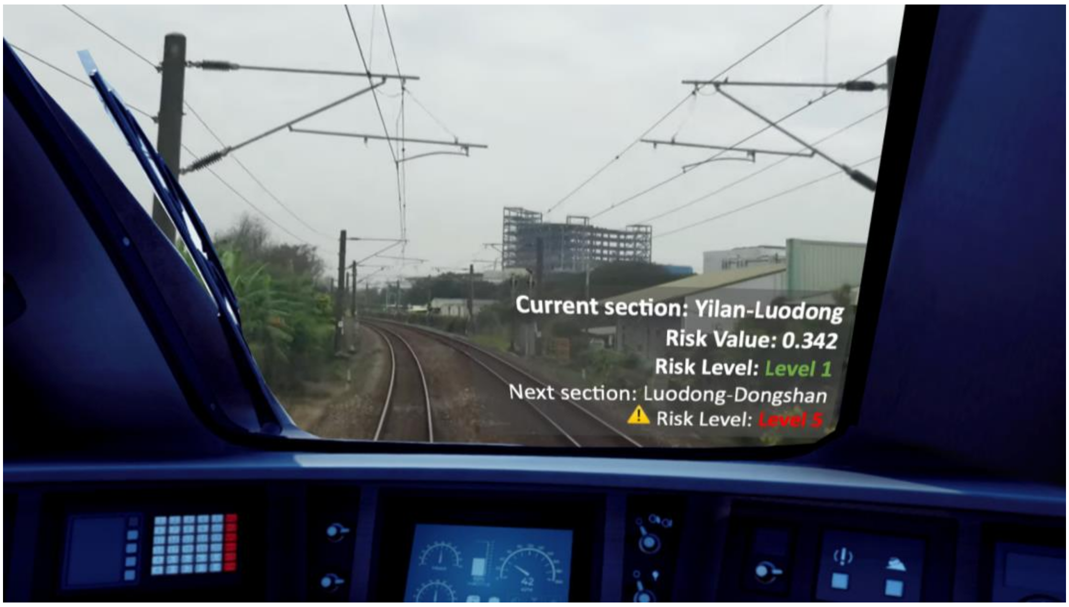

Figure 1-2 The application of FORAS in railways

1.3 Contribution Summary

The contributions of this research could be summarized into the following three points:

(1) Comprehensive identification of train operation risk factors

By investigating past accidents, the primary causes of these incidents are systematically identified. This analysis enables the definition of risk events, followed by a thorough exploration of the contributing factors. By selecting a robust framework for risk identification, this research aims to pinpoint all potential risk factors present during train operations. This method promises a detailed

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understanding of the underlying risks, thereby enhancing the ability to manage and mitigate these risks effectively.

(2) Understanding the relationship between risk events and risk factors using historical train operation data

Traditionally, the relationship between risk events and risk factors has heavily relied on expert experience. This research aims to improve this by identifying unsafe behaviors through existing identification modules using train operation data, integrated with environmental information and historical timetables to create a dataset. The objective is to perform network structure learning to uncover the underlying relationships among risk factors and establish conditional probability tables. This approach allows for accurate and objective risk analysis using Bayesian networks, enhancing the accuracy of risk assessments.

(3) Train operation risk assessment for each section

By pre-determining the risk status of each factor for every block within a section, the frequency of risk events and their potential consequences can be calculated. This approach enables a risk assessment, highlighting differences in risk levels across various sections. From the driver's perspective, this information is crucial as it allows for advance alerts, ensuring drivers are well-prepared when approaching high-risk sections. This significantly enhances operational safety and reduces the likelihood of accidents. This research aims to provide these insights, contributing to improved risk management and railway safety.

1.4 Thesis Organization

This thesis is organized into five chapters. CHAPTER 1 outlines the background and objectives of the research. In CHAPTER 2, a comprehensive review of literature related to railway safety measures and various risk identification and analysis methods is

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presented. CHAPTER 3 details the development process of the Train Operation Risk Assessment System, including the methodologies employed and their application to operational risk assessment. Chapter 4 presents a comprehensive risk assessment for train operations across different blocks within each section and proposes effective risk control strategies. Finally, CHAPTER 5 concludes the research and suggests potential directions for future work. Figure 1.3 provides an overview of the organization of this thesis.

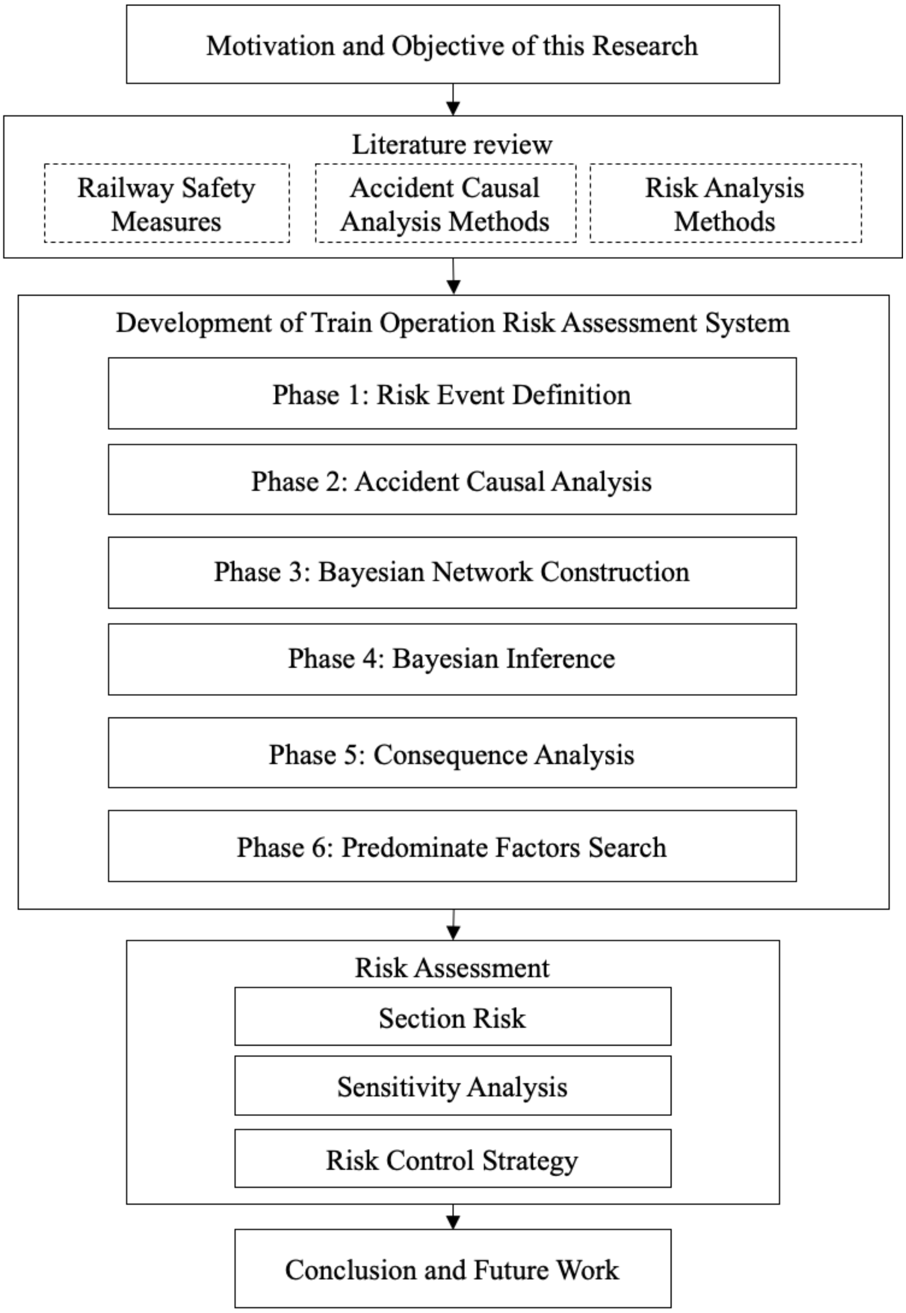

Figure 1-3 Thesis Organization

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CHAPTER 2 LITERATURE REVIEW

The purpose of this chapter is to review literature on railway safety and risk management, as well as various methods used for risk management. It begins with an overview of studies related to the development of railway safety prevention technologies and the application of existing safety management systems in Sections 2.1.1 and 2.1.2, respectively. Section 2.1.3 then discusses aviation risk management methods and explores which aspects we can learn from or refer to. Following this, Section 2.2 explores risk identification and assessment methods, emphasizing the need for a comprehensive system to examine and analyze all potential risk factors, and how to conduct risk analysis effectively and accurately. Finally, Section 2.3 summarizes the reviewed literature and discusses the innovative aspects of this research

2.1 Development and Applications of Railway Safety

Numerous studies have discussed railway safety. This section focuses on studies related to the safety and risk management of railway systems. Sections 2.1.1 and 2.1.2 respectively introduce the development of railway safety prevention technologies and the application of existing safety management systems. Section 2.1.3 discusses aviation risk management methods and explains what we can learn from them.

2.1.1 Development of Railway Safety Prevention Technologies

Rail transport is widely used in daily life and commercial activities. With the increase in rail transport volume, ensuring the safety of rail transport has become a crucial issue. To address this problem, new rail safety technologies have been continuously developed and widely applied.

Automatic Train Protection System (ATP) is a crucial rail safety technology that automatically controls train speed and stops to prevent collisions or overspeed (Bin, 1970). With continuous advancements, modern ATP systems now utilize machine learning and

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data analysis to enhance accuracy and response speed, ensuring the safe transport of passengers and goods. In addition, metro systems are typically equipped with Automatic Train Operation (ATO) systems, which do not rely on human operations to run the trains. The ATO system monitors and controls the speed, position, and signals of trains, ensuring that they operate within safe speed and distance ranges (Han et al., 1999). Li et al. (2013) introduced modern track detection technologies, including radar, satellite positioning systems, and drones, which enable comprehensive monitoring and detection of rail tracks, bridges, tunnels, and other facilities. Qin et al. (2022) developed intelligent monitoring systems that can automatically alert safety personnel to address issues or anomalies promptly when they are detected.

In recent years, technological innovations in the field of rail transport have been rapidly developing, with one key technology being the analysis of driver behavior. Drivers are a crucial part of the railway system, and their behavior can significantly impact the operation and safety of the entire system. Therefore, studying drivers' behavior and habits and applying this data to rail safety management can greatly enhance the safety of rail transport.

In terms of rail driver safety and performance, human factors analysis serves as the cornerstone of research methodologies. These investigations frequently employ experiments or interviews to evaluate driving performance and identify various factors that influence driving safety, subsequently analyzing their interrelationships and effects. Key risk factors of interest to researchers include workload and fatigue. For example, Dorrian et al. (2007) utilized a driving simulator to compare driving behaviors during consecutive night shifts against those during day shifts following normal sleep. Similarly, Jay et al. (2008) observed driver fatigue levels before and after each shift to explore the transmission of fatigue between alternating crew members. In another study, Dorrian et

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al. (2011) assessed the fatigue levels of drivers, controllers, and maintenance workers both before and after their shifts.

Beyond workload and fatigue, driver distraction and inattention also constitute critical areas of study. Naweed (2022) collected data on Signals Passed At Danger (SPAD) incidents and employed psychological models to analyze the relationship between SPAD risk and driver distraction. Furthermore, some studies delve into driver personality traits; Hickey and Collins (2017), for instance, examined the correlation between driving performance and behavior-related incidents. Additionally, several studies integrate multiple factors to construct comprehensive driving behavior models. Myrtek et al. (1994) evaluated the physical and mental states of train drivers across different railway systems to identify factors affecting driving performance. McLeod et al. (2005) developed a psychological situational model for railway drivers, elucidating their perception, decision-making processes, and actions. Naweed (2014) employed psychological methods to investigate driver characteristics, ultimately parameterizing regular driver behavior and creating a train driving behavior model. Lastly, Tabai et al. (2018) explored the impact of driver cognition on accident occurrences.

With the development of big data analysis technology, some studies have begun to use train operation records to assess driving performance and safety. Sun (2010) applied ATP record data to statistically analyze two behaviors defined as "near misses" and conducted statistical analysis to examine the relationships between near-miss incidents and factors such as personality, train type, track conditions, and environment. Zhao et al. (2018) used data from traditional signal systems to detect SPAD for future related research. El Rashidy et al. (2018) applied driving data from train monitoring recorders to establish indicators for assessing train driving performance. Driver behavior analysis technology can be implemented through data collection and analysis. For example,

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sensors can be installed to collect data on driver behavior, such as acceleration, braking force, and turning speed. This data can be used to analyze drivers' operating habits and behavior patterns, providing valuable information for the rail management system.

2.1.2 Applications of Railway Safety Management

In Taiwan's railway industry, in addition to hardware advancements, the implementation of a Safety Management System (SMS) stands as a critical technology for enhancing rail safety. An SMS is a comprehensive management framework focused on risk assessment and safety management, designed to help rail companies prevent and manage potential safety risks. However, the current system lacks the capability to predict risks and the accompanying measures to regularly review performance trends for establishing risk alerts. Therefore, the MOTC has formulated the "Railway State Safety Program" to guide operating organizations in developing effective safety leading indicators.

For other countries, the Safety Risk Model (SRM) has also been widely recognized as an effective method in this regard. Muttram (2002), Ellis (2015), and the Federal Railroad Administration (2021) have all highlighted the significance of SRM. In the UK, Muttram (2002) explained how SMS outcomes generate a regularly updated "Risk Profile Bulletin," which is utilized in the statutory Safety Cases of UK railways to test the impact of new controls on risk levels. Van Gulijk et al. (2018) further mentioned that the Safety Management Information System (SMIS) database, which supports SMS in the UK, contains over 2 million records.

Recent studies by Van Gulijk et al. (2018) and Hughes et al. (2018) have emphasized the potential of the Big Data Risk Analysis (BDRA) program. This initiative explores how big data can support and transform the Rail Safety and Standards Board (RSSB) risk analysis. BDRA projects include the development of an on-train data recorder-based

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SPAD safety indicator, visual analytics (VA), and geospatial models (GeoSRM) for identifying rail safety hazards.

In conclusion, the integration of SMS and advanced data analytics technologies plays a pivotal role in modern railway safety management. By leveraging comprehensive risk assessment and management frameworks, alongside the innovative use of big data, rail companies can significantly enhance their ability to predict, prevent, and respond to safety risks. This multifaceted approach not only improves operational safety but also contributes to the overall reliability and efficiency of rail transport systems.

2.1.3 Practices of Risk Management in Aviation

Despite these advancements, rail safety risk management still has gaps that can be addressed by learning from the aviation sector, where risk management is more mature. The Federal Aviation Administration (FAA) in the US proposed the Aviation Safety Action Program (ASAP), focusing on reducing human-factor accidents and predicting mechanical and software failures. Other models, such as the Aircraft Performance Risk Access Model (APRAM) and the Aviation System Risk Model (ASRM), emphasize reliability and overall system safety. The Fatigue Risk Management System (FRMS) manages fatigue risks under reduced rest conditions. Taiwanese scholars Wen-Kui Li and You-Heng Zhang proposed the application of fuzzy FMECA in constructing aviation risk assessment models.

Flight Operations Risk Assessment System (FORAS), initiated by the eIcarus Committee of the Flight Safety Foundation, was initially designed to address Controlled Flight Into Terrain (CFIT) but has expanded to other risk categories due to its flexible framework. FORAS uses a fuzzy inference system and knowledge base to calculate risk indices, emphasizing the interrelationships between hazard factors and providing a decision-making reference to reduce overall risk and avoid potential hazards.

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In summary, due to the insufficiencies in rail risk management, it is beneficial to adopt aviation practices, especially the FORAS model, which offers valuable insights into comprehensive risk assessment and management.

2.2 Risk Management Methodology

Based on the previous section's discussion on the current state of railway safety, it is evident that a comprehensive system is needed to thoroughly examine and analyze all potential risk factors. In this section, we will focus on risk identification and risk assessment as the two main subjects of discussion, exploring the available methods to address these challenges.

2.2.1 Risk identification method

The most direct method of accident analysis involves examining the causes of accidents through historical data. Katsakiori and Sakellaropoulos (2009) emphasize the critical importance of understanding the causation process to systematically and comprehensively analyze human errors in safety-critical systems. Heinrich's Domino Theory, proposed in 1931, is the first accident causation model, highlighting the chain reaction of accidents (Heinrich, 1941). Molloy and O'Boyle (2005) describe Edward's SHEL model, developed in 1972, to explain interactions between humans and machines. Sammarco (2005) emphasizes Perrow's Normal Accident Theory (NAT), which describes potential failures in complex technical systems. Drivalou and Marmaras (2009) discuss Rasmussen's "SPK" framework, developed in 1983, which is significant for analyzing human errors in accidents. Tong and Yuan (2013) mention the Swiss Cheese Model, introduced by Reason in the late 1980s, which has become one of the most widely applied accident causation models.

Rasmussen (1987) points out that identifying which errors (active and latent) cause accidents can be challenging because the accident causation chain has no clearly defined

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starting point, and the same events can lead to different outcomes. Kirwan (1994) introduces various Human Error Identification (HEI) tools and techniques to aid in error identification and classification, including the Technique for Human Error Rate Prediction (THERP), Human HAZOP, Systematic Human Error Reduction and Prediction Approach (SHERPA), Cognitive Reliability and Error Analysis Method (CREAM), and the Human Factors Analysis and Classification System (HFACS).

The Institute of Nuclear Power Operations (INPO, 1990) developed the Human Performance Enhancement System (HPES) and Human Performance Investigation Process (HPIP) to analyze and manage human errors in nuclear power plants. In the maritime industry, the Casualty Analysis Methodology for Maritime Safety (CASMET) and the UK's Marine Accident Investigation Branch (MAIB) human factors classification are widely used. Hollnagel (1998) introduced the Cognitive Reliability and Error Analysis Method (CREAM), a well-known technique that provides detailed classification schemes for error behaviors and causes. These techniques improve analysis efficiency but need to be refined and specified for practical use in specific fields. Hollnagel (1999) suggests that accident analysis should include both protection system responses and human responses.

Ferjencik (2011) introduced the Evolutionary Model of Near-Miss Accidents (EMMA), while Svenson (1991) proposed the Accident Evolution and Barrier Function (AEB) model, describing accident evolution as a series of interactions between humans and technical systems. Gordon et al. (2005) developed the HFIT model, similar to Reason's model, describing the causal sequence of incidents and introducing the "error recovery" category, emphasizing the process of error detection and recovery. However, HFIT does not consider technical failures and external intrusions, lacks cycles, and does not account for the role of protective systems in the recovery process. Shorrock and Kirwan (2002) introduced the Technique for Retrospective and Predictive Analysis of

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Cognitive Errors (TRACEr), which consists of eight classification schemes to describe the context of error occurrence, explain how errors happen, and describe error recovery.

Wiegmann and Shappell (2017) highlight the widespread application of HFACS in human error analysis. HFACS is a comprehensive framework initially developed by the U.S. Air Force to investigate and analyze aviation-related human factors. It considers the roles of management and organization in incidents and identifies latent errors. HFACS helps understand the relationships between failures at different levels of the system, aiding organizations in identifying weaknesses in their safety systems and implementing targeted, data-driven interventions (Ergai et al., 2016).

Katsakiori et al. (2009) note that analyses using these models can only provide fragmented information about accidents. To support more comprehensive analysis, Kim et al. (2010) describes the fault compensation process, explaining accident precursors or near-miss situations, types of adverse events that may lead to accidents, factors that may influence events, and how to prevent adverse events or accidents. However, they emphasize constructing accident sequences, with weaker identification of contributing factors.

Despite the advantages of the aforementioned techniques in terms of analysis efficiency and application in specific fields, HFACS remains the most valuable method in accident analysis due to its comprehensiveness. HFACS can systematically identify and analyze human errors and reveal latent errors at the management and organizational levels, helping organizations identify weaknesses in their safety systems and implement targeted, data-driven interventions.

In the railway sector, several studies have attempted to classify the contributing factors of railway incidents and accidents using HFACS. HFACS was initially modified to be more suitable for railways (HFACS-RR) and then applied to six incident and

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accident cases in railway yard switching (Reinach and Viale, 2006). The Federal Railroad Administration (FRA) used HFACS-RR to develop a software tool which helps the railway industry consider human factors at various system levels when investigating the causes and contributing factors of accidents and incidents. Baysari et al. (2008) demonstrated the effectiveness of HFACS in classifying errors in Australian railway accident investigation reports. Furthermore, the HFACS-RAs framework, proposed by Zhan et al. (2017), aims to identify and classify human and organizational factors involved in railway accidents. The establishment of this framework is achieved through the collection of a large amount of incident and accident data. The same methodologies are extensively employed in railway accident investigations to thoroughly analyze and identify all contributing causes and risk factors associated with the incident (Madigan et al., 2016; Ebrahimi et al., 2021). This indicates that HFACS is a powerful and comprehensive tool for systematically identifying and analyzing human errors in accidents, contributing to improved safety levels in the railway industry.

2.2.2 Risk evaluation method

A variety of techniques can be used to evaluate the risk in railway systems, and each of them has different characteristics and suitable conditions. Generally speaking, we define risk as the product of the frequency of a specific event and the consequences it causes, as shown in equation (1) (Boehm, 1989).

$$Risk = Frequency \times Consequence \tag{1}$$

This concept of risk is applied in various techniques for risk analysis and assessment. These techniques can be categorized into three types: quantitative techniques, semi-quantitative techniques, and qualitative techniques (ISO, 2010). Quantitative risk analysis, initially used in software risk assessment, has been gradually applied in fields such as railway operations. Macciotta et al. (2016) used Monte Carlo simulation to estimate the

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risk of a slope section. Leitner (2017) developed a model for railway risk assessment based on accident databases, calculating probability and consequence using fault tree analysis and event tree analysis, respectively.

Quantitative methods like Fault Tree Analysis (FTA) and Event Tree Analysis (ETA) are commonly used. Jong et al. (2020) applied FTA to analyze overspeed derailment accidents of Puyuma Train. Further research combines FTA and ETA, creating a bow-tie model structure for risk assessment with a single top event and multiple causes and consequences (Leitner, 2017; Esmaeeli et al., 2024). Lin et al. (2016) created an event tree to identify scenarios for adjacent-track accidents (ATA), and a fault tree analysis is performed to identify basic events that contribute to such accidents. Huang et al. (2022) used the bow-tie model to demonstrate the risk evolution process of railway intrusions.

However, these techniques have limitations. Nivolianitou et al. (2004) highlighted that ETA and FTA perform only "averagely" in handling event dependencies, while Khakzad et al. (2011) noted that Fault Trees assume event independence, which is not always accurate. Additionally, these methods primarily deal with binary outcomes and struggle to accommodate multi-state variables often essential in risk analysis. Quantitative methods can be too narrowly focused and grapple with uncertainty due to a lack of data for certain scenarios. To address these issues, Bayesian networks, which offer a more robust approach, are becoming increasingly popular in risk analysis (Weber et al., 2012).

Weber et al. (2012) noted the increasing use of Bayesian networks (BN) in risk analysis due to their superior structure learning and inference algorithms. Compared to traditional reliability analysis methods, BNs can model multi-state variables and multiple outputs. Khakzad et al. (2013) suggested mapping Fault Trees to BNs to overcome limitations in static structure and uncertainty. However, as the number of variables

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increases, the complexity of system modeling also increases.

Markov Chains (MC) analyze the probability of failure events using variable differences. Although MCs can represent multi-state variables, they become more complex with more variables. BNs require fewer parameters and smaller conditional probability tables. BNs are popular in railway risk modeling due to their ability to incorporate expert knowledge or data-driven methods. Huang et al. (2021) proposed a method combining Bayesian Network-K2 Algorithm-Expectation Maximization (BN-K2-EM) to process accident reports into failure data matrices, obtaining BN structure and parameters to predict and diagnose high-speed train operational failures. Liang et al. (2020) proposed a causal inference framework for risk analysis based on BNs, combining empirical knowledge with automatic learning methods, applied to level crossing (LX) accidents in France. Additionally, Bayesian Networks have been applied in railway safety management. The ERA uses it to evaluate performance, considering deterioration or improvement and comparing institutions. They define prior and posterior probabilities of reported events to categorize results from "strong evidence of deterioration" to "strong evidence of improvement."

Although quantitative risk analysis can calculate precise risk values, it involves complex calculations and assumptions, often neglecting important factors. Qualitative or semi-quantitative risk analysis can be more comprehensive, considering more latent influential factors. These methods require fewer resources and are more practical (Aven, 2008).

For qualitative and semi-quantitative risk analysis, fuzzy inference in FORAS is a common example (Cheng et al., 2014). Lin et al. (2022) proposed an index-based, semi-quantitative risk analysis framework to assess the probability and consequences of ATA. However, semi-quantitative methods often rely on subjective questionnaire analysis

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(Simić et al., 2020).

In practical applications, the risk matrix is frequently used in railway risk assessment. The EN 50126 standard refers to it as a technique for evaluating risk levels (CENELEC, 1999). Many railway operators, such as London Underground, Hong Kong MTR, Taiwan High-Speed Rail, and Taipei Metro, use risk matrices (NTURTRC, 2012). Although mature, risk matrices focus on apparent deaths and injuries, often neglecting lower-risk hazard events. The Health and Safety Executive (2004) distinguishes between accidents, which cause harm, and incidents, which are near misses or undesired circumstances that could potentially cause harm. In scenarios with fewer accidents, research focuses more on risk events during driving, which are leading indicators before accidents occur. In contrast with the risk evaluation methods, little literature proposed methods for near miss risk evaluation. Kaplan (1990) proposed a method based on the concept of event tree analysis and Bayesian theorem to evaluate the risk of near miss events. Gnoni and Lettera (2012) proposed a model to calculate a risk index for near miss events with consideration of the hazard of near miss events, effects of location, and feasibility of countermeasures. McKinnon (2012) considered the risk as a combination of probability, frequency, and severity. Although methodologies for near-miss risk assessment have been proposed, they are often inapplicable due to limited data. A new risk evaluation method for near-miss events is necessary.

In conclusion, this research aims to more objectively understand the impact of risk on train operations. Therefore, evidence-based quantitative methods will be chosen as much as possible for risk assessment.

2.3 Summary of Literature Review

The safety and risk management of railway systems have been extensively studied, with a focus on developing and applying various safety technologies and management

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systems. Key advancements include the ATP, ATO, track detection technologies, and intelligent monitoring systems. Despite these advancements, current railway safety technologies still have gaps, such as limited handling of unexpected anomalies and an over-reliance on technical solutions without sufficient integration of human factors. Learning from the aviation sector, where risk management practices are more mature, can provide valuable insights. Aviation models, such as FORAS, emphasize the interrelationships between hazard factors and offer a comprehensive approach to risk assessment.

Risk identification and evaluation are crucial for mitigating hazards in railway operations, utilizing both qualitative and quantitative methods like human factors analysis, accident data analysis, and train operation data analysis. Traditional methods such as FTA and ETA, while useful, are often complex, arbitrary, and prone to oversimplification. Given the limitations of traditional methods, past literature has highlighted their shortcomings in addressing real-world complexities. This study focuses on historical train operation data to establish a robust risk assessment framework while minimizing subjectivity.

Using Bayesian networks allows for the quantitative analysis of risk events during train operations, providing a dynamic and comprehensive approach to understanding and mitigating potential hazards. The unique aspect of this research is its integration of HFACS with quantitative data analysis, offering a more accurate and reliable framework for railway risk assessments.

In fact, multiple studies have combined HFACS and Bayesian networks for risk assessment. Rostamabadi et al. (2019) used Bayesian networks to enhance HFACS's capability in providing quantitative assessments, considering conditional dependencies among causal factors in process accidents. In the transportation sector, Uğurlu et al. (2020)

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utilized HFACS and Bayesian network models to analyze and identify patterns in marine accidents in the Black Sea.

Insights from past research underscore the need for a proactive approach to risk identification and management. Traditional railway SMS often lack real-time prediction capabilities and continuous monitoring of risk performance. From a risk management perspective, it is essential to comprehensively examine all potential risks and continuously conduct objective analyses. Thus, this research will address these deficiencies by establishing an integrated risk assessment framework that leverages historical data to anticipate and effectively predict risks.

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CHAPTER 3 METHODOLOGY

In this chapter, the framework and methods for establishing a train operation risk assessment will be described and discussed. Firstly, Section 3.1 introduces the overall process of this framework. Then, Sections 3.2 and 3.3 explain how the two methods used in this research, HFACS and Bayesian networks, are applied within the train operation risk assessment. Finally, Section 3.4 provides a comprehensive explanation of the six-phase framework.

3.1 The Framework of the Research

From the perspective of train operations, the true essence of risk management is to enable drivers, operating units, and all related personnel to anticipate various risks within the three main categories of Driver, Train, and Environment, as well as the risk events they may cause. In this research, the perspective of train drivers is used to examine the risks during the driving process. Through risk management methods, the aim is to identify the sections where drivers are most likely to make errors and determine the highest risk points throughout the operation. These insights are more helpful for managing risk than simple precursor trends. However, providing solutions to these challenges remains complex despite the abundance of available data today. The overall goal of this research is to develop a method that can regularly quantify risk using recorded driving data and address these critical issues.

This research proposes a six-phase approach to outline the framework for developing TORAS. This framework facilitates risk identification and analysis, enabling users to obtain accurate risk assessment results. The six-phase framework is illustrated in Figure 3-1.

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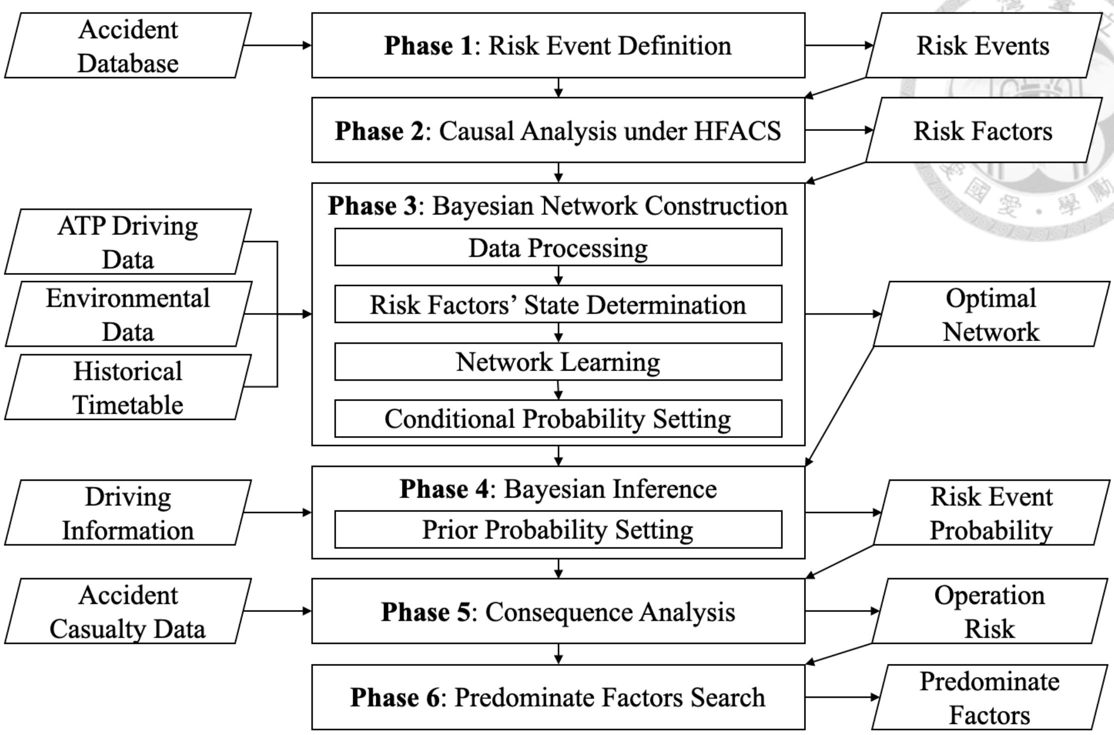

Figure 3-1 The process of developing TORAS

The first phase in exploring risk is defining it. For train operations, risk encompasses multiple dimensions. Using historical accident data, the aim is to identify frequently occurring unsafe conditions during train operations and define them as risk events. When a risk event occurs, it may lead to an accident or just a near-miss incident. Given the low probability of accidents in railway operations, the focus of this research is on understanding the occurrence of risk events.

Next, potential risk factors that could negatively impact train operations are identified through causal analysis of accident reports. By systematically classifying these events using the HFACS model, the underlying causes of risk events are revealed. This approach helps identify driver risk, section risk, and train and equipment risk, including human factors, environmental conditions, and vehicle equipment. However, due to the lack of detailed driver characteristics and vehicle differences in the existing operational data, this research explores the variations in driving behavior under different environmental conditions. Therefore, the subsequent analysis and assessment will

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primarily focus on operational risks caused by environmental factors.

Once risk factors are identified, risk analysis proceeds by constructing a Bayesian network based on these factors. Using a score-based algorithm and historical data, relationships between risk factors and events are uncovered, establishing an optimal network structure. This mapping helps understand how various factors interact and contribute to operational risk.

After establishing the network structure, the next crucial task is to set the conditional and prior probabilities. An automated procedure is employed to generate the Conditional Probability Table (CPT) using historical train operation data, ensuring accuracy and objectivity in the analysis results.

Both the probability and impact of risk events are then assessed. Using prior probabilities and the CPT, the occurrence probability of various risk events is estimated. An assessment considers not only the likelihood of an event but also the severity of potential outcomes. This dual consideration ensures a full-spectrum view of risk, critical for informed decision-making and effective risk management.

Finally, predominant risk factors are identified and controlled to mitigate accident risks. By pinpointing these key factors, railway operators can identify high-risk sections and understand the specific elements contributing to these risks. This insight allows for targeted, efficient, and effective interventions, reducing overall risk and enhancing the safety of train operations.

3.2 Application of HFACS in railway accident

To analyze the risks involved in train operations, it is essential to identify all potential risk factors that could negatively impact these operations. Using railway accidents as a risk identification database, a thorough examination of the underlying factors contributing to these occurrences is necessary. However, pinpointing which errors (including both

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active and latent errors) lead to accidents can be extremely challenging. This difficulty arises because the causal chain of accidents lacks a clearly defined starting point, and identical events can result in vastly different outcomes (Rasmussen, 1987).

The Swiss Cheese Model, proposed by Reason in the late 1980s, illustrates how accidents result from the alignment of systemic defects, represented as holes in slices of cheese. However, it lacks detailed explanations of these defects, limiting its practical use. To better analyze risk factors in train operations, this research adopts the HFACS. HFACS defines the defects in the Swiss Cheese Model through four levels of latent failures: unsafe acts, preconditions for unsafe acts, unsafe supervision, and organizational influences. Recognized as a robust framework for analyzing human factors in various accidents, HFACS is ideal for identifying risk factors and understanding the causes of risk events in train operations.

In fact, HFACS is a tool widely applied across various industries. However, due to differences in research objectives, the elements analyzed within the four-level framework may be modified accordingly. Furthermore, it is not limited to investigating human factors alone; any direct cause leading to an accident can be considered an unsafe act. The greater advantage of this framework lies in its ability to explore the connections between direct and indirect causes, and to provide a systematic classification for all indirect causes. This makes it an effective method for constructing the TORAS based on accident analysis. Therefore, the HFACS framework used in previous investigations of train derailments and collisions is referred to for identifying risk factors (Ebrahimi, 2021). The overall identification framework is illustrated in Figure 3-2.

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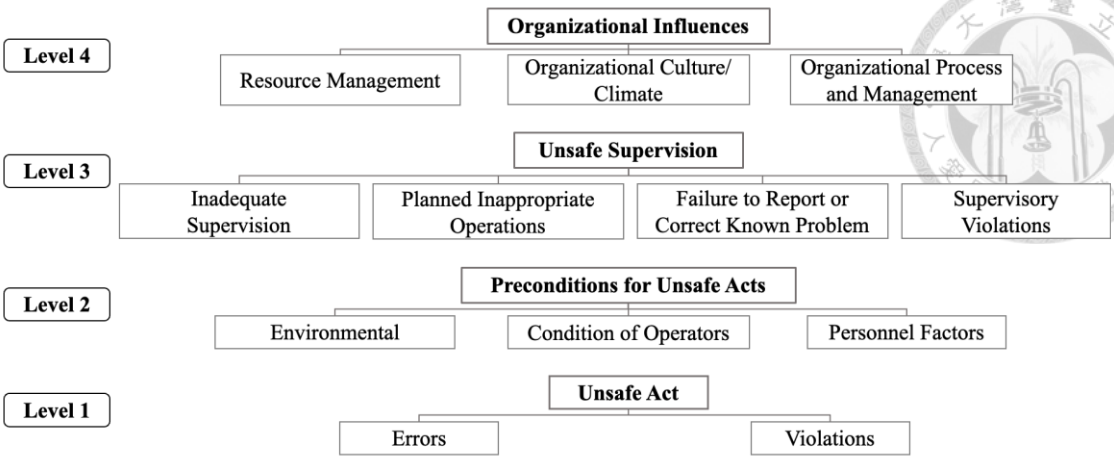

Figure 3-2 The framework of HFACS for train derailment and collision

Level 1: Unsafe Act

"Unsafe Acts," also known as "Active Failures," can be categorized into two major types: "Errors" and "Violations." Errors can be further divided into three subcategories: skill-based errors, decision errors, and perceptual errors. Skill-based errors are typically errors in situation assessment or occur when an individual incorrectly or insufficiently responds to rare situations. For example, a driver might start driving without having received the movement signal, fail to properly observe the route, or have inadequate knowledge of the timetable. Decision errors are related to incorrect judgments made by an individual in specific situations and inappropriate responses to emergencies. For instance, a driver might decide to proceed through a yellow signal without reducing speed, misjudging the distance to the next signal and causing a near-miss incident. Perceptual errors arise when the driver's ability to perceive is compromised, leading to decisions based on incorrect information. An example would be a driver who, due to visual impairment, misreads a speed limit sign and fails to slow down appropriately, resulting in overspeed.

Violations are divided into two subcategories: routine violations and exceptional violations. Routine violations refer to non-compliance with standard operating procedures, such as overspeed or SPAD (Signal Passed at Danger). On the other hand, exceptional

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violations are abnormal behaviors that may not directly cause risk but still deviate from regulations. For example, in traditional railways that rely on trackside signals, over-reliance on ATP for driving is considered an exceptional violation. Figure 3-3 provides the lists of unsafe acts.

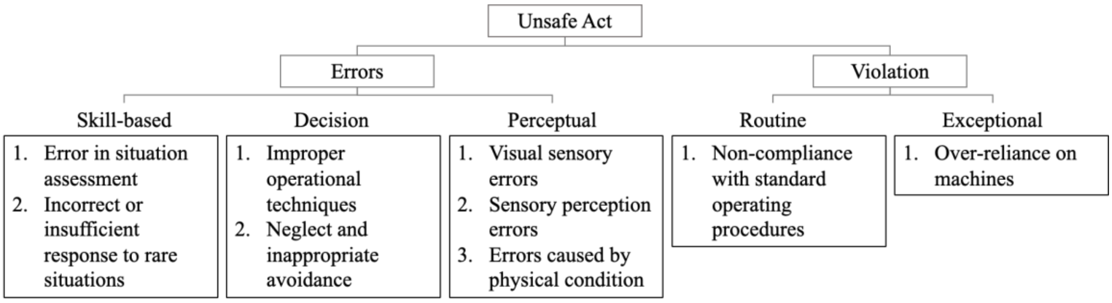

Figure 3-3 The lists of Unsafe Act

Level 2: Preconditions for Unsafe Acts

"Preconditions for Unsafe Acts" highlight a series of potential underlying causes and obvious errors leading to accidents, encompassing both "active failures" and "latent failures." These preconditions also provide detailed explanations of the contextual factors influencing operators' unsafe behaviors. Due to the nature of the railway system, the preconditions for unsafe acts arise from both environment and personnel, categorized into three main aspects: environmental factors, the condition of operators, and personnel factors.

First, environmental factors are divided into physical environment and technological environment conditions. The physical environment includes elements such as weather, terrain, and infrastructure, while the technological environment involves the design and maintenance of operating equipment.

Second, condition of operators, which encompasses adverse mental states, adverse physiological states, and physical/mental limitations. Adverse mental states, such as complacency or haste, can lead to judgment errors; adverse physiological states, such as illness or fatigue, can impair operational capabilities; physical/mental limitations refer to

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factors like insufficient reaction time or inadequate skills.

Lastly, personnel factors consist of crew resource management and personal readiness. Crew resource management involves interactions and leadership within the team, such as collaboration and communication among team members. Personal readiness pertains to whether operators adhere to rest and alcohol consumption guidelines, impacting their performance on the job.

Given the various challenges each task may present, the likelihood of operators' failure is closely related to these preconditions for unsafe acts. Therefore, it is foreseeable that the more adverse factors present in a given task, the higher the probability of drivers making erroneous decisions. Consequently, this level of analysis is of paramount importance and focus in this research. Figure 3-4 provides the lists of Preconditions for Unsafe Acts.

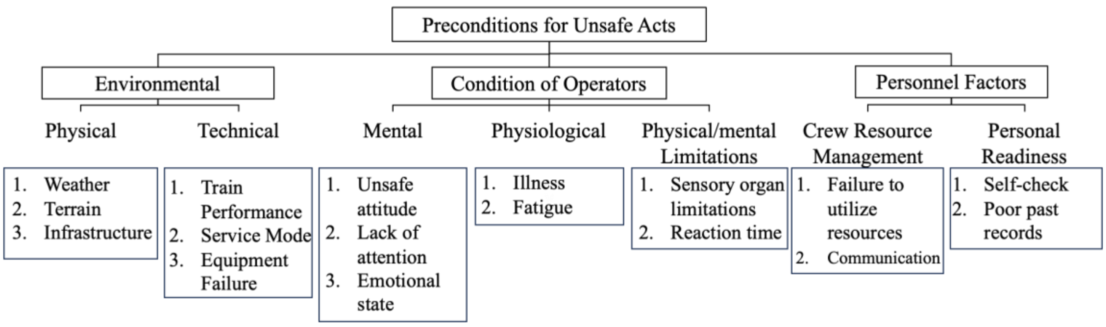

Figure 3-4 The lists of Preconditions for Unsafe Acts

Level 3: Unsafe Supervision

To address the latent failures that lead to accidents, we can trace these issues back to higher level of management to uncover the underlying causes of preconditions for unsafe acts. These underlying causes include four key categories. "Inadequate supervision" refers to situations where supervisory personnel fail to provide proper job training or adequate guidance according to regulations. Supervisors must also track and evaluate the effectiveness of technical and safety training to ensure long-term safety. "Planned

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inappropriate operations" involve supervisors authorizing tasks that violate regulations, including improper personnel pairing. "Failed to correct problems" refers to supervisors tolerating poor individual practices or systemic deficiencies, despite knowing these issues could compromise safety. "Supervisory violations" involve supervisors deliberately ignoring regulations, knowingly and willfully disregarding the rules. These factors significantly impact operator behavior and are critical issues that must be addressed to ensure system safety. Figure 3-5 provides the lists of Unsafe Supervision.

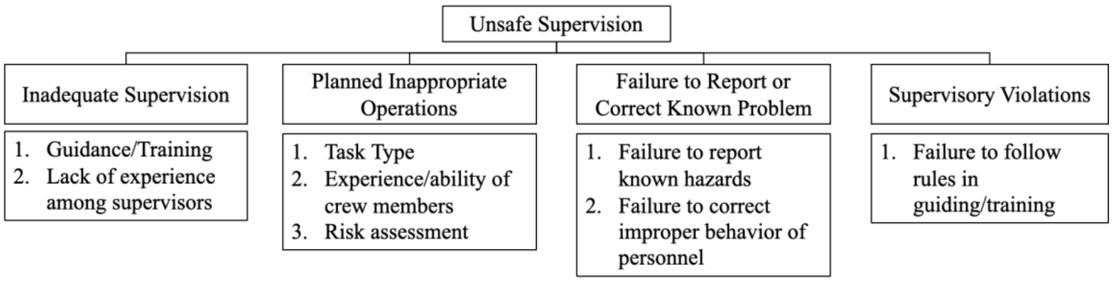

Figure 3-5 The lists of Unsafe Supervision

Level 4: Organizational Influences

"Organizational Influences" primarily focus on higher-level organizational management, which often remains overlooked yet represents the most challenging aspect to uncover latent failures. These failures directly impact the supervision and performance of operators and are largely associated with organizational management, personnel reward systems, training, and selection processes. "Resource Management" includes aspects such as personnel, finances, and equipment, reflecting deficiencies in organizational material resources. In the railway industry, a common issue is the lack of planned tracking for talent development, leading to complacency over time. Tracking and evaluating training quality are crucial. Inappropriate equipment procurement can also affect supervisory practices and operator behavior. "Organizational Climate" reveals serious issues affecting employees' moods, attitudes, perceptions, values, habits, and behavioral styles, including disciplinary and punitive systems. "Organizational

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Processes" refer to the policies, strategies, goals, plans, regulations, procedures, controls, and supervisory mechanisms issued by senior management to maintain daily operations and task execution. Neglecting safety in operational strategies and objectives can lead to a lack of overall safety awareness. Therefore, safety plans must be formulated and implemented by senior management. Figure 3-6 provides the lists of Organizational Influences.

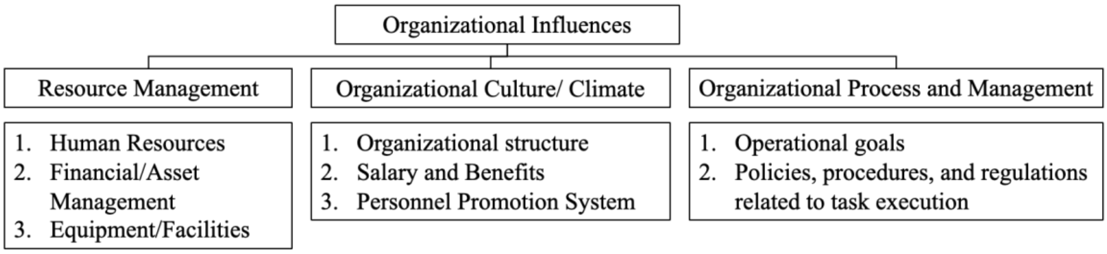

Figure 3-6 The lists of Organizational Influences

Within this four-layer framework, HFACS provides a comprehensive classification system to identify the causes of accidents. However, the risk assessment of train operations has three primary objectives.

First, understanding risk variations across railway sections, considering factors like curve radius, grade, and local weather, is essential. Detailed assessments will identify high-risk sections for targeted warnings and preventive measures. Assessing risk differences among train drivers is also crucial, as different driver conditions impact risk levels. Meticulous assessments support management decisions, including schedule adjustments and targeted training. Additionally, different types of trains vary in performance and maintenance needs. Risk assessments help determine the risk profiles of different models, enabling the development of specific operational guidelines and safety measures.

Thus, the focus will be on the conditions leading to unsafe acts, as identified by HFACS, and relevant to the objectives, for subsequent risk analyses. Organizational

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influences and supervisory actions, while important, will not be the primary focus as they relate more to policy and management impacts.

3.3 Application of Bayesian Network

Bayes' theorem is a conditional probability method that stems from the concept of subjective probability. The Bayesian model, or probabilistic directed acyclic graph model, is used to generate a network model. In other words, a Bayesian Network represents a network model composed of a set of variables with conditional dependencies. One significant advantage of Bayesian Networks is their flexibility and versatility, which allow them to handle various types of evidence and uncertainties. Additionally, their graphical structure aids in understanding causal relationships between variables and can update probability distributions in real-time based on new evidence, providing more accurate risk assessments.

The Bayesian network uses prior and conditional probabilities at each node to evaluate operation risks, considering factors such as terrain, time, and route conditions. For instance, to assess the operation risk of a particular section, we first analyze the probability of risk events occurring at each node, which gives us the prior probabilities (the root nodes). Next, we determine the relationship between these risk factors and their child nodes by setting the conditional probabilities within the Bayesian network.

The Bayesian network captures the dependence among a set of random variables through the directed edges in the network. An arc from A to B indicates that there is dependence of B on A, which is represented through the conditional probability $P(B|A)$ in probability theory. For a Bayesian network with n random variables x_1, x_2, …, x_n , the full joint probability distribution for Bayes' theorem is:

$$P(x_1, x_2, x_3, \dots, x_n) = P(x_1|x_2, x_3, \dots, x_n)P(x_2|x_3, x_4, \dots, x_n) \dots P(x_{n-1}|\, x_n)P(x_n) \tag{2}$$

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This can be reformulated as:

$$P(x_1, x_2, x_3, \dots, x_n) = \prod_{i=1}^{n} P(x_i | x_{i+1}, \dots, x_n) \tag{3}$$

Suppose *Parents* (x_i) denotes the set of parent nodes of node x_i, then we can simplify the joint probability distribution shown in equation (4) by using our knowledge of the parents of each node:

$$P(x_1, x_2, x_3, \dots, x_n) = \prod_{i=1}^{n} P(x_i | Parents(x_i)) \tag{4}$$

For example, curve and steep grade are significant terrain factors that can lead to unsafe act such as overspeed. In the simplified Bayesian network shown in the Figure 3-7, the child node "Overspeed" (occurrence/non-occurrence) has two parent nodes: "Curve" (yes/no) and "Steep grade" (yes/no). The state of the " Overspeed " node depends on the different conditions of its two parent nodes.

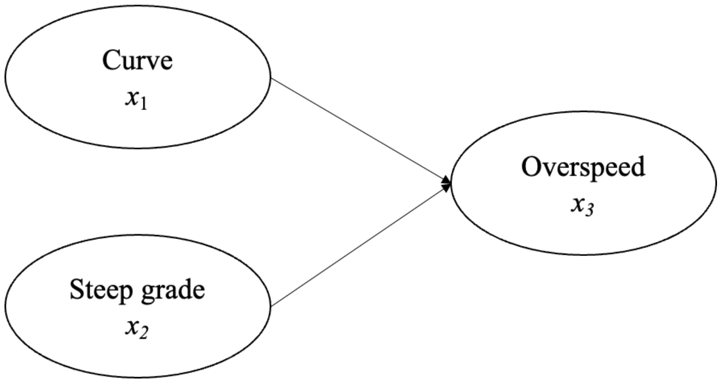

Figure 3-7 A simple Bayesian network illustrating the occurrence of unsafe act

Given equation (4), the joint probability distribution of the Bayesian network in Figure 3-7 can be rewritten as:

$$P(x_1, x_2, x_3) = P(x_3 | x_1, x_2) P(x_1) P(x_2) \tag{5}$$

To calculate $P(x_1, x_2, x_3)$, the prior probabilities of the factors, $P(x_1)$ and $P(x_2)$, must first be determined. To reflect the relative risk differences for each block, this research defines the prior probability as the proportion of the area exposed to risk

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conditions within the block, as shown in equation (6).

$$P(\,x_i) = \frac{Length\ in\ risk\ sate\ in\ block\ i}{Length\ of\ block\ i} \tag{6}$$

Another crucial component is the CPT for the child nodes. The CPT measures the probability of each value of one variable given the values of other variables. When setting up the CPT in a Bayesian Network, data can be obtained through expert questionnaires or historical driving data. However, establishing conditional probabilities based on expert experience can lead to excessive subjectivity.

This research aims to set conditional probabilities based on data to provide a more objective risk analysis method. The conditional probability of each node is determined as the probability of the child node occurring under specific conditions when the train passes through that section, as shown in equation (7).

$$P(x_i|Parents(x_i)) = \frac{Number\ of\ child\ node's\ unsafe\ act\ appear}{Number\ of\ train\ passing\ the\ block\ under\ specific\ condition} \tag{7}$$

Therefore, given evidence of the prior probability, the posterior probability of the occurrence of the child nodes can be updated through the calculation of conditional probability. All possible scenarios are specified in the CPT by evaluating the relevant parent nodes for each child node. However, when establishing the conditional probability table, one potential issue is that an excessive number of conditions can make the CPT difficult to construct. As illustrated in Figure 3-8, consider a Bayesian network with a Boolean node ω that has m Boolean parents e_1, e_2, ..., e_m. Typically, the CPT for ω and e_1, e_2, ..., e_m requires determining 2^{m+1} parameters, corresponding to the probabilities that each parent state combination is true. When m = 10, 2048 entries need to be filled in the conditional probability table. Obviously, as the number of variables and states increases, the size of the CPT can grow exponentially, the complexity of calculations increases with the number of variable states, which can be particularly cumbersome for large Bayesian Networks.

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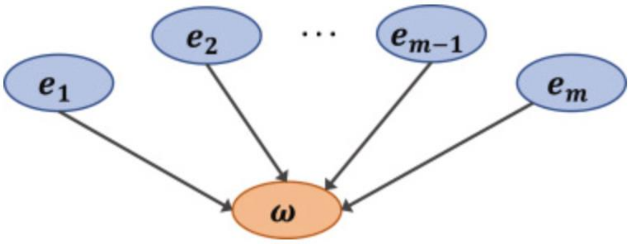

Figure 3-8 V-structure common effect in Bayesian network

Additionally, having too many conditions means an increased number of scenarios to analyze. With limited data, this results in fewer data points available for each scenario. In the context of railway operations, risk events occur relatively infrequently. If too many conditions are set, it may lead to many conditional probabilities being zero. Large conditional probability tables require a vast amount of historical data, and in the absence of such extensive data, we should first learn the network structure. By evaluating the relative importance of each arc, we can preliminarily filter out less important arcs, reducing the number of conditional probabilities that need to be handled.

Therefore, in this research, an automated procedure is developed to set conditional probabilities using data, alleviating the difficulties faced by experts in filling out these tables. Additionally, a method was proposed to generate the optimal model structure using data, aiming to construct a Bayesian network for train operation risk analysis.

Algorithms for learning the structure of Bayesian Networks can generally be categorized into three types. The first type is constraint-based algorithms, such as Peter-Clark (PC) and Grow-Shrink (GS), which perform conditional independence tests on the data to identify the network that best explains these independencies. The second type is score-based algorithms, including Tabu Search, K2, and Greedy Equivalence Search (GES), which use a goodness-of-fit score as an objective function to maximize. Finally, hybrid algorithms, such as Hybrid HPC (H^2PC) and Max-Min Hill-Climbing (MMHC), combine elements of both constraint-based and score-based methods (Ramos et al., 2021).

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Among these, the score-based algorithm is the most widely used method for deriving Bayesian Networks from data. Although score-based algorithms may not always provide elegant and efficient solutions to the search problem, they are generally more accurate and faster compared to constraint-based and hybrid algorithms. In this process, a score is assigned to each candidate BN, typically reflecting how well the BN represents the dataset D. Given a structure G, its score is:

$$score(G, D) = P(G|D) \tag{8}$$

In other words, this represents the posterior probability of the network G given the data set. The computation of the above can be reformulated using Bayes' theorem to a more convenient form:

$$score(G, D) = \frac{P(G|D)P(G)}{P(D)} \tag{9}$$

Among the scoring functions, Bayesian scores can be adopted, which take a Bayesian perspective of the structure learning process. Due to the complexity of the Bayesian score, approximations such as the Bayesian Information Criterion (BIC) are often used. The BIC score is computed as follows:

$$score_{BIC}(G, D) = l(\Theta_G, D) - \frac{logN}{2}|G| \tag{10}$$

where $l(\Theta_G, D)$ is the logarithm of the likelihood function, $\Theta_G$are the maximum likelihood parameters given G, $|G|$is the graph complexity, defined as the number of parameters of a certain structure candidate G, N is the number of the data point.

As shown in the equation (10), BIC penalizes more complex structures by introducing a penalty term to the likelihood score, thus avoiding the overfitting problem and resulting in structures with higher generalization capabilities. Furthermore, the BIC score also satisfies three essential characteristics for optimizing the structure learning procedure:

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1. **Equivalence**: If G_1 and G_2 are I-equivalent, then $score_{BIC}(G_1, D)$ =$score_{BIC}(G_2, D)$
2. **Consistency**: As the training data D tends to infinity, the global maximum of the BIC score corresponds to the structure that induces the underlying distribution.
3. **Decomposition**: The BIC score of a graph G can be computed as the sum of local scores calculated for each variable:

$$score_{BIC}(G, D) = \sum_{k} score_{BIC}(X_k | pa_G X_k, D) \tag{11}$$

Due to these characteristics, the BIC score has been selected for all structure learning experiments in this work. A score-based algorithm attempts to maximize this score. The optimization objective can be formalized as follows:

$$max \;\; score_{BIC}(G, D) \tag{12}$$

Under the score-based algorithms, one popular choice is hill-climbing. The search process begins with an initial network, which can be empty, full, or random. However, if background knowledge is available, it can be used to seed the initial candidate network. The main loop of the algorithm involves attempting every possible single-edge addition, removal, or reversal. Each modification is evaluated, and the network that increases the score the most becomes the new current candidate. This iterative process continues until no single-edge change can further improve the score.

Furthermore, once the Bayesian Network is constructed, its validity must be verified by ensuring two axioms are satisfied:

Axiom 1: A little increase/decrease in the prior subjective probabilities of each parent node should certainly result in the effect of a relative increase/decrease of the posterior probabilities of the child node.

Axiom 2: The total influence magnitudes of the combination of the probability variations from “x” attributes (parent nodes) on the values of the child node should always be greater

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than that from the set of “x–y” (y∈x) attributes.

3.4 Development of Train Operation Risk Assessment System

In this section, the development of the TORAS will be illustrated through a six-phase process. The process includes defining risk events from accident database and identifying risk factors using the HFACS. Historical driving data will be utilized to construct a Bayesian network, allowing for the analysis of the probability of risk events by inputting the latest train operation information. Furthermore, causal analysis will be conducted to evaluate overall operational risks and the consequences of various risk events.

Phase 1: Risk Event Definition

To conduct a systematic and thorough analysis of railway system risks, it is necessary to understand the causation process of accidents. In safety-critical systems, most accidents and incidents are not the result of a single event. The Human Error Analysis and Reduction (HEAR) model describes the circumstances surrounding accident or Near-miss (Kim, 2010). It identifies the types of adverse events that could lead to accidents and examines the factors that might influence these events. For an accident to occur, adverse events must first happen. The model categorizes adverse events into three types: (1) human failures (driver mistakes or violations), (2) technical failures (hardware or software malfunctions), and (3) external intrusions (foreign objects on the tracks). The occurrence of adverse events puts the entire train operation in an unsafe condition.

As previously mentioned, human failures are a major cause of railway accidents. Regarding technical failures, data shows that advancements in technology have led to a significant decrease in accidents due to technical failures, both in terms of equipment failures and track-related issues (Ebrahimi et al., 2021). While technical failures can create unsafe conditions, the key determinant of whether an accident occurs lies in the driver's judgment and response to such failures. For example, in the 2019 Puyuma

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accident, a compressor anomaly distracted the driver. However, the root cause of the accident was the driver's decision to speed through a curve after disabling the ATP. This illustrates that while technical failures present potential risks, human failure is the core cause of accidents.

Additionally, safety issues caused by intrusions along railway lines are serious. External intrusion is defined as the unauthorized entry of objects or individuals into the railway section, impacting the safe operation of trains and potentially leading to train stoppages or accidents. Intrusion can be proactive behaviors (e.g., pedestrians, animals, and vehicles entering the track area) or inadvertent events (e.g., objects falling from facilities or equipment beside the railway line). For instance, level crossing accidents, although causing fewer casualties, have a high frequency for non-elevated or non-underground railway sections. Even on routes without level crossings, personnel accidents due to passengers falling from platforms without safety doors are quite common. According to the Taiwan Railway 2023 accident statistics, with no major accidents reported, driver errors and external intrusions onto the tracks accounted for 39 out of 40 general operational accidents, as shown in Table 3-2. Although Taiwan Railway categorizes general accidents into seven types, for the purposes of this research, the table has been reorganized to classify accidents by their underlying causes. Moreover, the intrusion of foreign objects onto tracks from construction zones is also a serious problem. The 2021 Taroko train derailment was caused by a flatbed truck accidentally sliding and falling onto the track, subsequently colliding with an oncoming train traveling at high speed. Despite the application of emergency braking, the train was still unable to stop in time, resulting in a collision that caused 49 deaths and 245 injuries. This shows that intrusions pose significant safety threats and can lead to substantial losses.

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Table 3-1 2023 TR accident statistics

Accident Type	Number
Major Accident	0
General Accident	40
External intrusion	37
Driver’s error	2
Equipment failure	1

However, the unique challenge of intrusions lies in the fact that, despite numerous efforts to develop automatic railway intrusion detection systems in recent years, unless we can fully implement detection technologies along the railway line with 100% accuracy, we cannot mitigate the safety risks arising before or during intrusion events caused by various risk factors. Therefore, due to the unpredictability of external intrusions and their severe consequences, they are also crucial when discussing operational risks.

Thus, “Human Failure” and “External Intrusion” are the two major risk events in train operations in this research. It is important to note that a risk event represents an unsafe condition, not a type of accident. “Human Failure” specifically refers to errors made by the driver during train operations, causing the train to enter an unsafe condition. “External Intrusion” represents the condition where foreign objects intrude onto the tracks. Under these two risk events, whether the driver can react in time may determine if the unsafe condition becomes merely a near-miss or, if they fail to react, an actual accident.

However, given the scarcity of accident data, it is challenging to explore the relationship between the occurrence of risk events and actual accidents. Therefore, this research focuses on investigating risk events, understanding the causes of unsafe conditions in railway operations, and calculating their probabilities. The likelihood and consequences of these events ultimately leading to accidents are assumed based on previous literature.

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Phase 2: Accident Causal Analysis under HFACS

This research proposes an accident report text extraction and analysis method based on the HFACS framework. This method primarily involves extracting the direct causes of accidents from accident reports and further analyzing the indirect causes. These indirect causes are classified according to the unsafe act conditions in HFACS. The goal is to comprehensively identify the risk factors of train operations and transform this information into a Bayesian network model for subsequent risk analysis.

Step 1: Text Preprocessing and Extraction of Direct Causes

In the first step, we preprocess the accident report texts to extract the direct causes of accidents, defined as unsafe acts in HFACS. Specifically, we segment each accident report into words or phrases and assign numerical sequences to each word. Ultimately, we generate a set of cut words for each accident report.

Step 2: Text Analysis and Feature Extraction

In the second step, we analyze the extracted word features to identify unsafe acts. Specifically, we set the following sets: Human Failure (HF) and External Intrusion (EI). HF represents a set of human factors, including, decision errors, perceptual errors, and violations; EI represents a set of external factors, including foreign object intrusion and the driver's reaction to foreign object intrusion. Through this step, we can identify and extract unsafe acts, represented as:

$$unsafe\ acts = \{ua_1, ua_2, \ldots, ua_m\} \tag{12}$$

where ua_i is the type *i* of unsafe act for each accident.

Step 3: Extraction and Classification of Indirect Causes

In the third step, we extract and classify the indirect causes of unsafe acts based on the HFACS framework. Specifically, we classify the indirect causes into three categories:

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environment, condition of operators, and personnel factors. We set the following sets: indirect causes (ic), environment (env), condition of operators (co), and personnel factors (pf). Finally, we classify each indirect cause ic into the corresponding category $\{env, co, pf\}$.

Step 4: Establishing the Causal Model

In the fourth step, we establish the causal model by linking the direct and indirect causes. Specifically, we associate unsafe acts with their indirect causes to form a causal model of the accident. Using a graphical model to represent these associations, we can more intuitively understand the process and causes of the accident. The resulting causal chain is represented as:

$$causal\ chain = \{ua_i, ic_{ij}\} \tag{13}$$

where ua_i is the unsafe act i and ic_{ij} is the indirect cause j of unsafe act i.

Using the proposed risk identification steps, this research will utilize a database of 40 train operation accidents from Taiwan Railway in 2023. However, as no major railway accidents occurred that year, to ensure a comprehensive and thorough identification of risk factors, we will focus on driver operation errors and foreign object intrusions as the main subjects of analysis. Additionally, we have incorporated an investigation of 15 railway accidents examined by the Taiwan Transportation Safety Board (TTSB) from 2018 to 2023 to broaden the scope of our analysis.

According to the railway operation rules in Taiwan, accidents can be classified into various categories based on severity, location, and cause. However, for the purposes of research and readability, we further categorize them into five types: derailments, collisions, level crossing accidents, obstructions, and others (including signal overrun, train runaway, etc.). Additionally, investigating near-miss incidents allows us to more comprehensively examine all potential operational risks. In this case, not only accidents

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that caused casualties or property damage are analyzed, but near-miss incidents are also included.

Notably, previous literature on accident analysis often focuses on frequency analysis of factors. However, in this study, our goal is to identify all possible risk factors. Therefore, as long as a factor is mentioned in any accident, it is included in our analysis.

In our research of 55 cases, we systematically identified both the direct and indirect causes of each accident, adhering to the steps outlined in the previous section. Table 3-2 to Table 3-6 outlines the various types of accidents and identifies the possible causes associated with each type, correlating them with the cases documented in the accident database used in this research.

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Table 3-2 Causal Analysis of Accidents (Derailment)

Accident Type	Cause		Accident
Derailment	Environmental	Compressor failure	20180121 No.6432
		Insufficient ATP system	20180121 No.6432, 2021054 No.7142
		Switch not positioned	2021054 No.7142
		Curve	20180121 No.6432
		Poor track condition	20180121 No.6432
		Limited visibility	20210402 No.408
		Construction site	20210402 No.408
		Train speed	20180121 No.6432, 20210402 No.408
		Tunnel	20210402 No.408
	Condition of operators	Lack of familiarity with train systems	20180121 No.6432
		Delayed reporting of abnormalities	20180121 No.6432, 2021054 No.7142
		Misjudgment of fault causes	20180121 No.6432, 2021054 No.7142
		Operational pressure	20180121 No.6432
		Failure to execute speed reduction	20180121 No.6432
		Driver took action but brakes were insufficient	20210402 No.408
	Personnel factors	Inadequate training	20180121 No.6432, 2021054 No.7142
		Incomplete maintenance checklist	20180121 No.6432, 20210402 No.408
		Ambiguous communication standards	20180121 No.6432, 2021054 No.7142
		Lack of coordination and decision support	20180121 No.6432, 20210402 No.408, 2021054 No.7142

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Table 3-3 Causal Analysis of Accidents (Collision)

Accident Type	Cause		Related accident
Collision	Environmental	Signal system malfunction	20190808 No.3501&333
		Insufficient lighting	20190806 No.1231&129
		Missing station monitoring equipment	20200318 No.7101&2633
		Inadequate signaling and warning functionality	20190806 No.1231&129, 20190808 No.3501&333
		Construction site	20190808 No.3501&333
	Condition of operators	Unauthorized reverse operation	20190806 No.1231&129
		Lack of operational safety awareness	20190806 No.1231&129, 20190808 No.3501&333, 20200318 No.7101&2633
		Unauthorized personnel in the driver's cabin	20190806 No.1231&129
		Disabling ATP system and radio registration	20190806 No.1231&129, 20200318 No.7101&2633
	Personnel factors	Inadequate training and supervision mechanisms	20190806 No.1231&129, 20200318 No.7101&2633
		Lack of backup equipment and personnel deployment	20190806 No.1231&129
		Unclear reporting procedures and regulations	20190806 No.1231&129

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Table 3-4 Causal Analysis of Accidents (Level-crossing)

Accident Type	**Cause**		**Related accident**
Level Crossing	Environmental	Design and maintenance flaws in crossings	20191231 No.118, 20200410 No.3198, 20230215 No.3023, 20230329 No.4553, 20230907 No.3054, 20230910 No.445
		Lack of emergency buttons or their non-use	20230215 No.3023, 20200410 No.3198, 20191231 No.118
		Short visibility distance	20200410 No.3198, 20230329 No.4553, 20230403 No.273, 20230907 No.3054
	Condition of operators	Delayed response	20191231 No.118, 20200410 No.3198
		Failure to notice	20230120 No.121, 20230403 No.273, 20230907 No.3054
		Driver took action but brakes were insufficient	20191231 No.118, 20200410 No.3198, 20230104 No.2203, 20230120 No.2608, 20230215 No.3023, 20230329 No.4553, 20230910 No.445, 20231023 No.1211, 20231230 No.2723
	Personnel factors	Insufficient road and crossing inspection	20191231 No.118, 20200410 No.3198, 20230104 No.2203, 20230120 No.2608, 20230120 No.121, 20230821 No.401, 20230907 No.3054, 20230910 No.445, 20231023 No.1211, 20231230 No.2723
		Insufficient training and safety education mechanisms	20191231 No.118, 20200410 No.3198

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Table 3-5 Causal Analysis of Accidents (Obstruction)

Accident Type	Cause		Related accident
Obstruction	Environmental	Improper track clearing	20200519 No.3218, 20211201 No.611, 20230202 No.1276, 20230203 No.377, 20230212 No.219, 20230225 No.1273, 20230329 No.128, 20230410 No.378, 20230411 No.401, 20230406 No.2273, 20230503 No.2284, 20230509 No.3121, 20230605 No.2124, 20230627 No.175, 20230712 No.727, 20230719 No.3165, 20230731 No.117, 20230825 No.1170, 20230907 No.114, 20230924 No.272, 20230927 No.442, 20230928 No.1188, 20230930 No.155, 20231007 No.3229, 20231119 No.2008, 20231128 No.439, 20231231 No. 257
		Short visibility distance	20230329 No.128, 20230410 No.378, 20230411 No.401, 20230406 No.2273, 20230503 No.2284, 20230731 No.117, 20230509 No.3121
		Leaving construction equipment on tracks	20211201 No.611, 20230509 No.3121
	Condition of operators	Lack of hazard awareness	20200519 No.3218, 20230509 No.3121
		Delayed response	20200519 No.3218, 20230509 No.3121
		Failure to notice	20211201 No.611, 20230329 No.128, 20230410 No.378, 20230411 No.401, 20230406 No.2273, 20230503 No.2284, 20230731 No.117, 20231119 No.2008, 20200519 No.3218,
		Driver took action but brakes were insufficient	20230202 No.1276, 20230203 No.377, 20230212 No.219, 20230225 No.1273, 20230605 No.2124, 20230627 No.175, 20230712 No.727, 20230719 No.3165, 20230825 No.1170, 20230907 No.114, 20230924 No.272, 20230927 No.442, 20230928 No.1188, 20230930 No.155, 20231007 No.3229, 20231128 No.439, 20231231 No. 257,
	Personnel factors	Incomplete inspection mechanism	20211201 No.611, 20230202 No.1276, 20230203 No.377, 20230212 No.219, 20230225 No.1273, 20230329 No.128, 20230411 No.401, 20230605 No.2124, 20230627 No.175, 20230712 No.727, 20230825 No.1170, 20230907 No.114, 20230924 No.272, 20230930 No.155, 20231007 No.3229, 20231119 No.2008, 20231128 No.439, 20200519 No.3218,
		Unclear work standards	20200519 No.3218
		Poor work area management	20230509 No.3121

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Table 3-6 Causal Analysis of Accidents (Others)

Accident Type	Cause			Related Accident
Others (Train run-away)	Environmental	Limited visibility		20200610 No.7202
	Condition of operators	Subjective assumption by driver		
	Personnel factors	Failure to communicate		
Others (Abnormal Train Oscillation)	Environmental	Inadequate ballast filling	Speed limits	20210611 No.6046
		Track subsidence	Construction	
		Heavy locomotive		
	Condition of operators	Failure to adhere to speed limits		
	Personnel factors	Insufficient training		
Others (SPAD)	Environmental	Poor visibility of signal	ATP system not warning properly	202300422 No.4111
	Condition of operators	Misinterpretation of signals	Reliance on incorrect assumptions	
		Inadequate response to ATP warning		
	Personnel factors	Error in manual route setting		

Applying the HFACS framework allows for a comprehensive discussion of both the direct and indirect causes of these 55 accidents. Similar causes were categorized, leading to the identification of related risk factors, as shown in Table 3-7. This detailed identification and classification of risk factors facilitate a more thorough operational risk analysis and establish a solid foundation for future Bayesian network modeling and analysis.

Table 3-7 Risk factors derived from the cause of accidents

Cause	Risk factor
Adverse weather and visibility issues	Rain, Light, Visibility, Curve
Foreign object on the track	Construction, Level Crossing, Steep Grade, Catenary, Platform
Equipment and infrastructure failures	Maintenance Status, Train Performance, Construction, Steep Grade, Catenary, Platform
Train Operation	Train Type, Train Performance, Maintenance Status, Rest Hour, Duty Hour, Age, Experience
Inadequate response	Steep Grade, Curve, Communication, Duty Hour, Disease, Experience, Rest Hour, Age
Inadequate training	Age, Experience, Construction, Maintenance Status, Communication
Miscommunication and misunderstanding	Communication
Coordination and operational pressure	Communication, Train Type, Maintenance Status, Train Performance, Duty Hour, Age, Experience
Unauthorized and improper actions	Communication, Experience, Age

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Phase 3: Bayesian Network Construction with Historical Data

After identifying the risk factors, the association model containing unsafe acts and risk factors is transformed into a Bayesian network model. Specifically, based on the causal chain obtained in the previous phase, the nodes and edges of the Bayesian network are established, and the conditional probabilities between the nodes are set. This step aims to facilitate subsequent risk analysis and assist in identifying and assessing key risk factors.

Unsafe acts, which often lead to risk events, are typically the result of latent failures identified as risk factors in the previous phase. These risk factors form the leaf nodes in our Bayesian Network and contribute to unsafe behaviors, ultimately triggering risk events.

In addition to evaluating the likelihood of risk events, the potential consequences of these events are also assessed. Thus, this research not only utilizes the Bayesian Network to calculate the probability of risk events but also considers the potential outcomes, providing an assessment of overall risk. The proposed Bayesian Network for train operation risk is illustrated in Figure 3-9.

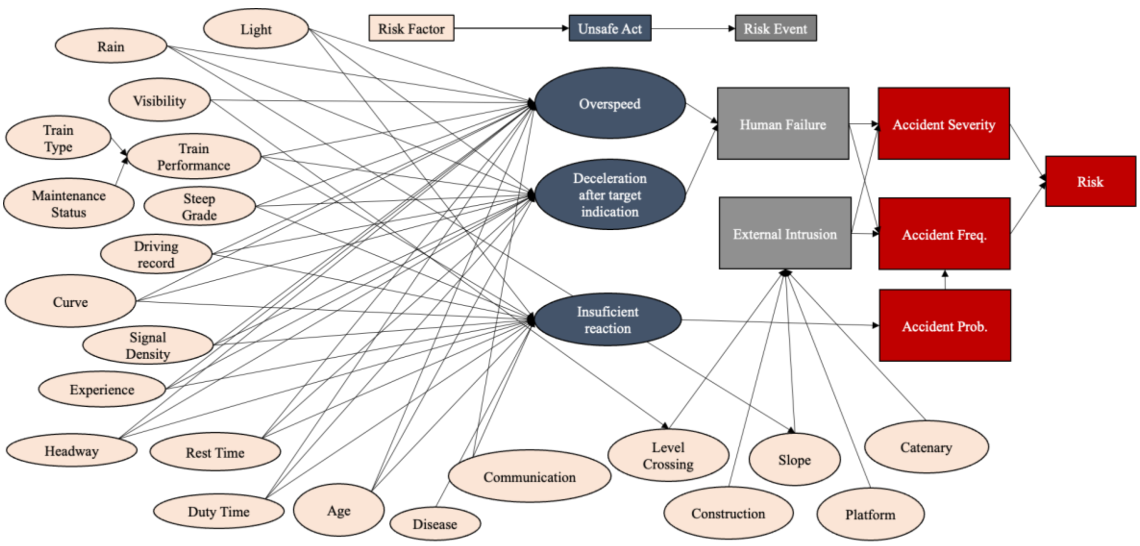

Figure 3-9 Complete Bayesian Network for Train Operation Risk

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Understanding the risk differences when driving on various sections can help train drivers prepare in advance. Thus, this research will establish a smaller-scale Bayesian network to focus on the impact of different risk factors on “Human Failure” by drivers and the risk of “External Intrusion” on various sections, as shown in Figure 3-10. This network will calculate the probabilities of these two risk events occurring. Subsequently, using historical accident casualty data, the possible consequences they may cause will be determined, thereby combining them to derive the overall train operation risk.

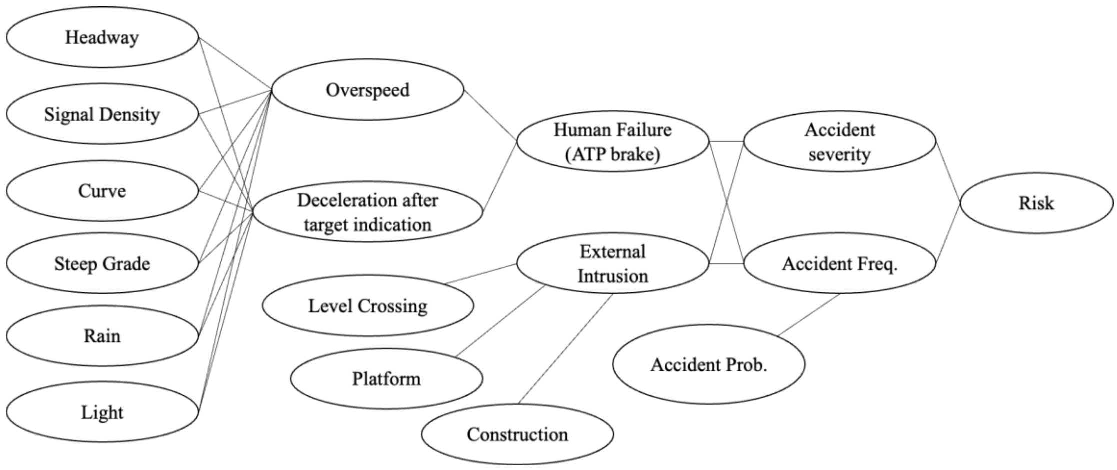

Figure 3-10 Initial Bayesian network of operation risk analysis for different section

Regarding “Human Failure”, this research explores two aspects: Overspeed and over-reliance on ATP for deceleration after target indication. Overspeed is a common type of driving error. Over-reliance on ATP for deceleration after target indication suggests that the driver only moves the master controller from acceleration or constant speed to deceleration upon hearing the ATP warning. This unsafe act indicates that the driver may not be fully attentive to operating the train. In railway systems that require adherence to wayside signals, this is highly undesirable. If braking only occurs upon receiving an ATP’s indication, it could lead to more severe situations such as SPAD. Therefore, a preliminary investigation into these two unsafe acts will be conducted.

However, with the ATP system functioning correctly, these unsafe acts can be mitigated through the train's protective mechanisms. Thus, the activation of brake by the

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ATP can be considered the last line of defense for train protection. When a train overspeed or passes a signal, if the driver can immediately react and reduce the train's speed below the permissible limit, the ATP will not activate. However, if the driver fails to respond in time, causing the train's speed to exceed the permissible speed profile set by the ATP, the system will activate brake. This means that, assuming the ATP is functioning normally, the activation of brake indicates that the train has entered a high-risk state, which is one of the most severe states. Therefore, in this research, the activation of brake by the ATP is considered a representative risk event of “Human Failure”.

Additionally, regarding the risk of “External Intrusion”, three high-risk zones will be considered: level crossings, platforms, and construction sites. The risk of “External Intrusion” will be assessed based on the frequency with which trains pass through these high-risk zones along the section, and the probability of such events will be calculated and analyzed.

However, before conducting Bayesian inference, the relationship between risk factors and risk events is not well understood. For “Human Failure”, the occurrence of each unsafe act could be related to multiple risk factors, as assumed in the Bayesian network illustrated in Figure 3-10. In such cases, the setting of an excessive number of conditional probabilities may lead to data loss issues.

Therefore, a series of steps is proposed to address this problem. First, the data is processed by analyzing historical driving records and route data to determine the states of the risk factors. This processed dataset is then used for optimizing the Bayesian network structure and setting CPTs. The detailed steps are outlined as follows.

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Step 1: Data processing

Using the Bayesian network constructed in this research, the aim is to identify how risk factors lead to unsafe acts. To obtain a more objective and quantitative assessment of driving risk, data on risk factors and unsafe behaviors will be collected from historical driving records and various route data.

For driving data, collection will be from TR's ATP system. This research will analyze data such as train speed, location, vehicle status, and route conditions, transmitting this information to the train control center to aid in operational decision-making. Based on received signals and pre-entered train characteristics, the ATP system calculates the allowable speed profile, helping to monitor train speed and ensure compliance with trackside signals and speed limits.

Additionally, the system provides detailed data on movement authorization, speed limits, curve and slope information, switch information, and distances to the next signal. The speed limits and operational data derived from the ATP system ensure enhanced safety and efficiency in railway transportation. Figure 3-11 illustrates the various types of information that can be obtained from the ATP system.

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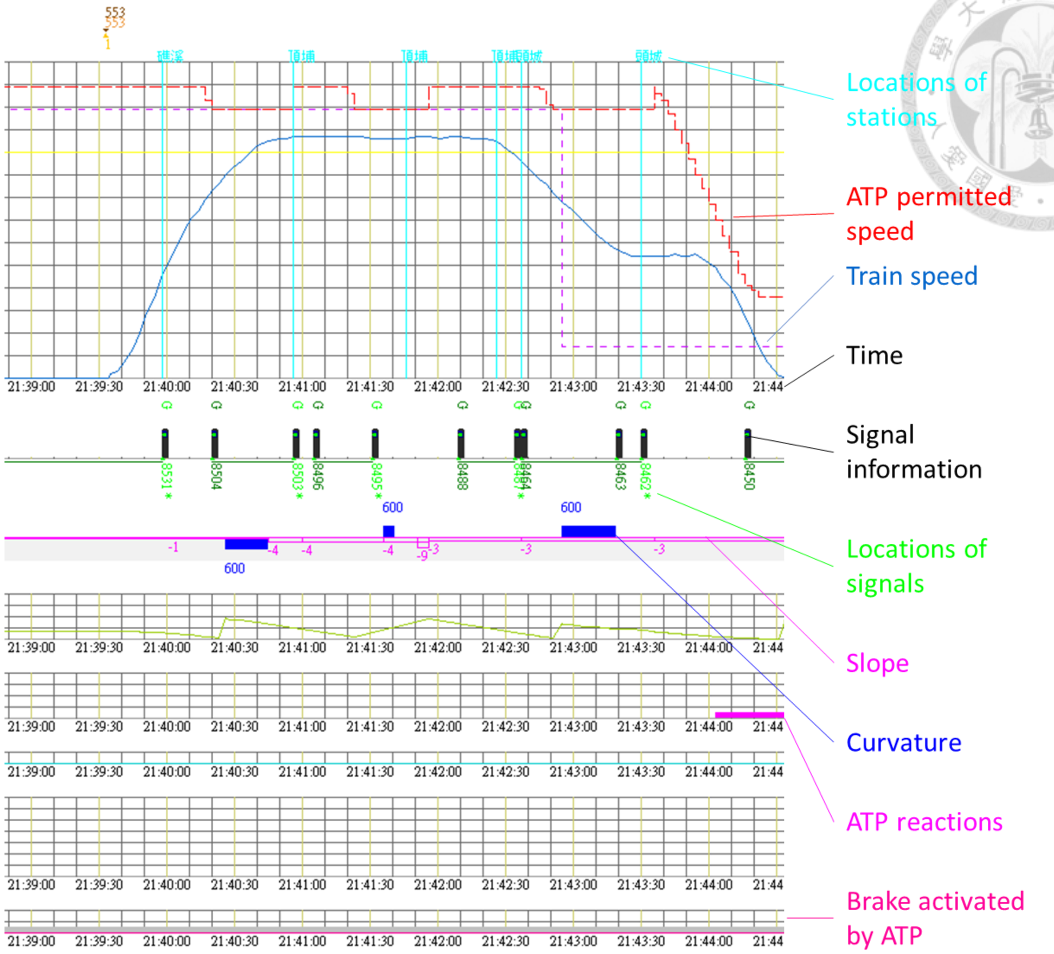

Figure 3-11 Part of the driving record figure and the contained information

For determining unsafe acts, the high-risk behavior identification module established by Chen (2019) is utilized to analyze ATP data. This module, by converting the graphical data of ATP, comparing the actual train speed with the ATP permitted speed, and determining ATP activations, allows us to automatically identify six high-risk driving behaviors from ATP data, such as overspeed and emergency brake activations.

Over a three-month period, this research collects the ATP driving record figures of Puyuma express trains. A total of 4,586 effective data entries were obtained, involving 540 drivers and covering an operational mileage of 811,004.7 train-kilometers. In this research, to achieve more precise conditions for each section, we analyze the data based on block. From this dataset, we obtained usable data for 523 trains and 74,266 blocks. According to our Bayesian network model, which focuses on the risk events related to

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"Human Failure", the probabilities of unsafe acts such as overspeed, deceleration after target indication, and the ATP activating brake are presented in the Table 3-8. It can be observed that among all the blocks we analyzed, the probability of overspeed is the highest, while the ATP activating brake is the lowest. This aligns with our Bayesian network definition, where ATP activating brake represents a relatively high-risk state.

Table 3-8 Unsafe acts and risk event appear probability

Unsafe acts/ Risk event	Number	Probability
Deceleration after target indication	719	0.0097
Overspeed	1403	0.0189
ATP brake	28	0.0004

Step 2: Risk factor state determination

Next, determining the state of the risk factors is crucial. For "Human Failure", the following six risk factors will be considered: headway, signal density, curve, steep grade, rain, and light. Referencing past literature on driving behavior, Taiwan Railway's operating regulations, and definitions from the Central Weather Administration (CWA), the risk states for the six factors contributing to "Human Failure" are defined in Table 3-9.

Table 3-9 Unsafe condition for each risk factor

Risk factor	Unsafe Condition	Reference
Headway	Train headway < 10 minutes	Sun (2012)
Signal Density	Block length < 1200 m	Fan (2022)
Curve	Curve radius < 900 m	TR regulation
Steep Grade	Grade > 5‰ (Downhill)	TR regulation
Rain	Hourly rainfall > 0.1 mm	CWA
Light	Insufficient lighting (tunnel, nighttime)	Sun (2014)

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To ensure that our defined risk states align with historical driving data, headway, signal density, curve, and steep grade are classified to determine the probability of driver risk behaviors within different categories. The determination of risk behaviors is calculated using the Integrated Risk Index for Driving Behaviors (IRIDB) proposed by Chen (2019), and the results are shown in Figure 3-12.

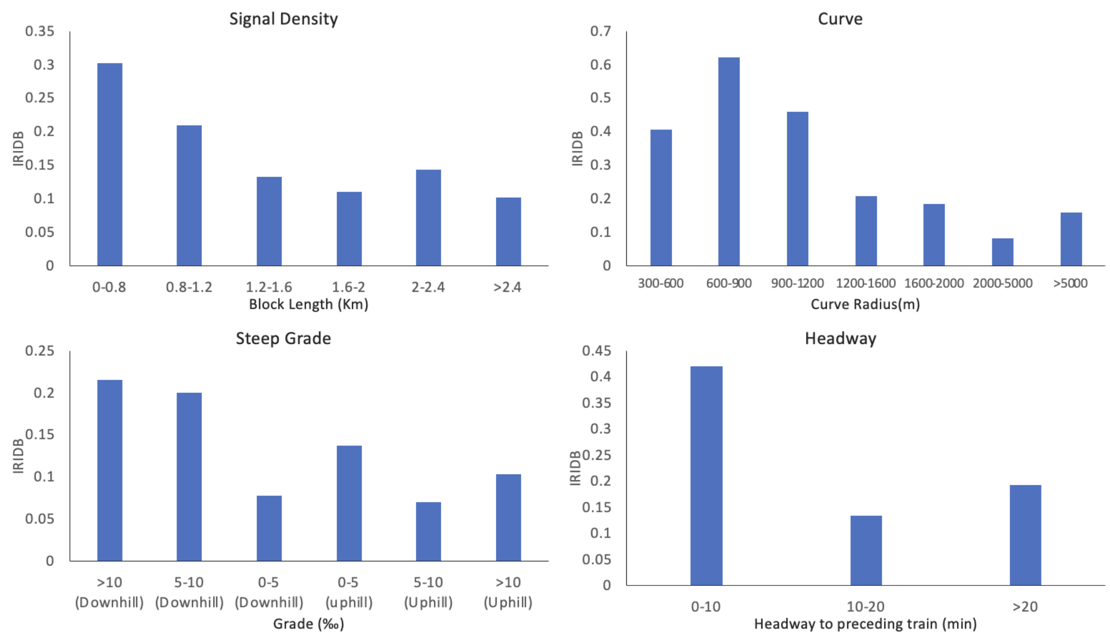

Figure 3-12 IRIDB under each category of risk factors

The results show that the defined risk states align with the driving data. When the headway is less than 10 minutes, the risk increases, likely due to reduced reaction time for train operators. For signal density, a block length of less than 1200 meters is considered unsafe because it may lead to higher signal density, increasing the cognitive load on train operators. Curve radius of less than 900 meters is considered unsafe due to the stricter speed limits required, which can increase the difficulty in maneuvering the train and potentially lead to “Human Failure”. Steep grade, observed from the figure, show that when the grade exceeds 5‰ (downhill), the risk significantly increases. This heightened risk is likely due to the additional challenges in braking and acceleration control.

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Furthermore, rain is considered unsafe when the hourly rainfall exceeds 0.1 mm, as defined by the CWA. Rain can affect visibility and cause slippery tracks, which may lead to train slippage and increased braking distances. Insufficient lighting, such as in tunnels or during nighttime, is considered unsafe because it reduces visibility for train operators, increasing the risk of “Human Failure”.

For the 74,266 block data records obtained through the ATP system, this dataset will be enhanced by incorporating weather data from the CWB, corresponding to the time when each train passed. Additionally, route data from the TR will be used to obtain the maximum grade and curve radius for each section, and the headway between trains will be calculated using historical timetables.

Using Table 3-9, this research determines whether each factor in the dataset meets the risk criteria. Furthermore, a high-risk behavior identification module will be employed to evaluate whether unsafe behaviors occurred. This approach will form the dataset required for subsequent analysis.

Step 3: Network learning

In this research, an initial hierarchical structure is utilized to construct and learn optimal Bayesian networks. Given the clear hierarchical relationships, each arc is evaluated and eliminated based on their scores to build the optimal network structure.

First, the initial Bayesian network structure is set up, including connections between risk factors and intermediate nodes (unsafe acts) as well as between intermediate nodes and outcome nodes (risk events). The HillClimbSearch algorithm is employed for the search, and BIC is used as the scoring method to guide the optimization of the model.

Each node and arc are configured according to its specific hierarchical level. For instance, risk factors are only parent nodes, intermediate nodes can be both parent and child nodes, and outcome nodes are only child nodes. This configuration effectively

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controls the structure of the model, ensuring it aligns with the logical relationships in the real-world application.

To further learn the network structure, it is ensured that each risk factor is connected to at least one unsafe act. The connection is selected by calculating the BIC score for each potential link to the intermediate nodes, ultimately choosing the link with the higher score. This approach guarantees that the model is not only structurally sound but also statistically robust.

Additionally, fixed edges are established (such as ensuring that unsafe acts must connect to risk events) to prevent the deletion of certain crucial structures. These fixed edges reflect necessary associations in practical applications, ensuring the model's stability and interpretability.

Finally, the performance of the optimal model is evaluated by calculating the BIC score. This method, based on hierarchical structure and arc score evaluation, enables the construction of efficient and accurate Bayesian network in complex data environments. Pseudo code for the Bayesian network learning is shown below.

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```
Input: ATP data, weather data, route data, condition for each factor
Output: Optimized Bayesian Network structure
function determine_optimal_structure(ATP_data, weather_data, route_data, conditions):
    // Set conditions
    conditions = input conditions
    // Determine the state of each factor
    for each record in ATP_data:
        state = determine_state(record, weather_data, route_data)
        update record with state
    // Use high-risk behavior identification module to determine unsafe behaviors for each record
    for each record in ATP_data:
        record.unsafe_behavior = identify_unsafe_behavior(record)
    // Generate dataset
    dataset = create_dataset(ATP_data)
    // Set initial structure
    initial_structure = set_initial_structure()
    // Use HillClimbSearch algorithm to obtain optimal structure
    optimized_structure = hill_climb_search(dataset, initial_structure)
return optimized_structure
```

By following the learning process for network structure described, the scores for each arc were analyzed to determine their significance. The detailed scores for each arc are presented in Table 3-10. From this analysis, it can be concluded that among the proposed section risk factors, those related to overspeed have more direct connections. Specifically, overspeed is connected to headway, light, rain, and curve. Shorter headways may cause trains to be more affected by the preceding train, leading to speed restrictions. Additionally, other special environmental conditions might prevent drivers from quickly recognizing signal or cause difficulties in accelerating and decelerating. On the other hand, unsafe act associated with excessive reliance on ATP driving appear to be more directly linked to the driver's operations and personality traits. Deceleration after target indication is only linked to steep grade and signal density.

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Table 3-10 BIC increment score for each arc

Parent Node	Child Node	BIC Increment Score
Headway	Deceleration after target indication	-9205.04
Light	Deceleration after target indication	-9264.53
Rain	Deceleration after target indication	-9287.9
Steep Grade	Deceleration after target indication	-9283.76
Curve	Deceleration after target indication	-9286
Signal Density	Deceleration after target indication	-9286.67
Headway	Overspeed	-9196.19
Light	Overspeed	-9263.05
Rain	Overspeed	-9287.97
Steep Grade	Overspeed	-9282.97
Curve	Overspeed	-9285.76
Signal Density	Overspeed	-9287.11
Overspeed	Human Failure (ATP brake)	-9282.27
Deceleration after target indication	Human Failure (ATP brake)	-9282.17

The resulting optimal network in Figure 3-13, shows these relationships clearly. This optimal network provides a robust foundation for understanding the intricate relationships between various risk factors and driver behaviors. However, with the acquisition of more information about the drivers themselves in future research, differences between drivers based on these behaviors can be further explored.

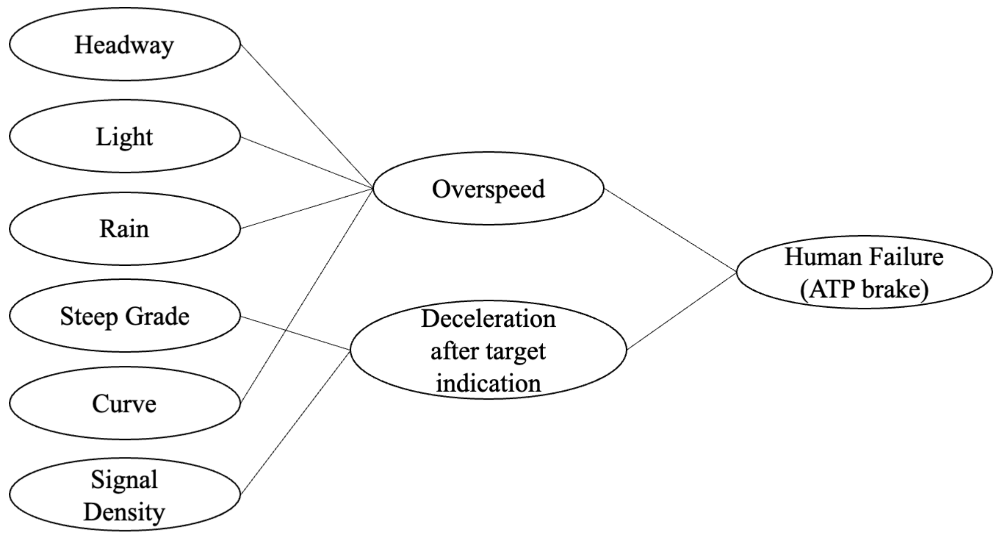

Figure 3-13 Optimal network structure for “Human Failure”

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Step 4: Conditional probability setting

In this step, this research defines the conditions for filtering data and calculate the conditional probabilities for each scenario. These conditions form the basis for generating different scenarios to evaluate potential unsafe acts. All possible combinations of these conditions are generated, and the probability of an unsafe act for each scenario is calculated using historical data.

```
Input: conditions, historical data
Output: conditional probabilities for each scenario
function define_conditions_and_calculate_probabilities(conditions, df):
    // Define conditions for filtering data
    conditions = input conditions
    // Generate all possible condition combinations (scenarios)
    scenarios = generate all combinations of True and False for conditions
    // Initialize list for probabilities of each unsafe act
    probabilities_list = initialize empty list
    // Calculate probabilities for each scenario
    for each scenario in scenarios:
        selected_rows = df
        for each condition in scenario:
            filter selected_rows based on condition
        probability = calculate probability for the filtered rows
        append probability to probabilities_list
    return conditions, probabilities_list
```

Using the procedure mentioned above, the conditional probabilities for each of the six risk factors under different states can be calculated. This involves analyzing the frequency with which each risk factor condition correlates with the occurrence of an unsafe act or risk event. Here, the CPT for the initial network structure is first presented. A total of 128 conditional probabilities for unsafe acts are generated, representing all possible combinations of the six risk factors. The detailed CPTs are illustrated in Table 3-11 and Table 3-12.

doi:10.6342/NTU202404075

Table 3-11 The CPT of overspeed for initial network

Scenario	Headway	Light	Rain	Steep Grade	Curve	Signal Density	Prob.
1	Y	Y	Y	Y	Y	Y	0.048
2	Y	Y	Y	Y	Y	N	0.006
3	Y	Y	Y	Y	N	Y	0.027
4	Y	Y	Y	Y	N	N	0.005
5	Y	Y	Y	N	Y	Y	0.037
6	Y	Y	Y	N	Y	N	0.022
7	Y	Y	Y	N	N	Y	0.015
8	Y	Y	Y	N	N	N	0.019
9	Y	Y	N	Y	Y	Y	0.032
10	Y	Y	N	Y	Y	N	0.005
11	Y	Y	N	Y	N	Y	0.005
12	Y	Y	N	Y	N	N	0.016
13	Y	Y	N	N	Y	Y	0.031
14	Y	Y	N	N	Y	N	0.016
15	Y	Y	N	N	N	Y	0.012
16	Y	Y	N	N	N	N	0.020
17	Y	N	Y	Y	Y	Y	0.028
18	Y	N	Y	Y	Y	N	0.007
19	Y	N	Y	Y	N	Y	0.002
20	Y	N	Y	Y	N	N	0.007
21	Y	N	Y	N	Y	Y	0.023
22	Y	N	Y	N	Y	N	0.006
23	Y	N	Y	N	N	Y	0.017
24	Y	N	Y	N	N	N	0.007
25	Y	N	N	Y	Y	Y	0.028
26	Y	N	N	Y	Y	N	0.005
27	Y	N	N	Y	N	Y	0.003
28	Y	N	N	Y	N	N	0
29	Y	N	N	N	Y	Y	0.019
30	Y	N	N	N	Y	N	0.008
31	Y	N	N	N	N	Y	0.014
32	Y	N	N	N	N	N	0
33	N	Y	Y	Y	Y	Y	0.010
34	N	Y	Y	Y	Y	N	0
35	N	Y	Y	Y	N	Y	0.009
36	N	Y	Y	Y	N	N	0.030
37	N	Y	Y	N	Y	Y	0.008
38	N	Y	Y	N	Y	N	0.005
39	N	Y	Y	N	N	Y	0.001
40	N	Y	Y	N	N	N	0.025
41	N	Y	N	Y	Y	Y	0.013
42	N	Y	N	Y	Y	N	0
43	N	Y	N	Y	N	Y	0.005
44	N	Y	N	Y	N	N	0
45	N	Y	N	N	Y	Y	0
46	N	Y	N	N	Y	N	0.004
47	N	Y	N	N	N	Y	0
48	N	Y	N	N	N	N	0
49	N	N	Y	Y	Y	Y	0.007
50	N	N	Y	Y	Y	N	0
51	N	N	Y	Y	N	Y	0
52	N	N	Y	Y	N	N	0
53	N	N	Y	N	Y	Y	0
54	N	N	Y	N	Y	N	0.004
55	N	N	Y	N	N	Y	0.004
56	N	N	Y	N	N	N	0
57	N	N	N	Y	Y	Y	0.015
58	N	N	N	Y	Y	N	0.030
59	N	N	N	Y	N	Y	0
60	N	N	N	Y	N	N	0
61	N	N	N	N	Y	Y	0
62	N	N	N	N	Y	N	0.010
63	N	N	N	N	N	Y	0.002
64	Y	N	N	N	N	N	0

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Table 3-12 The CPT of deceleration after target indication for initial network

Scenario	Headway	Light	Rain	Steep Grade	Curve	Signal Density	Prob.
1	Y	Y	Y	Y	Y	Y	0.024
2	Y	Y	Y	Y	Y	N	0.002
3	Y	Y	Y	Y	N	Y	0
4	Y	Y	Y	Y	N	N	0
5	Y	Y	Y	N	Y	Y	0.014
6	Y	Y	Y	N	Y	N	0.017
7	Y	Y	Y	N	N	Y	0.002
8	Y	Y	Y	N	N	N	0
9	Y	Y	N	Y	Y	Y	0.035
10	Y	Y	N	Y	Y	N	0
11	Y	Y	N	Y	N	Y	0.005
12	Y	Y	N	Y	N	N	0
13	Y	Y	N	N	Y	Y	0.018
14	Y	Y	N	N	Y	N	0.008
15	Y	Y	N	N	N	Y	0
16	Y	Y	N	N	N	N	0
17	Y	N	Y	Y	Y	Y	0.008
18	Y	N	Y	Y	Y	N	0.001
19	Y	N	Y	Y	N	Y	0
20	Y	N	Y	Y	N	N	0
21	Y	N	Y	N	Y	Y	0.006
22	Y	N	Y	N	Y	N	0.003
23	Y	N	Y	N	N	Y	0.013
24	Y	N	Y	N	N	N	0.004
25	Y	N	N	Y	Y	Y	0.011
26	Y	N	N	Y	Y	N	0.002
27	Y	N	N	Y	N	Y	0
28	Y	N	N	Y	N	N	0
29	Y	N	N	N	Y	Y	0.007
30	Y	N	N	N	Y	N	0.002
31	Y	N	N	N	N	Y	0.009
32	Y	N	N	N	N	N	0.011
33	N	Y	Y	Y	Y	Y	0
34	N	Y	Y	Y	Y	N	0.108
35	N	Y	Y	Y	N	Y	0.011
36	N	Y	Y	Y	N	N	0
37	N	Y	Y	N	Y	Y	0.013
38	N	Y	Y	N	Y	N	0.007
39	N	Y	Y	N	N	Y	0.005
40	N	Y	Y	N	N	N	0
41	N	Y	N	Y	Y	Y	0
42	N	Y	N	Y	Y	N	0.106
43	N	Y	N	Y	N	Y	0
44	N	Y	N	Y	N	N	0
45	N	Y	N	N	Y	Y	0.010
46	N	Y	N	N	Y	N	0.004
47	N	Y	N	N	N	Y	0.002
48	N	Y	N	N	N	N	0
49	N	N	Y	Y	Y	Y	0.018
50	N	N	Y	Y	Y	N	0.116
51	N	N	Y	Y	N	Y	0.003
52	N	N	Y	Y	N	N	0
53	N	N	Y	N	Y	Y	0.002
54	N	N	Y	N	Y	N	0.009
55	N	N	Y	N	N	Y	0.004
56	N	N	Y	N	N	N	0.009
57	N	N	N	Y	Y	Y	0.012
58	N	N	N	Y	Y	N	0.091
59	N	N	N	Y	N	Y	0
60	N	N	N	Y	N	N	0
61	N	N	N	N	Y	Y	0
62	N	N	N	N	Y	N	0.008
63	N	N	N	N	N	Y	0.005
64	Y	N	N	N	N	N	0.025

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In Table 3-11 and Table 3-12, it is observed that the occurrence of unsafe acts is infrequent, resulting in many scenarios with conditional probabilities of zero. This confirms the issue highlighted earlier: with a limited dataset or an increasing number of risk factors, there will be more instances of missing data. This underscores the importance of learning the network structure.

In the optimal network, reducing the number of connections between risk factors and unsafe acts significantly improves the accuracy of the CPTs. As shown in Table 3-13 to Table 3-15, for three key nodes, the CPTs provide clearer and more reliable probability estimates for each condition. It is evident that with fewer connections, the probabilities under each scenario can be determined more accurately.

Table 3-13 The CPT for overspeed for optimal network

Scenario	Headway	Light	Rain	Curve	Probability
1	Y	Y	Y	Y	0.038
2	Y	Y	Y	N	0.018
3	Y	Y	N	Y	0.017
4	Y	Y	N	N	0.017
5	Y	N	Y	Y	0.024
6	Y	N	Y	N	0.007
7	Y	N	N	Y	0.012
8	Y	N	N	N	0.006
9	N	Y	Y	Y	0.008
10	N	Y	Y	N	0.004
11	N	Y	N	Y	0.003
12	N	Y	N	N	0.020
13	N	N	Y	Y	0.007
14	N	N	Y	N	0.006
15	N	N	N	Y	0.003
16	N	N	N	N	0.000

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Table 3-14 The CPT for deceleration after target indication for optimal network

Scenario	Steep Grade	Signal Density	Probability
1	Y	Y	0.015
2	Y	N	0.002
3	N	Y	0.009
4	N	N	0.006

Table 3-15 The CPT of “Human Failure” (ATP brake)

Overspeed		Y		N	
Decelerate after target indication		Y	N	Y	N
ATP brake	Y	0.25	0.017	0	0.00002
	N	0.75	0.983	1	0.99998

Phase 4: Bayesian Inference

Upon obtaining the optimal network structure and the CPTs for each node, the next step involves inputting the latest data for each train service. This process involves setting the prior probabilities for each factor using equation (6), which combines these prior probabilities with the scenario-specific conditional probabilities to determine the total probability of each unsafe act occurring in each scenario. Ultimately, using the CPTs for the risk event—specifically, the activation of the ATP brake—allows for the estimation of overall risk event probabilities. The pseudocode for this phase is outlined below.

In this phase, actual train data is inputted to calculate the probability of risk events occurring on each block of the section. For instance, using a block between Shulin and Banqiao as an example, the initial probabilities for the six risk factors related to “Human Failure”—headway, light, rain, steep grade, curve, and signal density—are set as follows: 1, 0.2, 0.8, 0.6, 0.6, 0.2. The final calculated probability of an ATP brake occurrence is 0.00026. The complete assessment will be detailed in case study, providing a full evaluation of the train's risk event probabilities for each block in every section.

doi:10.6342/NTU202404075

```
Input: prior probabilities, conditional probabilities
Output: overall risk event probabilities
function calculate_risk_event_probabilities(prior_probabilities, probabilities_list):
    // Initialize list to store total probabilities
    total_probabilities = initialize empty list
    // Iterate through each set of section conditions
    for each section_condition in prior_probabilities:
        scenario_probabilities = initialize empty list
        // Calculate the probability for each scenario
        for each scenario in scenarios:
            probability = initialize to 1.0
            for each condition in scenario:
                calculate probability based on section_condition and
                condition
            append calculated probability to scenario_probabilities
        // Calculate total probability for each unsafe act
        total_probability = {"Unsafe Act Probabilities": calculate
        combined probability for each unsafe act}
        append total_probability to total_probabilities
    // Return the total probabilities
    return total_probabilities
```

Phase 5: Consequence Analysis

Based on the prior probabilities of factors and the CPTs derived from historical data, the probability of risk events can be estimated. However, when determining the final risk, it is essential to consider both the probability of the risk event causing an accident and the severity of the potential outcomes. Different risk events can lead to various consequences, and both aspects must be taken into account for risk assessment.

McKinnon (2012) conceptualized risk as a combination of probability, frequency, and severity. Here, probability refers to the likelihood that near-miss events will turn into accidents, frequency denotes the number of near-miss events over a given period, and severity represents the consequences of the worst-case scenarios. This can be expressed as equation (14).

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$$Risk = Frequency \times Probability \times Consequence \tag{14}$$

In fact, a risk event can also be seen as a near-miss because its occurrence does not necessarily lead to an accident. However, in situations with few accidents, assessing the ultimate risk based on the frequency of risk events is a viable method. As illustrated in Figure 3-13, n represents the frequency of risk events, k is the number of accident types considered, p_j represents the rate of occurrence of the type j of accident caused by the risk event, x_j is the occurrence number of the type j of accident, and s_j is the severity of the type j of accident. Since x_j can be calculated as:

$$x_j = n \times p_j \tag{15}$$

By combining x_j and s_j, we can determine the consequence of the type j of accident caused by the risk event. Therefore, we can change equation (14) to equation (16).

$$R = \sum_{j=1}^{k} n \times p_j \times s_j \qquad \forall j \in J \tag{16}$$

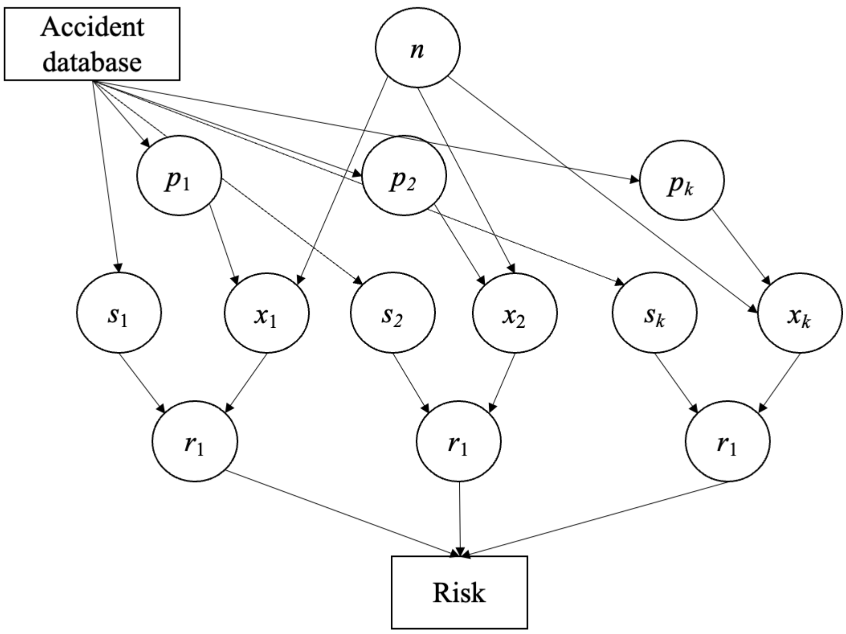

Figure 3-14 Bayesian Network of Risk Consequences

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In this research, the probability of risk events is converted into relative frequency to calculate the collective risk. The rationale behind this conversion, as explained by Stone (1994), is that when the probability of risk events is extremely low, discussing the data in isolation becomes meaningless and does not provide practical insights for risk management. By focusing on relative frequencies, more meaningful comparisons can be made between different sections to better understand their relative risk levels.

The risk events defined in this research may lead to accidents such as train derailments, collisions, level crossing accidents, and obstruction accidents. Each of these accidents has different probabilities and consequences. After determining the frequency of risk events, historical accident data is used to obtain the number and consequences of accidents.

To establish the ability to rank risks, this research combines the Bayesian Network synthesized relative frequencies of risk events and the severity of accidents, converting this information into clear values. After calculating the risk value for each block in every section, the highest block risk is taken as the risk for that section, as shown in equation (17). The rationale behind this setup is that it might be too complex for drivers to pay attention to the risk of each individual block. Considering the average risk across a section could obscure the risk of specific blocks by offsetting them with others. By setting the section risk based on the highest-risk block within that section, drivers can quickly and clearly understand the risk of the entire section without overlooking the risk of any single block. This approach helps ensure that drivers are aware of the most significant risks as they navigate each section.

$$R_i = \max R_{ij} \qquad \forall i \in I, j \in J \tag{17}$$

where R_i is the section risk of section i and R_{ij} is the block risk of block j in section i.

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Phase 6: Predominate Factors Search

In railway risk management, identifying and controlling predominate risk factors is a crucial step in mitigating accident risks. The following outlines a systematic method to identify predominate risk factors for specific sections of the railway, based on the third definition of critical risk factors proposed by Hadjimichael (2009), which involves identifying factors that provide the greatest marginal reduction in overall risk. Let r_{root} represent the risk function at the root node, and f_i denote the risk factor i. The marginal impact of adjusting a factor can be expressed using the following equation:

$$i^* = argmax_i \left| \frac{\partial r_{root}}{\partial f_i} \right| \tag{18}$$

However, since r_{root} does not have an explicit functional form, directly using the above equation is impractical. Therefore, the following algorithm is employed to approximate this equation. The algorithm traces from the root node to the leaf nodes (i.e., the risk factors) and identifies the necessary changes at these nodes to reduce the root node's risk to the target value.

Step 1: Set the target risk value

Begins by setting an optimal risk value for each section, ensuring that this value falls within an acceptable safety range, typically below a specific risk level. This optimal risk value is denoted as R_{Target}, aims to reduce the risk to this safe range, thereby ensuring the safety of train operations.

Step 2: Calculate Necessary Adjustments and adjust risk factors systematically

After establishing the target risk value, calculate the necessary adjustments in the prior probabilities of each risk factor. These adjustments must adhere to certain constraints to ensure they remain within a reasonable range.

The process involves iteratively adjusting each risk factor's probability, p_i, within a predefined range and observing the impact on the overall risk value:

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$$R_{new} = f(p_1, p_2, \dots, p_i + \Delta p, \dots, p_n) \tag{19}$$

where Δp is the adjustment made to the probability of the risk factor i.

Step 3: Identify effective adjustments

Once the required adjustments are identified, the predominate risk factor for that section is selected. The chosen factor should be the one with the smallest adjustment yet the greatest impact, ensuring the maximum risk reduction effect with minimal adjustment.

If adjusting a single factor is not sufficient to reach the target risk value, consider combinations of two factors. This iterative approach is formalized as follows:

$$R_{new} = f(p_1, p_2, \dots, p_i + \Delta p_i,\ p_j + \Delta\, p_j, \dots, p_n) \tag{20}$$

where Δp_i and Δp_j is the adjustment made to the probability of the risk factor *i* and *j* respectively.

Step 4: Select final adjustments

Continue the iterative process until the target risk value is achieved. This may involve adjusting multiple factors in combination to identify the optimal set of adjustments. Ensure that the selected factors and their adjustments provide the greatest impact on risk reduction within the constraints of reasonable adjustments.

This systematic methodology ensures that the identification of predominate risk factors is effectively achieved, thereby enhancing the overall safety of train operations. By following these steps, railway operators can not only understand which sections are high-risk but also gain insights into the specific factors contributing to these risks. This enables targeted interventions that are both efficient and effective in reducing the overall risk, ensuring safer operations.

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CHAPTER 4 CASE STUDY

In this chapter, a case study using a Bayesian Network focused on section-specific risk factors is conducted to illustrate the differences in train operation risks across various sections. Section 4.1 introduces the analysis network and presents the results of the risk assessment. This includes the probability of risk events and the final risk, which combines the likelihood of accidents and their consequences. Section 4.2 performs a BN validation. Finally, in section 4.3, corresponding risk control measures are proposed, aiming to reduce risk through the analysis and implementation of appropriate countermeasures.

4.1 Risk Assessment

In the risk assessment phase, this research focuses primarily on environmental risk factors. Through data analysis, network learning, conditional probability and prior probability settings, and consequence analysis, the risk assessment of each section will be able to provide drivers with a basis for judgment before driving.

4.1.1 Analysis Network

Taiwan Railway started operating conventional railway in Taiwan since 1887. The railway network in Taiwan forms a big circular mainline surrounding Taiwan with nine branch lines goes deep into plains and hills.

In 2023, the Taiwan Railway's network comprised a total of 241 stations and 1,065 kilometers of operational mileage. The Taiwan Railway's network can be broadly divided into four parts: the Western Main Line, the Eastern Main Line, the South-link Line, and the branch lines. Figure 4-1 illustrates the network used for case study of train operation risk assessment. This route starts from Shulin and ends at Hualien, encompassing three lines.

The section between Shulin and Badu is part of the Western Main Line, which is the busiest section in TR due to the operation of trains from both the Western Main Line and

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the Eastern Main Line. The section between Badu and Su'aosin belongs to the Yilan Line. The northern half of this section is in a mountainous region with numerous sharp curves, while the southern half is in a plain region. Xinma Station, where the Puyuma derailment accident occurred, is also located in this section. The section between Su'aoxin and Hualien is the North-link Line. Although this section crosses a mountain range, long tunnels and bridges make it relatively straight compared to the other two parts.

Notably, two major accidents occurred in 2018 and 2021, respectively, both happened along the route from Shulin to Hualien, which is one of the reasons this particular route was chosen for the case study in this research.

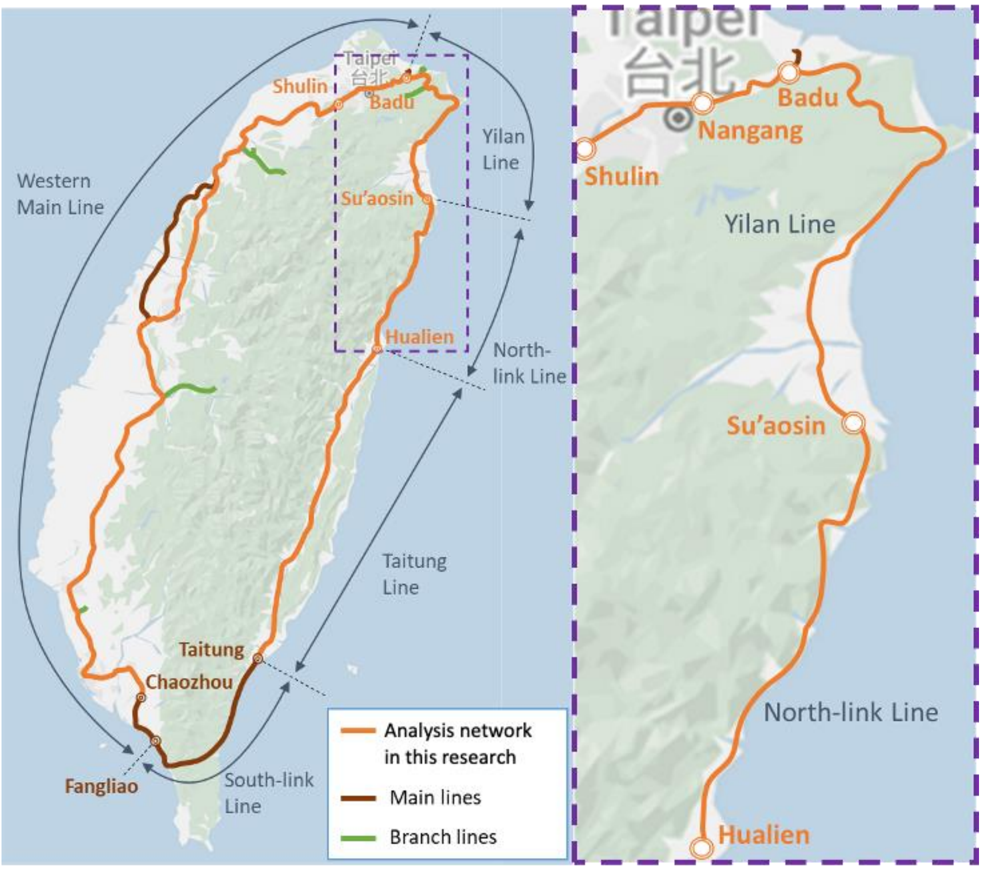

Figure 4-1 Analysis network

For setting the prior probabilities, Train No. 408 is analyzed as an example. This train departs from Shulin at 07:06 and arrives in Hualien at 09:40. It is assumed that rainfall might impact the segment from Nangang to Su'aoxin. The prior probabilities of

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other factors are determined based on the risk standards defined in Table 3-6 and equation (6) are shown in Table 4-1.

Table 4-1 Prior probability setting for Train No.408

Section	Block Number	Headway	Light	Rain	Steep Grade	Curve	Signal Density	Level Crossing	Platform	Construction
Shulin-Banqiao	1	1	0	0.8	0.16	0.23	0	0.19	0	0
	2	1	0	0.8	0.06	0.3	0	0.15	1	0
	3	1	0.35	0.8	1	0.22	0	0	0	0
	4	1	1	0	0.2	0.1	1	0	0	0
	5	1	1	0	0	0	0	0	1	0
Banqiao-Wanhua	6	1	1	0	0	0	0	0	0	0
	7	1	1	0	0.87	0.18	0	0	0	0
	8	1	1	0	0.74	0.33	1	0	0	0
	9	1	1	0	0	0.3	0	0	1	0
Wanhua-Taipei	10	1	1	0	0	0.41	1	0	0	0
	11	1	1	0	0	0	1	0	0	0
	12	1	1	0	0	0.41	0	0	1	0
Taipei-Songshan	13	1	1	0	0.34	0.27	0	0	0	0
	14	1	1	0	0.2	0.19	0	0	0	0
	15	1	1	0	0	0.21	1	0	0	0
	16	1	1	0	0	0	1	0	0	0
	17	1	1	0	0.79	0	0	0	1	0
Songshan-Nangang	18	1	1	0	0.66	0	0	0	0	0
	19	1	1	0	0	0	1	0	1	0
Nangang-Xizhi	20	1	1	0	0	0	1	0	0	0
	21	1	1	0	0	0	0	0	0	0
	22	1	1	0	0	0	1	0	0	0
	23	1	0	0.8	0	0.36	0	0	1	0
Xizhi-Qidu	24	1	0	0.8	0	0.73	0	0	0	0
	25	1	0	0.8	0.41	0.35	0	0	0	0
	26	1	0	0.8	0	0.14	0	0	0	0
	27	1	0	0.8	0	0.19	0	0	0	0
	28	1	0	0.8	0	0.56	0	0	1	0
Qidu-Badu	29	0	0	0.8	0	0.23	0	0	0	0
	30	0	0	0.8	0.51	0.4	0	0	1	0
Badu-Ruifang	31	0	0	0.9	0	0.78	1	0	0	0
	32	0	0	0.9	0	0.29	0	0.18	1	0
	33	0	0	0.9	0	0.41	1	0	0	0
	34	0	0	0.9	0	0.21	0	0.18	1	0
	35	0	0.52	0.9	0	0.26	0	0	0	0
	36	0	0	0.9	0	0.52	1	0	0	0
	37	0	0.15	0.9	0	0.59	0	0	0	0
	38	0	0.19	0.9	0	0.25	0	0.3	1	0
Ruifang-Shuangxi	39	1	0.24	0.9	0	0.48	1	0.29	0	0
	40	1	0.61	0.9	0	0.37	1	0	0	0
	41	1	0.23	0.9	0	0.23	0	0	1	0
	42	1	0.58	0.9	0	0.05	1	0	0	0
	43	1	0	0.9	0	0.59	1	0	0	0.44
	44	1	0.16	0.9	0.2	0.55	0	0	1	0
	45	1	0.56	0.9	1	0.28	0	0	1	0
	46	1	0	0.9	1	0.49	0	0	0	0
	47	1	0	0.9	1	0.61	1	0	0	0
	48	1	0.46	0.9	0.52	0.41	0	0	1	0
Shuangxi-Fulong	49	0	0.31	0.9	1	0.21	1	0	0	0
	50	0	0	0.9	0.07	0.43	0	0	0	0
	51	0	0	0.9	0.74	0.62	1	0	0	0
	52	0	0	0.9	0	0.37	0	0	1	0
	53	0	0	0.9	0.28	0.08	0	0	0	0.12
	54	0	0	0.9	0.38	0.38	1	0	0	0
	55	0	0	0.9	0.35	0.26	0	0	1	0
Fulong-Daxi	56	0	0.64	0.9	0.55	0.24	0	0	0	0
	57	0	0	0.9	0.48	0.38	0	0	1	0
	58	0	0	0.9	0	0	1	0	0	0
	59	0	0	0.9	0.16	0.22	0	0	1	0
	60	0	0.33	0.9	0	0.44	1	0	0	0
	61	0	0.32	0.9	0	0.21	0	0	0	0
	62	0	0	0.9	0	0.13	0	0.16	1	0

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Section	Block Number	Headway	Light	Rain	Steep Grade	Curve	Signal Density	Level Crossing	Platform	Construction
Daxi-Tuocheng	63	0	0.78	0.9	0	0.39	0	0	0	0
	64	0	0.33	0.9	0	0.55	1	0	0	0
	65	0	0	0.9	1	0.38	1	0	1	0
	66	0	0	0.9	0	0.23	0	0	0	0
	67	0	0.26	0.9	0.53	0.56	0	0	0	0
	68	0	0	0.9	0	0.24	0	0	1	0
	69	0	0	0.9	0	0	0	0	0	0
	70	0	0	0.9	0	0	1	0	0	0
	71	0	0	0.9	0	0.14	0	0.17	1	0
Tuocheng-Yilan	72	0	0	0.9	0.32	0.24	0	0.39	0	0
	73	0	0	0.9	0	0.08	0	0.3	1	0
	74	0	0	0.9	0	0	0	0.22	0	0
	75	0	0	0.9	0	0.52	1	0.61	0	0
	76	0	0	0.9	0	0	0	0.18	1	0
	77	0	0	0.9	0.3	0.15	0	0.35	0	0
	78	0	0	0.9	0.09	0	0	0	0	0
	79	0	0	0.9	0.25	0	0	0.29	1	0
	80	0	0	0.9	0	0	0	0	0	0
	81	0	0	0.9	0	0.2	0	0.2457	0	0
	82	0	0	0.9	0.28	0	0	0.14	1	0
Yilan-Luodong	83	0	0	0.9	0	0.23	0	0.11	0	0
	84	0	0	0.9	0	0	1	0	0	0
	85	0	0	0.9	0.19	0	0	0	1	0
	86	0	0	0.9	0.09	0.09	0	0.22	1	0
	87	0	0	0.9	0	0	1	0	0	0
	88	0	0	0.9	0	0	0	0.18	1	0
Luodong-Dongshan	89	0	0	0.9	0	0.12	0	0.28	0	0
	90	0	0	0.9	0	0	1	0	0	0
	91	0	0	0.9	0	0	1	0.27	0	0
	92	0	0	0.9	0	0	0	0	1	0
Dongshan-Su'aoxin	93	0	0	0.9	0	0	0	0	0	0
	94	0	0	0.9	0	0	1	0	0	0
	95	0	0	0.9	0.75	0.88	0	0	1	0
	96	0	0	0.9	0	0.24	0	0	1	0.09
Su'aoxin-Dong'ao	97	0	0	0.3	0	0.3125	1	0	0	0
	98	0	0.2	0.3	0	0.4	0	0	0	0
	99	0	0.36	0.3	0	0.14	0	0	1	0
	100	0	0.81	0.3	0	0	0	0	0	0
	101	0	1	0.3	0	0	0	0	0	0
	102	0	1	0.3	0.26	0	1	0	0	0
	103	0	0.34	0.3	0.74	0.14	0	0	1	0
Dong'ao-Wuta	104	0	0.37	0.3	0	0.25	0	0	0	0
	105	0	1	0.3	0	0	0	0	0	0
	106	0	1	0.3	0.59	0	0	0	0	0
	107	0	0.68	0.3	1	0	1	0	0	0
	108	0	0	0.3	0.64	0	0	0	1	0
	109	0	0	0.3	0	0.15	0	0.12	0	0
	110	0	1	0.3	0	0.45	0	0	1	0.11
Wuta-Hanben	111	0	0.24	0.3	0	0	0	0	0	0
	112	0	1	0.3	0	0	0	0	0	0
	113	0	1	0.3	0	0	0	0	0	0
	114	0	1	0.3	0.62	0	0	0	0	0
	115	0	1	0.3	1	0	0	0	0	0
	116	0	1	0.3	1	0	0	0	0	0
	117	0	0.7	0.3	1	0	0	0	1	0
Hanben-Heren	118	0	0	0.3	0	0	0	0	0	0
	119	0	0	0.3	0	0	0	0	0	0
	120	0	0	0.3	0.57	0	0	0	1	0
	121	0	0	0.3	0	0	0	0	0	0
	122	0	0	0.3	0	0	0	0	0	0
	123	0	0.66	0.3	0	0	0	0	0	0
	124	0	1	0.3	0	0	0	0	0	0
	125	0	0.53	0.3	0	0	0	0	1	0.11
Heren-Xincheng	126	0	0	0.3	0	0.21	0	0	0	0
	127	0	0.4	0.3	0	0.04	0	0	0	0
	128	0	1	0.3	0.32	0	0	0	0	0
	129	0	1	0.3	1	0	1	0	0	0
	130	0	0.33	0.3	0.33	0	0	0	1	0
	131	0	0	0.3	0	0.18	0	0	0	0
	132	0	0	0.3	0	0.43	1	0	0	0
	133	0	0	0.3	0.28	0	0	0	1	0
Xincheng-Hualien	134	0	0	0.3	0.52	0.15	0	0.12	0	0
	135	0	0	0.3	0.62	0	0	0.234	0	0
	136	0	0	0.3	0.8	0	1	0	0	0
	137	0	0	0.3	0	0	0	0.12	1	0
	138	0	0	0.3	0	0	0	0.24	0	0
	139	0	0	0.3	0.17	0	0	0.16	0	0
	140	0	0	0.3	0	0	1	0	0	0
	141	0	0	0.3	0.52	0	0	0.29	1	0
	142	0	0	0.3	0.2	0.1	0	0.2	1	0

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4.1.2 Human Failure

Based on the Bayesian network established in Section 3.4, six risk factors contribute to two unsafe acts: overspeed and deceleration after target indication. These unsafe acts can then lead to the activation of the ATP brake. In the case study, the prior probabilities for each factor along the route from Shulin to Hualien are set, and Bayesian inference is used to calculate the probability of ATP brake activation.

Using Bayesian inference described in Section 3.4, the results are presented in Figure 4-2. The results indicate a significantly high probability of “Human Failure” in certain blocks between Shulin and Qidu, Ruifang and Shuangxi, and Su'aoxin and Xincheng. This is closely related to the conditions we have set. In the northern sections, due to the high frequency of trains, the risk of “Human Failure” is increased by the short headway intervals between trains. Additionally, the high density of signals in these areas contributes to the elevated risk. Between Ruifang and Shuangxi, curves are a likely factor contributing to the increased probabilities in these sections. Conversely, between Daxi and Luodong, there is a noticeable decline in the probability of “Human Failure”. This decrease is likely due to the sections becoming straighter and less influenced by preceding trains.

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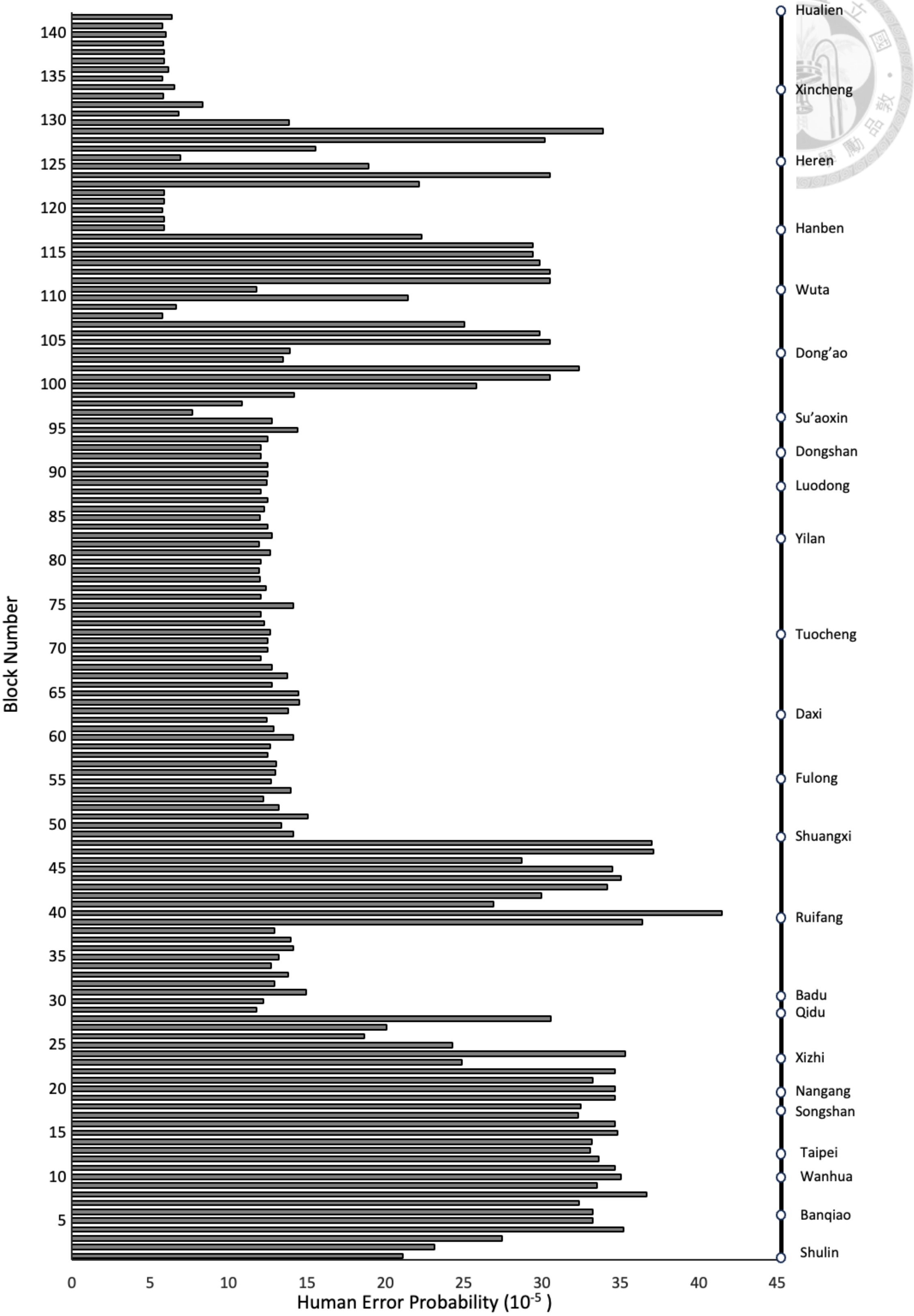

Figure 4-2 The probability of "Human Failure" (ATP brake) occurred

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4.1.3 External Intrusion

Regarding "External Intrusion", due to the lack of actual data, the probabilities of foreign objects intruding onto the tracks have been estimated by referencing Huang (2022), as shown in Table 4-2. The probability is defined as the likelihood of foreign object intrusion occurring in these high-risk zones each time a train passes through. Notably, the risk factors at level crossings, platforms, and construction sites are treated as independent events. Therefore, no additional Conditional Probability Tables (CPTs) will be set for these factors. Instead, the prior probabilities of these sections will be directly used to calculate the overall probability of "External Intrusion". This approach allows for more accurate and efficient risk estimation, ensuring that the individual characteristics of each risk factor are accounted for without overcomplicating the model.

Table 4-2 The probability of "External Intrusion" factors

Risk factor	Probability
Level crossing	2.3989×10^{-4}
Construction	6.6875×10^{-6}
Platform	4.2036×10^{-4}

The results indicate that the risk of "External Intrusion" is higher in certain blocks between Ruifang and Shuangxi, and between Tuocheng and Yilan. The higher number of level crossings and ongoing construction along these routes contribute to this elevated risk. Conversely, the risk is significantly lower between Banqiao and Badu, primarily because this section consists mainly of elevated tracks and underground tunnels, reducing the impact of level crossings. Similarly, the section between Wuta and Heren, characterized by long tunnels, also shows a lower risk. Furthermore, due to the initial data settings, the platform risk is comparatively lower than the other two factors, which also explains the observed trend.

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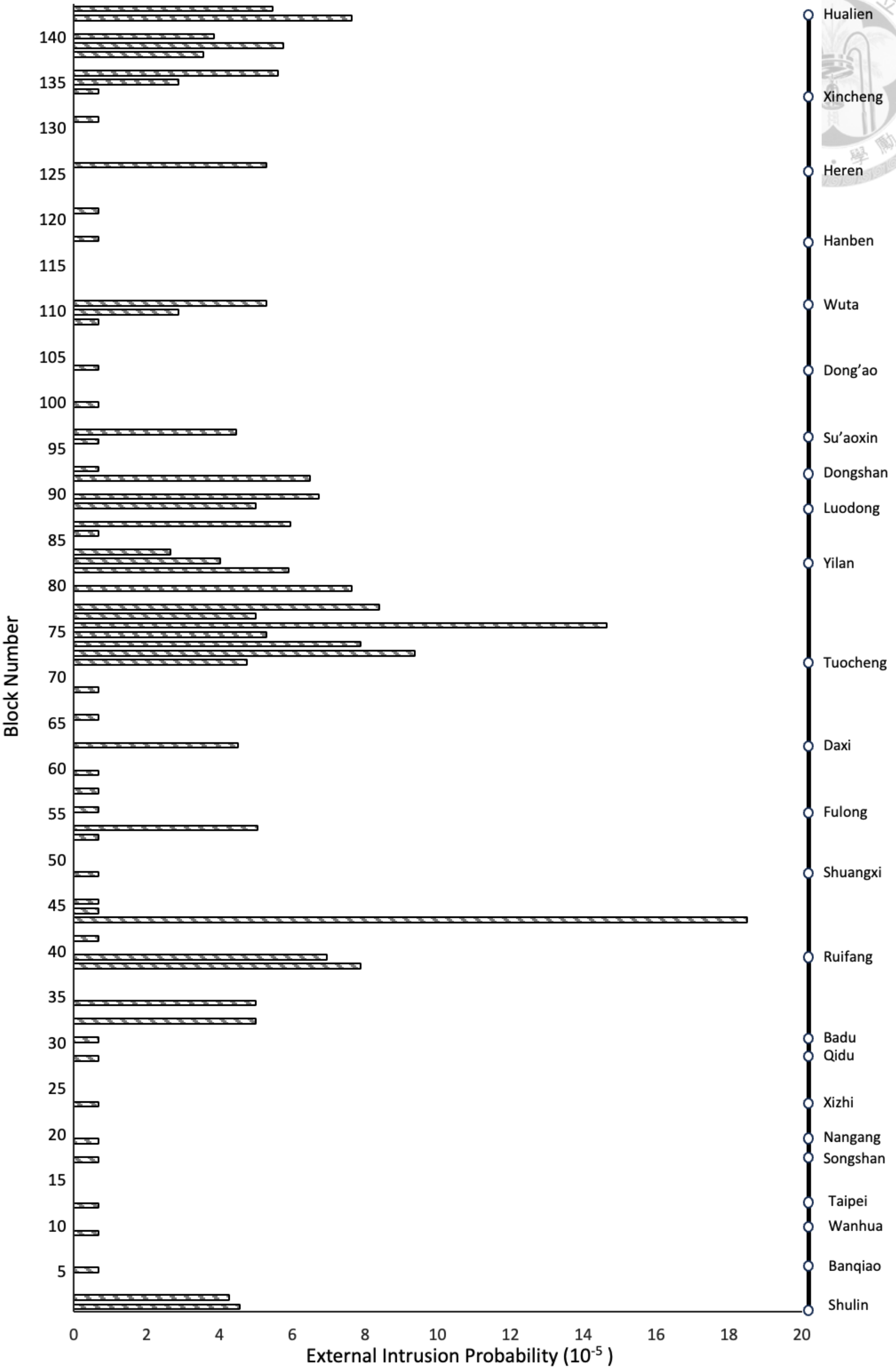

Figure 4-3 The probability of "External Intrusion" occurred

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4.1.4 Train Operation Risk Assessment

When the probability of risk events occurring in a block increases, it means that the number of potential risk events on that section also increases. After calculating the occurrence probabilities of “Human Failure” and “External Intrusion”, these probabilities are converted into ten levels of relative frequencies. This classification allows for a more effective assessment of the risk levels for each section. The relative frequency levels are determined based on the maximum and minimum probabilities of risk events occurring.

If all factors in all blocks of a section are in a risk state, meaning the entire section is in a completely unsafe condition, the prior probability of each factor will be 1. This results in occurrence probabilities for “Human Failure” and “External Intrusion” of 0.00082 and 0.00067, respectively. Conversely, when all factors are safe, the prior probability of each factor will be 0. This results in occurrence probabilities for “Human Failure” and “External Intrusion” of 0.00003 and 0, respectively. Using the maximum and minimum values of these risk event probabilities, relative frequency classifications were established. The range for each level is shown in Table 4-3.

Table 4-3 The range of frequency level for risk event

Freq. Level	HF	EI
1	(0.00003, 0.00011)	(0, 0.00007)
2	(0.00011, 0.00019)	(0.00007, 0.00013)
3	(0.00019, 0.00027)	(0.00013, 0.00020)
4	(0.00027, 0.00035)	(0.00020, 0.00027)
5	(0.00035, 0.00043)	(0.00027, 0.00033)
6	(0.00043, 0.00050)	(0.00033, 0.00040)
7	(0.00050, 0.00058)	(0.00040, 0.00047)
8	(0.00058, 0.00066)	(0.00047, 0.00053)
9	(0.00066, 0.00074)	(0.00053, 0.00060)
10	(0.00074, 0.00082)	(0.00060, 0.00067)

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After obtaining the occurrence frequencies of risk events, the final risk can be determined by considering the frequencies and severities of different types of accidents. In this research, accidents are classified into four categories based on the classification used in causal analysis: derailments, collisions, level crossing (LX) accidents, and obstructions. By analyzing risk events and combining past accident data, the number and consequences of accidents are estimated to determine the final risk, as shown in Figure 4-3. Additionally, the occurrence probabilities and casualties caused by accidents are set based on historical accident investigation data (Lin, 2020). In this research, it is assumed that Train Operation Human Factor (TOHF) in the accident data are all due to driver operations, and "External Intrusion" directly lead to accidents. After adjustments, the occurrence probabilities for each type of accident are shown in Table 4-4. However, if more precise data becomes available in the future, these probabilities can be updated accordingly.

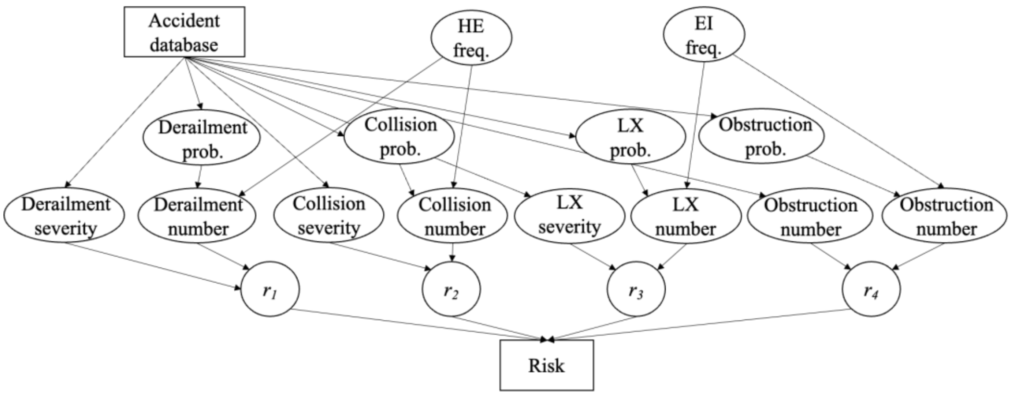

Figure 4-4 Risk event consequence

Table 4-4 Accident rate, and average casualties for different types of accidents

Type	Derailment	Collision	Level crossing	Obstruction
Probability	0.0554	0.013	0.3743	0.2084
Average casualties	6.76	21.05	1.86	1.11

Based on equation (15), the final risk for each block of train operation can be calculated.

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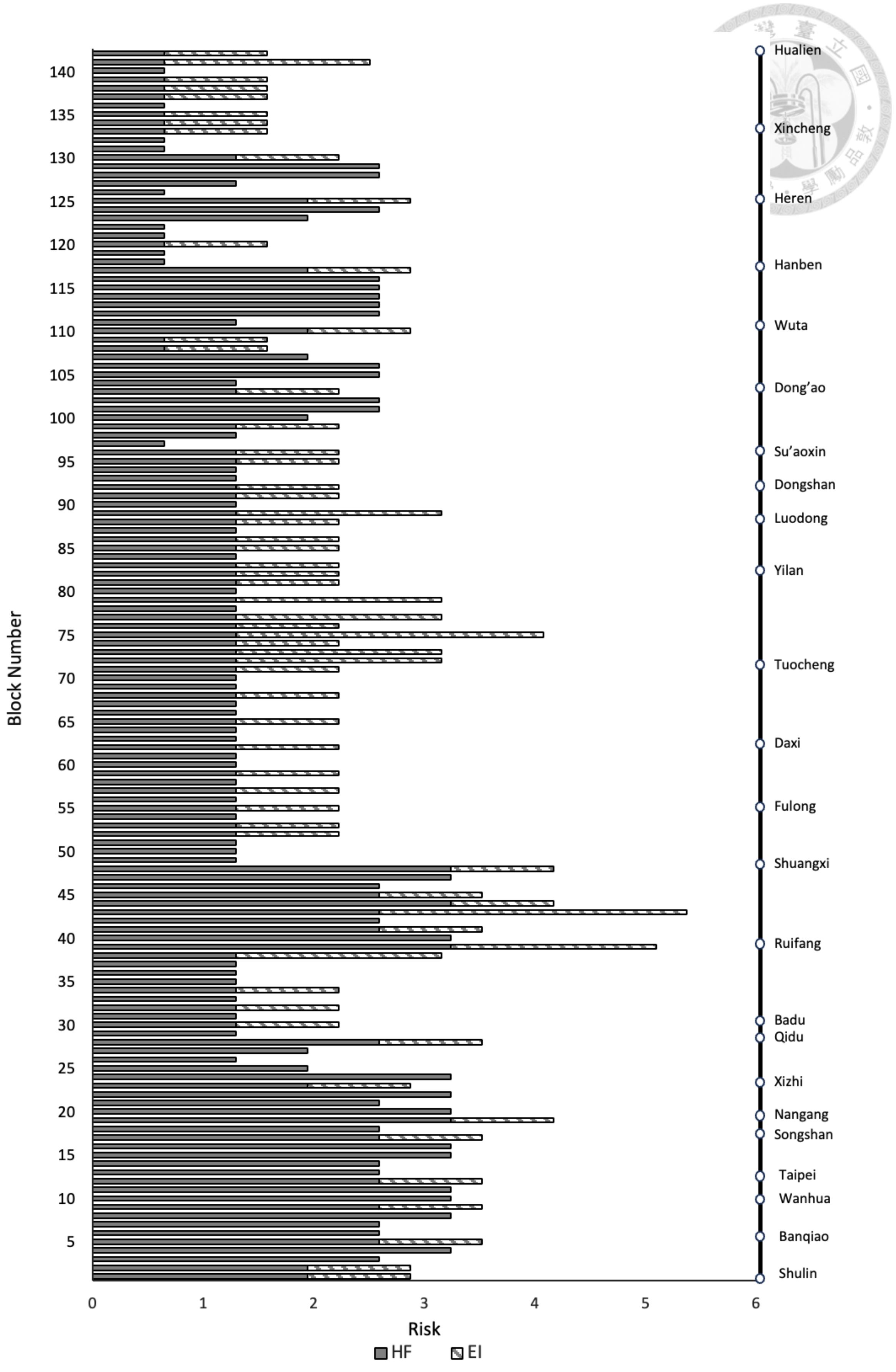

Figure 4-5 Operation risk assessment of train 408

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To enhance train drivers' comprehension and usability, this research adopts a relative grade to visually display risk levels. The maximum and minimum risk values of the block are classified into five levels. The ranges for each level are detailed in Table 4-5. Furthermore, to rigorously represent the risk of each section, we use the highest risk value among all blocks within that section as the section risk. The corresponding results are illustrated in Table 4-6.

Table 4-5 Relative Risk Level Range

Relative Risk Level	Range
Level 1	(1.576, 2.336)
Level 2	(2.336, 3.095)
Level 3	(3.095, 3.855)
Level 4	(3.855, 4.615)
Level 5	(4.615, 5.375)

Table 4-6 Section Risk and Level

Section	Block Number	Risk Value	Risk Level	Section Risk
Shulin-Banqiao	1	2.872	2	4.168
	2	2.872	2	
	3	3.520	3	
	4	4.168	4	
	5	3.520	3	
Banqiao-Wanhua	6	3.520	3	4.168
	7	3.520	3	
	8	4.168	4	
	9	3.520	3	
Wanhua-Taipei	10	4.168	4	4.168
	11	4.168	4	
	12	3.520	3	
Taipei-Songshan	13	3.520	3	4.168
	14	3.520	3	
	15	4.168	4	
	16	4.168	4	
	17	3.520	3	
Songshan-Nangang	18	3.520	3	4.168
	19	4.168	4	
Nangang-Xizhi	20	4.168	4	4.168
	21	3.520	3	
	22	4.168	4	
	23	2.872	2	
Xizhi-Qidu	24	4.168	4	4.168
	25	2.872	2	
	26	2.224	1	
	27	2.872	2	
	28	3.520	3	
Qidu-Badu	29	2.224	1	2.224
	30	2.224	1	
Badu-Ruifang	31	2.224	1	3.151
	32	2.224	1	
	33	2.224	1	
	34	2.224	1	
	35	2.224	1	
	36	2.224	1	
	37	2.224	1	
	38	3.151	1	
Ruifang-Shuangxi	39	5.096	5	5.375
	40	4.168	4	
	41	3.520	3	
	42	3.520	3	
	43	5.375	5	
	44	4.168	4	
	45	3.520	3	
	46	3.520	3	
	47	4.168	4	
	48	4.168	4	

Section	Block Number	Risk Value	Risk Level	Section Risk
Shuangxi-Fulong	49	2.224	1	2.224
	50	2.224	1	
	51	2.224	1	
	52	2.224	1	
	53	2.224	1	
	54	2.224	1	
	55	2.224	1	
Fulong-Daxi	56	2.224	1	2.224
	57	2.224	1	
	58	2.224	1	
	59	2.224	1	
	60	2.224	1	
	61	2.224	1	
	62	2.224	1	
Daxi-Tuocheng	63	2.224	1	2.224
	64	2.224	1	
	65	2.224	1	
	66	2.224	1	
	67	2.224	1	
	68	2.224	1	
	69	2.224	1	
	70	2.224	1	
	71	2.224	1	
Tuocheng-Yilan	72	3.151	3	4.079
	73	3.151	3	
	74	2.224	1	
	75	4.079	4	
	76	2.224	1	
	77	3.151	3	
	78	2.224	1	
	79	3.151	3	
	80	2.224	1	
	81	2.224	1	
	82	2.224	1	
Yilan-Luodong	83	2.224	1	2.224
	84	2.224	1	
	85	2.224	1	
	86	2.224	1	
	87	2.224	1	
	88	2.224	1	
Luodong-Dongshan	89	3.151	3	3.151
	90	2.224	1	
	91	2.224	1	
	92	2.224	1	
Dongshan-Su'aoxin	93	2.224	1	2.224
	94	2.224	1	
	95	2.224	1	
	96	2.224	1	

Section	Block Number	Risk Value	Risk Level	Section Risk
Su'aoxin-Dong'ao	97	1.576	1	3.520
	98	2.224	1	
	99	2.224	1	
	100	2.872	2	
	101	3.520	3	
	102	3.520	3	
	103	2.224	1	
Dong'ao-Wuta	104	2.224	1	3.520
	105	3.520	3	
	106	3.520	3	
	107	2.872	2	
	108	1.576	1	
	109	1.576	1	
	110	2.872	2	
Wuta-Hanben	111	2.224	1	3.520
	112	3.520	3	
	113	3.520	3	
	114	3.520	3	
	115	3.520	3	
	116	3.520	3	
	117	2.872	2	
Hanben-Heren	118	1.576	1	3.520
	119	1.576	1	
	120	1.576	1	
	121	1.576	1	
	122	1.576	1	
	123	2.872	2	
	124	3.520	3	
	125	2.872	2	
Heren-Xincheng	126	1.576	1	3.520
	127	2.224	1	
	128	3.520	3	
	129	3.520	3	
	130	2.224	1	
	131	1.576	1	
	132	1.576	1	
	133	1.576	1	
Xincheng-Hualien	134	1.576	1	2.503
	135	1.576	1	
	136	1.576	1	
	137	1.576	1	
	138	1.576	1	
	139	1.576	1	
	140	1.576	1	
	141	2.503	2	
	142	1.576	1	

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This visualization allows drivers to quickly comprehend the relative risk associated with each section as shown in Figure 4-6. From the figure, it can be observed that the sections from Ruifang to Shuangxi is the highest-risk sections for Train 408. By presenting the risk levels in an intuitive graphical format, drivers can easily identify high-risk areas and take necessary precautions to ensure safety. This approach not only aids in immediate risk recognition but also supports proactive safety measures on the railway.

Figure 4-6 Relative risk level of each section for Train No.408

4.2 BN Validation

To verify the consistency of the developed model, the prior probability of the headway factor is adjusted from 0 to 1 incrementally, and the changes in the probabilities of the child nodes are observed. In this Bayesian Network, headway influences the occurrence of overspeed, which in turn may lead to a more serious condition – ATP brake activation. Table 4-7 presents the computational results showing the probability changes for overspeed and ATP brake as the prior probability of headway is varied, while keeping the probabilities of other contributory factors constant.

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Table 4-7 Impact of incrementally increasing headway probability on risk event

Prior prob. of headway	Prob. of overspeed	Prob. of ATP brake
0	0.0062	0.00015
0.1	0.0073	0.00017
0.2	0.0085	0.00019
0.3	0.0096	0.00021
0.4	0.0107	0.00023
0.5	0.0118	0.00025
0.6	0.0129	0.00027
0.7	0.0140	0.00029
0.8	0.0151	0.00032
0.9	0.0162	0.00034
1.0	0.0173	0.00036

As shown in Table 4-7, increasing the prior probability setting for headway leads to a corresponding rise in unsafe behaviors and risk events. The same testing approach can be applied to the other six risk factors related to “Human Failure”. Starting with a prior probability setting of 0.5 for each factor, their prior probabilities can then be incrementally increased separately to understand their individual impacts on risk events, while keeping the other factors constant at 0.5.

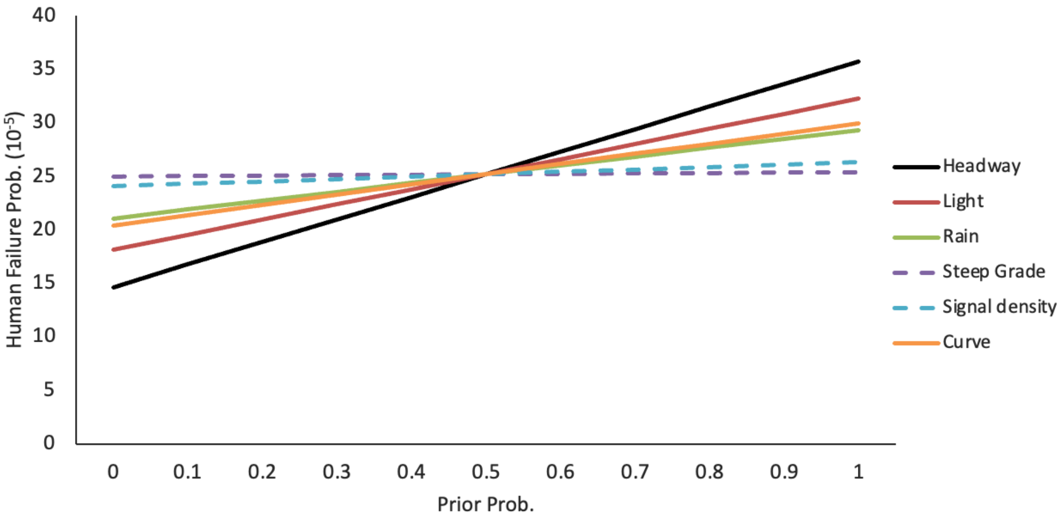

Figure 4-7 Impact of increasing all factors probability related to “Human Failure”

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As shown in Figure 4-6, each factor adheres to Axiom 1. It is also evident that overspeed has a greater impact on triggering the ATP brake compared to deceleration after target indication. This suggests that while deceleration after target indication does occur, it seldom reaches a point necessitating ATP brake activation. This implies that even if the driver only decelerates after the target indication, it typically does not result in severe consequences. On the other hand, general train overspeed is highly correlated with the “Human Failure” . Therefore, even in scenarios where the frequency of risk events is low, identifying sections prone to general overspeed can help prevent more severe outcomes.

Through the setting of posterior probabilities in Bayesian networks, at first, assuming the prior probabilities of each factor affecting “Human Failure” are set to 0.5, the final probability of “Human Failure” occurrence is 0.00024. In Figure 4-8, setting the “Human Failure” to occur 100% allows for the observation of the posterior probability of each factor. It is found that under this evidence, the probabilities of Headway and Light increase significantly, while Rain and Curve remain roughly the same, and Steep Grade and Signal Density show almost no change. This result is consistent with the observations made when individually changing the prior probabilities of each factor to observe the variation in the probability of “Human Failure”.

Regarding Axiom 2, the probabilities of ATP brake activation for each of the six factors—headway, light, rain, steep grade, signal density, and curve—occurring independently are 0.000135, 0.000395, 0.000131, 0.000028, 0.000027, and 0.000089, respectively. When all these factors occur simultaneously, the probability increases to 0.000823. This demonstrates that the model adheres to Axiom 2.

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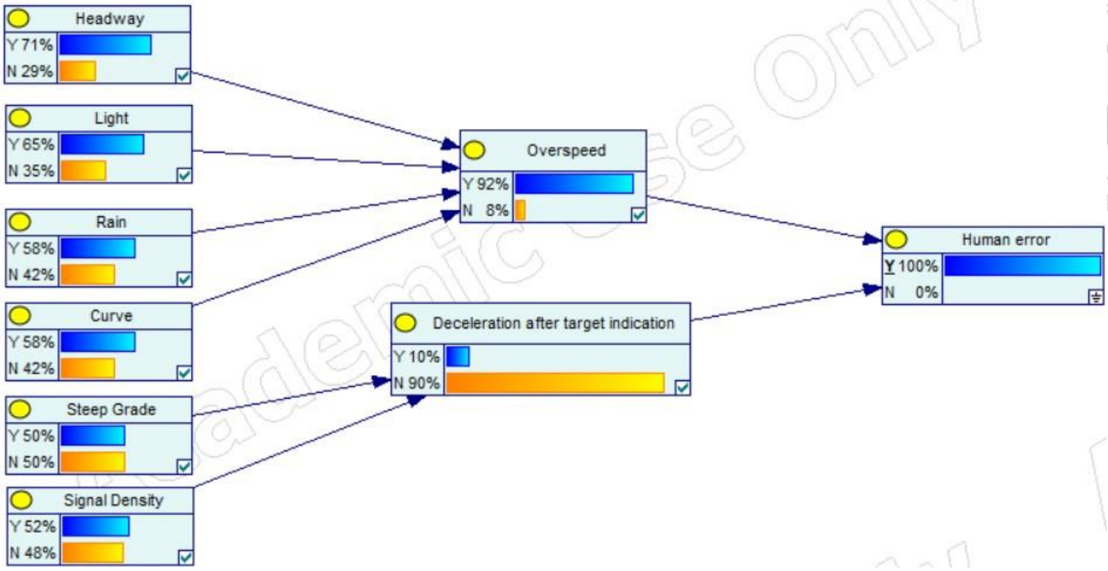

Figure 4-8 The posterior probability given the evidence that “Human Failure” occur

4.3 Risk Control

During the risk control phase, our focus is on identifying predominant factors for sections. This approach allows drivers to better prepare for these key factors. Additionally, if operational units can understand which risk factors can effectively reduce risks, they can implement more efficient risk control measures. By examining the contribution of each factor for each section, we can see that these contributions generally correspond to the initial probability settings, as shown in Figure 4-8.

In the underground section from Banqiao to Nangang, headway and lighting are significant contributing factors, as reflected in their initial probabilities. Similarly, lighting issues are evident in the long tunnels between Suao and Xincheng. Moreover, the figure shows that certain sections are more susceptible to risks due to “External Intrusion”, such as those caused by construction or level crossings, including sections from Toucheng to Dongshan, Ruifang to Shuangxi, and Xincheng to Hualien. These are all high-contribution factors for specific sections, and drivers must pay extra attention to these key factors while operating the train.

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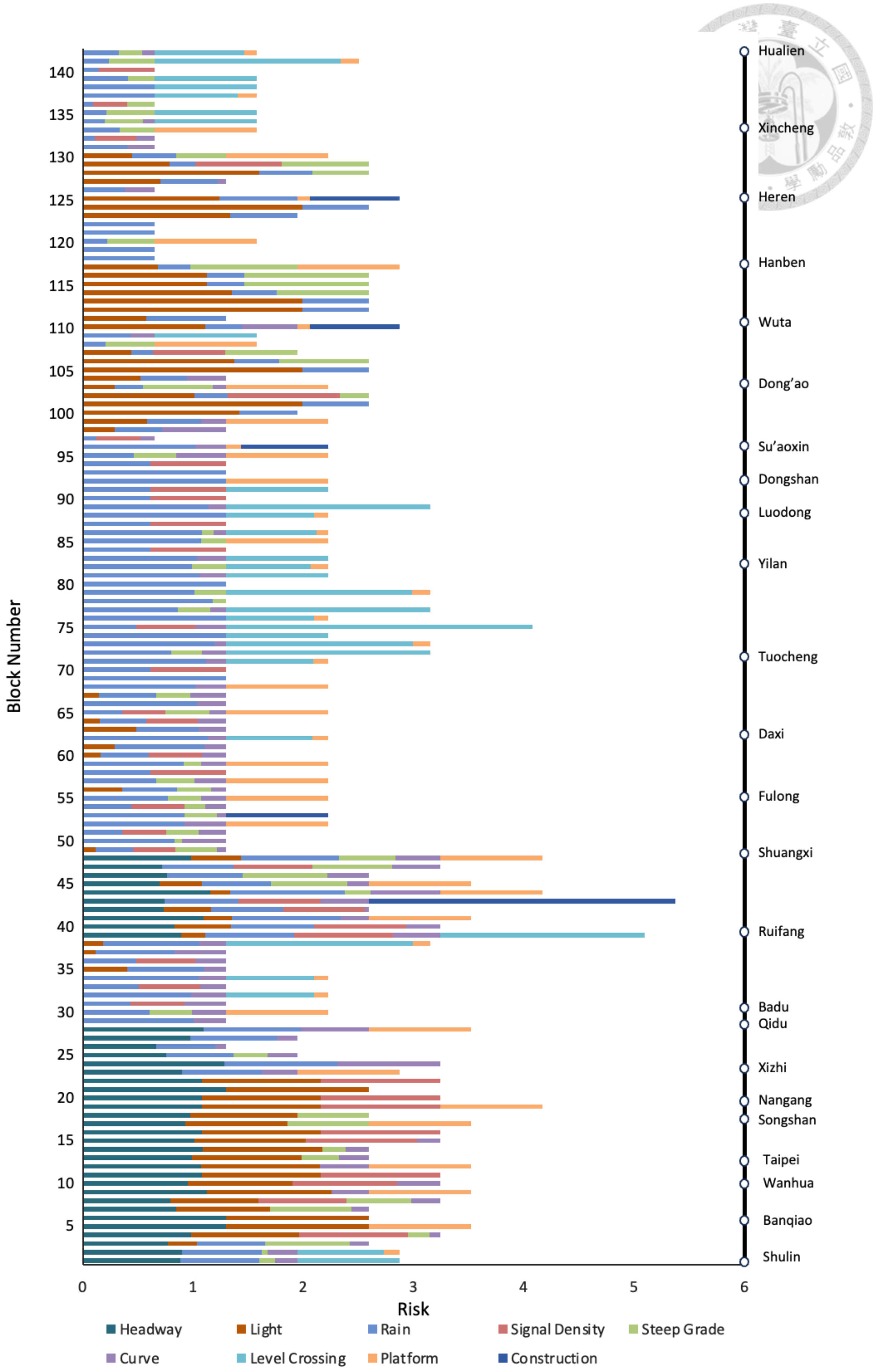

Figure 4-9 The contribution of each risk factor

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However, as a risk control measure, the goal is to identify factors that can effectively reduce risk, especially in situations with limited resources. It is essential to recognize that the impact of each factor's risk increase or decrease varies in magnitude. Therefore, to reduce overall risk with limited resources, it is necessary to further identify which factors can achieve the desired reduction in overall risk with minimal adjustments. This identification process helps determine the predominant factor for each section.

In this case, three scenarios were explored: reducing the target risk value by 20%, reducing it by 50%, and lowering it to the average value. According to the risk assessment results, the average risk was 2.727. Using Python, these tasks were completed in 48.39 and 242.26 seconds, respectively. The results are shown in Table 4-8. For the 20% risk reduction task, all sections could achieve the target with the adjustment of a single factor. However, in the 50% risk reduction task, 12 out of 23 sections required changes in an additional factor to meet the target. This analysis reveals both the primary and secondary predominant factors for each section. For lowering to the average risk, 16 sections had risk values above the average, but most sections could achieve the target with the adjustment of a single factor.

This approach ensures that the highest contributing factors are not merely relied upon but also considers their efficiency in reducing risk, allowing for the implementation of the most effective risk control measures even with constrained resources.

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Table 4-8 Predominate factor searching under different scenario

Section	Original risk	Scenario 1: 20% Reduction	Scenario 2: 50% Reduction	Scenario 3: Average Risk
Shulin-Banqiao	4.168	Level Crossing	Level Crossing, Headway	Level Crossing
Banqiao-Wanhua	4.168	Headway	Headway	Headway
Wanhua-Taipei	4.168	Headway	Headway	Headway
Taipei-Songshan	4.168	Headway	Headway	Headway
Songshan-Nangang	4.168	Headway	Headway	Headway
Nangang-Xizhi	4.168	Headway	Headway	Headway
Xizhi-Qidu	4.168	Headway	Headway, Light	Headway
Qidu-Badu	2.224	Headway	Headway, Platform	--
Badu-Ruifang	3.151	Level Crossing	Level Crossing	Level Crossing
Ruifang-Shuangxi	5.375	Construction	Headway, Construction	Headway, Construction
Shuangxi-Fulong	2.224	Construction	Construction	--
Fulong-Daxi	2.224	Rain	Rain, Platform	--
Daxi-Tuocheng	2.224	Level Crossing	Level Crossing	--
Tuocheng-Yilan	4.079	Level Crossing	Level Crossing	Level Crossing
Yilan-Luodong	2.224	Construction	Steep Grade, Construction	--
Luodong-Dongshan	3.151	Level Crossing	Level Crossing	Level Crossing
Dongshan-Su'aoxin	2.224	Curve	Rain, Curve	--
Su'aoxin-Dong'ao	3.520	Light	Light, Level Crossing	Light
Dong'ao-Wuta	3.520	Light	Light, Construction	Light
Wuta-Hanben	3.520	Light	Light	Light
Hanben-Heren	3.520	Light	Light	Light
Heren-Xincheng	3.520	Construction	Construction	Construction
Xincheng-Hualien	2.503	Level Crossing	Level Crossing	--

Based on the computational analysis results, it can observe that most of the predominant factors are those with high contributions to specific sections. However, for sections with a more evenly distributed contribution of factors, our proposed method allows for the convenient identification of predominant factors. Additionally, it is evident that some factors, while having a significant contribution to specific sections, do not markedly impact overall risk reduction. For instance, platform illustrate that the impact of each factor's risk increases or decreases varies in magnitude, as discussed earlier.

Based on the results, it can be concluded that headway, level crossings, construction,

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and light are predominate factors that can significantly reduce section risks. Possible measures include extending intervals between trains, eliminating level crossings, managing construction areas, and increasing lighting. However, in reality, maximizing both safety and efficiency is often challenging. For instance, maximizing capacity makes it impractical to reduce headway to lower operational risks.

In this research, due to limited data on identified risk factors, it is not feasible to devise specific improvement strategies for every factor. Nevertheless, this method allows for pinpointing the most contributing factors for each section and evaluating the extent to which modifying these factors can mitigate risk levels. This approach assists in identifying the predominant factors for each section. By providing operators with the most efficient solutions within limited resources, the risks associated with different railway sections can be effectively reduced.

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CHAPTER 5 CONCLUSION AND FUTURE WORK

Railway safety is becoming increasingly important in today's society. Traditional risk assessment systems typically focus on post-event evaluations, aimed at analyzing and addressing accidents that have already occurred. However, given the various uncertainties in train operations, it is crucial to conduct a risk assessment to identify all potential risk factors in advance. By notifying train drivers of the risk differences across various sections before their journey, they can prepare in advance, achieving proactive prevention. This research combines the HFACS with Bayesian networks to develop TORAS.

Historical data is utilized to conduct quantitative risk assessments. The specific steps include collecting past train operation data, such as accident data, driver behaviors, and environmental factors; constructing a Bayesian network model to quantify the relationships and impacts of various risk factors; and analyzing these data to predict and identify potential risks in advance. Ultimately, this approach aims to enhance the overall safety of train operations.

5.1 Conclusion

This research proposes a framework of train operation risk assessment. The conclusions and contributions are summarized as follows:

(1) To infer ultimate risk through risk events and systematic analysis using HFACS

Data on railway accidents alone may not provide a complete picture for risk analysis. Therefore, this research proposes a method to analyze risk events that could potentially lead to accidents. By examining these events, it is possible to more thoroughly assess all potential risks in train operations. Utilizing the HFACS, each accident record is systematically reviewed to identify all contributing causes. From these causes, risk factors are then identified. This layered analysis, covering drivers, equipment, and environmental factors, enables a more systematic understanding and

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management of risks. This approach helps in identifying and managing low-frequency but high-consequence potential risks, ultimately enhancing train operational safety more effectively.

(2) To utilize data-driven risk analysis model

In this research, subjective judgments are minimized by analyzing historical driving data and various historical records, applying them to the conditional probability tables in the Bayesian network. This data-driven approach not only improves the accuracy of risk assessment but also provides more specific and actionable risk management recommendations, ensuring scientific and reliable decision-making. For instance, data collected from the ATP system is used to conduct the analysis, ensuring that the conditional probabilities of each risk factor are based on actual operational data rather than subjective assumptions. This allows for more accurate prediction of risks under different operational conditions and the development of appropriate management strategies.

(3) To establish a complete framework for TORAS

This research establishes a complete framework for TORAS, detailing the steps and methodologies for risk assessment at various phases. This framework can be used by operators to develop their own TORAS, providing pre-departure risk assessments to help drivers understand which sections require advanced preparation. By identifying and analyzing risk factors across different railway sections, including terrain, weather, and other route information, the framework helps predict risks in advance, enhancing drivers' risk awareness and effectively reducing the occurrence of potential accidents. With the integration of more data, this framework can be continuously expanded and refined.

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5.2 Future Work

This section summarizes some applications that could be extended in the future. Although the developed process can analysis and evaluation train operation risk, there are still some restrictions and limitations to be improved. These future works are listed below.

(1) To gather driver and vehicle data for the Bayesian Network analysis

Currently, due to the lack of data, the selection of factors is primarily based on environmental factors that can highlight the differences between sections of the railway. However, as mentioned in previous chapters, a thorough risk assessment should also account for the differences between various drivers and vehicles. Future work should aim to integrate these aspects to provide a more detailed and accurate evaluation of operation risks.

(2) To search for more useful information in the operational data

The unsafe acts and risk events discussed in this research are defined based on previous research. However, there are many other behavior of train operations that should be considered. For example, extracting more detailed driver operation information from ATP data, such as the frequency of train acceleration and deceleration, or the differences in these operations under various train conditions, such as deceleration rate, can provide valuable insights. Obtaining such data will enable an analysis from multiple perspectives. Future efforts should focus on extracting more effective information from operational data to conduct thorough analyses and accurately record driving behaviors.

(3) To acquire additional complete data on both accidents and near-miss events

The biggest challenges in this research is the shortage of data, particularly concerning driver information. Although obtaining such data might involve privacy issues, if the operating units could conduct in-depth analyses of each driver's

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behavior, it would help in identifying risks early. Furthermore, Currently, Taiwan Railway's investigation of general accidents is limited, including only train numbers and locations. If railway operators could record more detailed information, such as the train's speed at different times and emergency braking distances, it would greatly aid in understanding how drivers handle unsafe situations. Additionally, efforts should be made to record more occurrences of risk events. For example, documenting the driver's reactions when a level crossing warning system is activated. A comprehensive analysis of all incidents, including near-miss events, and evaluating the adequacy of the driver's responses will provide more precise and actionable insights into the consequences of risk events.

(4) To practice risk reduction strategy under the application of TORAS

This research has constructed a preliminary framework for the TORAS. However, practical application is essential for effective risk mitigation. Given limited resources, railway operators should record as much operational data as possible. Continuous use of the system and comparison of risk assessment results with actual conditions are necessary to enhance the system's accuracy. Additionally, long-term observation of various risk indicators and the proposal of practical improvement actions for each factor are crucial for effective risk mitigation. Ultimately, the primary goal of risk management is not only to enable accurate prediction of operational risks but also to take actions to eliminate these risks.

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