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A Graph Network for High-speed Railway Operation Risk Prevention and Control

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Abstract: With the rapid expansion of China's high-speed railway (HSR) network, safety concerns in HSR operations have garnered increasing attention. Currently, various railway departments have devised numerous feasible risk control plans. However, these plans predominantly exist in an unstructured textual format, leading to challenges in automation, standardization, content updates, and cross-departmental collaboration. To address these limitations, this study introduces a novel graph-based Risk Scenario Decision (RSD) model, which systematically structures unstructured emergency risk scenarios into an explicit graphical format. The RSD model utilizes graph theory principles and incorporates LLM for precise knowledge extraction and alignment. This approach significantly enhances automation, consistency, and efficiency in railway operational risk management. By transforming traditional risk control plans into a graph-based network, the RSD model facilitates efficient decision-making and rapid response, thereby improving the overall management and effectiveness of HSR operational risk control. Experimental validation demonstrates the high accuracy (up to 98.38%) of the RSD construction process. Ultimately, this research provides a robust, interpretable, and automated framework that substantially enhances proactive risk management in HSR operations, ensuring greater safety and operational efficiency.

Keywords: graph network; high-speed railway; risk prevention and control; risk scenario decision

1 INTRODUCTION

As of 2024, China boasts the world's longest operational HSR network, spanning a vast distance of 47,000 kilometers. HSR, characterized by its remarkable attributes of high speeds, frequent departures, extensive informatization, and stringent operational safety requisites, is a paramount element of China's transportation infrastructure. The safety of HSR operations entails a comprehensive evaluation, considering not only the status of internal personnel and equipment but also external security threats, including strong winds, rainstorms, earthquakes, debris flows, and potential intrusions by foreign materials. Any compromise in safety parameters may result in extensive train delays, substantial casualties, and significant property losses. Consequently, the research into HSR operational safety prevention and control is of paramount significance. It necessitates a thorough exploration of the multifaceted risk factors within HSR operations, a diligent identification of potential safety hazards, and the formulation of corresponding preventive strategies. This collective effort is essential to bolster the safety and reliability of HSR operations, thereby ensuring the well-being and comfort of passengers.

Despite the extensive knowledge and experience accumulated by various departments within the railway system in risk prevention and control, primarily stored in the form of emergency plans, operating manuals, and risk-handling decision tables, several significant gaps and challenges remain: (1) Lack of a Structured Emergency Response Mechanism. Existing emergency plans and risk management strategies are largely unstructured, mainly in textual formats, which hinders automation, standardization, and efficient inter-departmental collaboration. Previous research has focused on specific risks or individual scenarios but lacks a unified, standardized, and automated decision-making framework, particularly for complex and dynamic emergency response situations. (2) Reliance on Human Interpretation and Manual Execution. Traditional risk management methods heavily depend on human interpretation and manual execution. When unforeseen events occur, operators must manually consult emergency plans for guidance. This approach has inherent limitations, as the effectiveness of emergency responses depends on the operators' expertise and experience. Inexperienced personnel may inadvertently overlook critical information or execute responses incompletely. Additionally, coordinating responses across multiple departments remains difficult due to the absence of a clear, structured process. (3) Standardization and Update Challenges. Existing emergency plans lack precise quantitative descriptions, leading to inconsistent interpretations and executions of response strategies across departments. This divergence results in non-standardized responses and complicates inter-departmental coordination. Moreover, as risk management standards and regulations evolve, updating emergency plans becomes a cumbersome process. The unstructured nature of these plans makes timely, effective updates challenging, reducing the overall effectiveness of risk management.

To address these gaps and limitations, this paper proposes a graph-based RSD model that transforms unstructured emergency plans into a graphical format. Unlike traditional textual emergency plans, the RSD model enhances automation, standardization, and inter-departmental coordination by providing a structured, visual representation of the decision-making process. By leveraging large language model (LLM) for precise knowledge extraction and alignment, the RSD model significantly improves the automation, accuracy, and timeliness of risk responses, effectively handling various complex risk scenarios in high-speed railway (HSR) operations. The introduction of the RSD model enables more efficient, automated, and less error-prone decision-making, thereby enhancing the overall safety and reliability of HSR operations.

The main contributions of this paper are as follows: First, a comprehensive definition of the RSD model is provided. Next, methods for constructing the RSD graph using LLMs are explored. Finally, the practical application of the RSD model in automating risk management within the high-speed railway context is examined. A schematic representation of this framework is presented in Fig. 1.

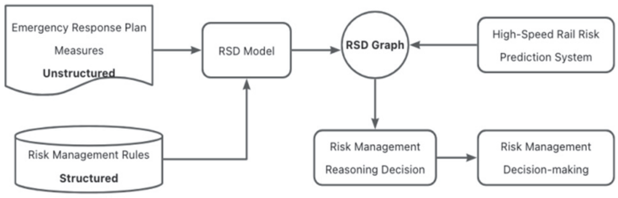

Figure 1 Railway operation risk handling system based on the RSD

2 LITERATURE REVIEW

The field of risk prediction holds significant importance in the realm of HSR operation safety prevention and control. It can be categorized into two key research areas: internal risk prevention and control, and external risk prevention and control. The internal risk prevention and control research mainly includes the study of facilities and equipment such as trains, tracks, bridges, and communication facilities. For example, research on railway track crack detection [1], the impact of bridge pier settlement on train safety [2], and strong wind prediction [3].

The external risk prevention and control research for train operation mainly includes the prediction of natural disasters and foreign object intrusion. Natural disasters include wind, rain, thunder and lightning, and earthquakes. In the case of heavy rain or flash floods, tunnels, steep slopes, and gravel roadbeds are among the most vulnerable assets, which may lead to system failures, deterioration of operations, and ultimately train service delays [4]. When trains pass through windy areas, strong winds can cause derailment accidents, so it is necessary to control the speed of trains passing through windy areas [5, 6]. Guo W et al. proposed an experimental method for evaluating the safety of train operation on bridges after earthquakes [6]. Foreign object intrusion is a common risk hazard during the operation of HSR. Currently, the identification of the risk of foreign object intrusion mainly involves video and radar monitoring of HSR intrusion [8]. The field of railway safety prevention and control is actively adopting big data technologies to improve safety management levels. Some studies mainly adopt the "platform + application" design pattern, utilizing big data platform technologies to provide safety prevention and control algorithms and knowledge for safety management applications, and achieve safety monitoring of equipment, personnel, and the external environment along the railway [9-11]. In terms of new technology applications, deep learning, AI, 5G, and other technologies are used in HSR safety prevention and control, improving the real-time and accuracy of risk prevention and control [12-15].

In 2012, Google proposed the concept of the Knowledge Graph, with the goal of providing users with more accurate, comprehensive, and relevant search results [16]. Since the introduction of the concept of the Knowledge Graph by Google, it has been widely applied in various fields. Glavas and Snajder proposed the concept of Event Graph [17]. The Event Graph can be seen as a domain-specific extension of the Knowledge Graph, emphasizing the importance of events and highlighting temporal and behavioral information in knowledge representation. With further research, concepts such as event-centric KG [18], Event evolutionary graph [19], Event-centric temporal KG [20], and Event logic graph [21] have been proposed in the field of Event Graphs. These studies are the extension and deepening of Event Graphs in specific domains. The applied research of Event Graphs mainly focuses on using neural network algorithms to extract event entities and relationships, constructing vertical domain-specific Event Graphs, and performing knowledge inference and analysis. For example, applying event graphs to pre-control research on power safety accidents, flight conflict accidents, and emergencies [22-26]. In the field of railway safety prevention and control, a graph-based approach can be employed to uncover potential patterns of accidents by representing accidents and hazards within a heterogeneous network [27].

Based on our preliminary research and investigations, we have identified three key deficiencies in the current research on HSR risk prevention and control: (1) Limited research on risk emergency response. Current studies predominantly focus on risk identification, with insufficient attention to emergency response methods, leaving a gap in managing risks once they occur. (2) Lack of collaborative risk management. Existing methods focus on individual risks and overlook the complex interdependencies between them. Effective HSR safety requires coordinated risk management across various domains, which current approaches fail to address comprehensively. (3) Insufficient interpretability and scalability. Although neural network methods are widely used for risk prediction, their limited interpretability hinders practical application. In contrast, our graph-based RSD model explicitly captures risk-event relationships, offering enhanced interpretability and practical usability. Furthermore, their scalability is limited, making them unsuitable for dynamic, real-world HSR environments where timely responses are critical. These limitations highlight the need for a more structured, interpretable, and collaborative approach, such as the RSD model proposed in this paper, to improve both the efficiency and effectiveness of HSR risk management.

3 RESEARCH METHODOLOGY

In this section, we will delve into the fundamental components of RSD, encompassing its definition, attributes, and construction methodology. The purpose of this section is to provide a comprehensive understanding of the concept of RSD, facilitating a mastery of the process of building and effectively applying this essential tool for risk management. Subsequently, we will systematically explore the following three key aspects one by one to deepen our comprehension of the essence and practical application of RSD.

3.1 Concepts of RSD

This paper delves into the core concepts of the RSD model. To begin with, we will introduce the definition of RSD, elucidate its model structure, and emphasize its crucial role in enhancing the real-time and collaborative aspects of HSR risk prevention and control. Subsequently, we will introduce the concept of the RSD graph, a visual tool designed to provide a clear representation of the intricate relationships between risks and their corresponding response measures in the context of HSR operations. Lastly, we will conduct an in-depth exploration of the concept of RSD subgraphs, which play a pivotal role in ensuring the uniqueness and determinacy of risk response plans.

(1) Definition of RSD. In order to enhance the real-time, integrated capabilities of high-speed rail risk prevention and control, this paper introduces a graph-based risk prevention and control model called RSD. The RSD model systematically organizes knowledge, significantly improving automated responses in railway operations. RSD can be used to indicate the relationship between risks during train operation and their handling measures. Here we provide the detail description: $R=\{r_1,r_2,r_3,\ldots,r_m\}$, R represents the set of various risks during railway operation, where m indicates the number of risks. Each r includes features such as source, type, level, time, location, and impact scope, which serve as the basis for risk response. $S=\{s_1,s_2,\ldots,s_m\}$, S represents the set of internal and external environmental features when a risk occurs. Each risk occurs in a specific scenario. Risk management needs to be based on scenario characteristics. s_i indicates the scenario in which r_i occurs and is composed of multiple rules and conditions. $D=\{d_1,d_2,d_3,\ldots,d_n\}$, D represents the set of risk response measures, where d_j indicates a risk response measure. D_i indicates the set of response measures for risk r_i. d_i includes attributes such as measure name, action subject, execution action, and action object.

(2) Definition of RSD Graph. There are complex interrelationships between the risks of HSR operation and the measures to handle them. The intersection of these relationships forms a complex network. In order to visually analyse the internal structure of RSD and the inherent relationships between risk response measures, this paper proposes a graph-based structure, namely RSD graph, for HSR operation risk prevention and control management. By utilizing the characteristics of graphs, it can better represent the risk handling process of train operation and the multi-party collaboration mechanism. Let $G(R,S,D)$ be a directed graph network, which is an abstract representation of RSD. RSD can be represented by a directed graph as shown in Fig. 2.

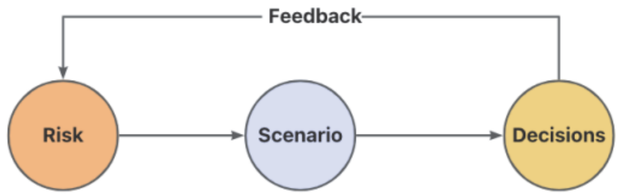

Figure 2 RSD graph structure

In the context of HSR operations, risk events (*R*) are identified, followed by the determination of appropriate response decisions (*D*). The scenario (*S*) defines the condition or context that links a particular risk to its response. This structure enables multi-party collaboration, where the decisions depend on the dynamic interactions between different risk events and the context in which they occur. For instance: If Heavy Rain is identified as a risk event (R_1), it may trigger a Speed Reduction (D_1) decision, which is the appropriate response when considering the context of the scenario (S_1). Similarly, if an Earthquake is detected (R_2), it could lead to Route Diversion (D_2), with the scenario of an earthquake being the linking context.

Table 1 Definitions of nodes and edges in the RSD graph

Type	Name	Description
Node	Risk Event	Represents a risk event
Node	Measure Event	Represents the measure event to respond to the risk, one risk usually requires one or more measure nodes for handling
Node	Entity Node	Represents the entities involved in the risk response process, including individuals, organizations, equipment, systems, etc.
Edge	Event Connection Edge	Indicates the relationship between events, including two types: conditional and sequential.
Edge	Event-Entity Connection Edge	Indicates the relationship between events and entities, including two types: execution and notification.

(3) Definition of RSD Subgraph. To ensure the uniqueness and determinacy of the risk response plan, and guarantee that each risk has only one corresponding emergency response plan, this paper introduces the concept of a subgraph. Let *g* be a subgraph of *G* representing a risk scenario and its corresponding mitigation measures, forming a complete RSD network structure.

3.2 Properties of RSD

RSD represents a collection of HSR operational risks and response measures. It serves as a systematic methodology that automatically selects and implements risk response strategies based on the characteristics of the risks, ensuring the safety and reliability of railway operations. The following are some characteristics of RSD: (1) Structured risk management tool. RSD functions as a structured management tool for risk handling. Leveraging the RSD framework, it transforms unstructured emergency plans into a structured knowledge system. The graphical representation facilitates qualitative and quantitative analysis of risk response decisions, enhancing the standardization and conformity of risk handling. (2) Knowledge repository for risk response decisions. The ultimate goal of risk management is to achieve maximum benefits at minimal costs. RSD consolidates and incorporates years of railway risk prevention and control experience. It provides detailed descriptions of various risk response strategies, offering decision-makers standardized and effective response options. (3) Foundation for automated risk response. RSD forms the foundation for automating risk response. When the system issues a risk warning signal, the response measures within the RSD table can automatically execute based on actual circumstances. This aids in swift responses to risk events, reducing human intervention and mitigating the damages caused by risks. The significance of RSD in railway risk prevention and control lies in its provision of a comprehensive reference framework for risk management. It assists railway managers in making informed decisions in complex risk environments, ensuring the safety, stability, and sustainability of railway operations.

Knowledge graphs mainly describe the relationships between entities and their attributes, as well as the relationships between entities. However, they do not express events and the logical relationships between them. The emergence of event graphs has filled this gap. Event graphs focus on events and describe the evolution patterns and rules between events. The nodes in an event graph represent events, and the edges represent the evolutionary relationships between events, including causal relationships, sequential relationships, hierarchical relationships, temporal relationships, and more. RSD is a special type of event graph with a similar structure to an event graph. The biggest difference between the two is the transfer relationship between events. Event graphs use conditional probabilities, while RSD graphs use deterministic conditional relationships. To illustrate the relationship between event graphs and RSD graphs, this paper uses a tabular method to compare and analyze the two types of graphs as shown in Tab. 2.

Table 2 The difference between RSD and event graph

Type	Event Graph	RSD Graph
Definition	A graph network with events as nodes and relationships between events as edges, where most relationships are uncertain and transfer with a certain probability.	A graph with railway risk events and their response measures as nodes, and the conditional relationships between them as edges, where the conditions are deterministic.
Knowledge Described	Social logic	Specific scenarios for HSR risk prevention and control
Research Object	Predicative events and their internal and external (spatial and temporal) connections	The relationship between HSR operation risks and their response measures in specific scenarios
Construction Goal	A complete logic library and logic evolution model	A model of global risk response measures during HSR operation
Questions Answered	Why, How	Why, How
Organizational Form	Directed graph, cyclic graph	Directed graph
Knowledge Form	A multi-tuple of <event, argument set, logical relationship>	A multi-tuple of <risk event, response measure, scenario condition>
Knowledge Certainty	Logically uncertain with transfer probability	The logical relationship is deterministic in a specific scenario
Knowledge Sensitivity	Can tolerate certain errors with reference to logic	Deterministic knowledge requires exact compliance

3.3 Construction of RSD

There are primarily two methods for constructing knowledge graphs, including RSD. One is expert knowledge and experience-based construction method. This approach involves building the knowledge graph based on the expertise and experience of domain experts. It is suitable for domains with strong specialization, limited data sources, or high data quality. The advantage of this method is the accuracy and reliability of the resulting knowledge graph. However, it comes with higher costs and a slower process. And the other is supervised machine Learning-based construction. This method relies on supervised machine learning techniques and requires a substantial amount of annotated training data. The effectiveness of the model depends on the quantity and quality of the training data. The advantage is the ability to quickly extract knowledge, but the downside is that accuracy may not be high. Due to the specific requirements of accuracy and reliability in RSD graph construction, and the fact that the RSD graph structure differs from typical knowledge graphs, traditional graph construction methods may not fully meet the needs of RSD graph construction. In recent years, the remarkable performance of LLM in the field of Natural Language Processing (NLP) has introduced new methods for knowledge graph construction [28, 29]. Many researchers have explored how to utilize LLM for building knowledge graphs and enhancing the quality of content production using these graphs. Based on this research and considering the characteristics of RSD, this paper proposes a method for constructing RSD using LLM. Consequently, they offer a cost-effective means to achieve good results. This approach combines the prompt framework with LLM to extract the RSD graph. The construction process of an RSD graph based on LLM is depicted in Fig. 3 below.

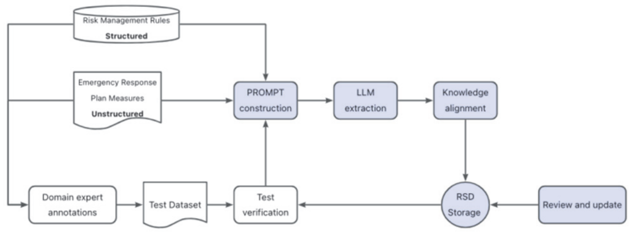

Figure 3 LLM-based RSD graph construction process

Fig. 3 illustrates the process of transforming unstructured emergency response information into a structured knowledge graph. First, risk response rules are structured, and emergency measures are collected in textual form. These are combined into a prompt, which guides a LLM to extract relevant knowledge. The extracted knowledge is then aligned for accuracy, with domain experts annotating it for correctness. A test dataset is created to validate the alignment. The final result is the RSD graph, containing both risk rules and emergency measures. This iterative process is continuously optimized to improve the graph's quality and practical value.

The core of the construction process is the development of prompts. Once knowledge to be extracted is structured using the prompt framework, it can be readily extracted using LLM. After aligning the extracted knowledge, the graph construction is completed. To validate the accuracy of the construction, this model applies a test set annotated by experts and updates the prompts based on the verification results, facilitating iterative optimization of the process. The following sections of this paper will focus on introducing the prompt framework, knowledge alignment, testing and validation, as well as domain expert reviews and other related aspects. The following sections will provide a comprehensive exposition of this approach:

(1) Prompt engineering (PE) for RSD construction. PE is an artificial intelligence technology that improves the output quality of LLM by designing and refining their prompts. The goal of PE is to enable LLM to perform specific tasks accurately and reliably. Based on the knowledge extraction requirements of RSD graphs and the framework of PE, this paper proposes a prompt structure for RSD knowledge extraction, as shown in Tab. 3.

Table 3 Prompt template design for LLM-based reasoning

Component	Function Description	Example Configuration
Capacity/Role	Model role setting	You are an expert in event graph construction.
Instruction	Clear task goal	Extract risk events and handling events, along with their causal, conditional, and sequential relationships.
Input Data	Input text	"When the train driver notices swaying during operation, they should immediately reduce speed and report to the dispatcher..."
Output Indicator	Output format guideline	Output event type, structure, and relationships in structured JSON or table format.
Context/train data	Training data or task type	Zero-shot.

To validate the accuracy of the RSD graphs constructed using the LLM-based approach, this study manually annotated 30 representative risk disposal rules based on risk management texts curated by domain experts. Each text contains multiple RCD rules, totaling 185 rules. The samples cover various typical scenarios such as weather risks, equipment failures, and operational anomalies, ensuring strong generalizability and representativeness. Each RCD rule was standardized into a triplet format. The model's output results were compared with the manually annotated labels on a rule-by-rule basis, using accuracy as the primary evaluation metric:

$$Precision = \frac{TP}{TP + FP} \tag{1}$$

where: TP represents the number of correctly identified RCD triplets, requiring that the triplets output by the model match the manual annotations in terms of semantics, structure, and logic; FP represents the number of incorrectly identified RCD triplets, where errors occur if the structure is missing, the sequence is incorrect, or the content does not align, which is considered a mismatch.

This experiment selected four LLMs-llama-3-70B, Qwen3-32B, ERNIE-4.0-Turbo, and DeepSeek-V3 - to test the extraction performance. These four mainstream large language models support strong Chinese processing capabilities and represent different architectural approaches and parameter scales. All models used the same prompt input format, with unified task descriptions, output requirements, and semantic paradigms to ensure fairness in the experiment. The experimental results are shown in Tab. 4.

Table 4 Verification results of LLM extracting RSD

Model Name	TP	Total No.	Precision
LLaMA-3-70B	176	185	95.14
Qwen3-32B	179	185	96.76
ERNIE-4.0-Turbo	180	185	97.30
DeepSeek-V3	182	185	98.38

From the experimental results, all four large language models achieved high accuracy in the RCD extraction task, with each surpassing 95%, and the highest reaching 98.38%. This indicates that the LLM-based RCD rule extraction method has strong recognition ability and stability. The overall accuracy validates that this method, without the need for additional training, is practically feasible for extracting structured rules from railway risk disposal texts. Generally, the model's parameter size and structure directly impact its reasoning ability. Larger models, like ERNIE-4.0-Turbo and DeepSeek-V3, tend to perform better, achieving higher accuracy in tasks such as RSD extraction.

(2) Knowledge alignment in the RSD graph. The construction of the RSD graph involves collecting and integrating information from different data sources. Different data sources may use varying names or descriptions for the same entity or relationship. For example, driver, train driver in the RSD graph all refer to a train driver. To create a unified RSD graph, it is necessary to align these different expressions. Alignment ensures they are standardized into a common representation, enhancing the consistency and accuracy of the RSD graph. There are typically two primary methods for knowledge alignment. Word vector similarity-based matching method relies on word vector similarity to find matches, while machine learning-based method employs machine learning techniques for knowledge alignment; since the RSD graph contains a significant amount of domain-specific knowledge, both methods require substantial preliminary training efforts, resulting in high alignment costs.

The essence of knowledge alignment lies in calculating semantic similarity. This paper proposes a knowledge alignment method based on LLM, as illustrated in Fig. 4. Fig. 4 illustrates the knowledge alignment process using LLM's NLP capabilities. It begins with the identification of risk entities, which are used to construct input prompts for the LLM. The LLM processes these prompts to compute semantic similarity. A check is then performed to see if any new entities are generated. If new entities are identified, the dataset is updated, and the process loops back for further iteration. If no new entities are found, the aligned knowledge is finalized and output, completing the alignment procedure. This method leverages LLM's proficiency in understanding natural language for efficient semantic alignment.

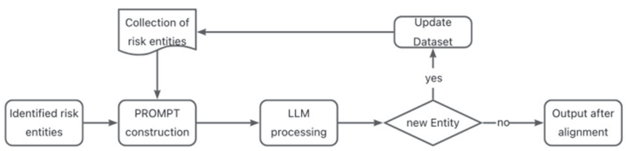

Figure 4 Knowledge alignment method based on LLM

(3) Storage of RSD. To facilitate the management of the RSD graph, it is advantageous to employ a graph database for storing RSD knowledge. A graph database is a type of database designed for storing a substantial volume of interconnected information. Graph databases offer

features such as relationship modeling and representation, relationship querying and analysis, graph traversal and path analysis, real-time transaction processing, and data visualization. These functionalities are well-suited to support the application of RSD in railway operation risk management. Several mainstream graph databases are available, including Neo4j, Tiger Graph, Orient DB, Arango DB, and others. From a technical perspective, these databases are all capable of meeting the storage requirements of RSD. Neo4j, in particular, provides an array of features and tools to assist users in managing and analyzing graph data effectively. It is one of the most popular and mature graph databases available. Therefore, this research opts to utilize Neo4j as the database for storing the RSD graph.

(4) Review and update mechanism for RSD. The direct application of the RSD graph in HSR safety risk decision-making necessitates ensuring the validity and interpretability of each piece of knowledge within the RSD. Therefore, before RSD can be applied to real-world scenarios, it must undergo a review by domain experts to ensure the rationality and interpretability of every risk decision made by RSD. The RSD expert review can be conducted using the following steps: 1) Establish Clear Guidelines and Protocols. Provide clear guidelines and protocols to instruct domain experts on how to evaluate the knowledge points extracted by the model, including potential risks and assessment criteria. 2) Comprehensive and Sampled Reviews Combined. To ensure the accuracy of RSD, every item within the RSD graph should undergo a review. Only those that meet the requirements can be applied. 3) Cross-Validation and Collaboration. Encouraging experts from various fields such as engineering, power supply, and dispatch to engage in cross-validation and collaboration is crucial for ensuring the comprehensiveness and accuracy of the knowledge graph. 4) Model Iteration and Updates. When new equipment is introduced, new rules are established, or new procedures are implemented, the RSD must be updated and iterated upon to ensure its accuracy and effectiveness.

The core value of emergency measures lies in maintaining the effectiveness and real-time relevance of emergency knowledge. RSD accomplishes structured and standardized management of emergency plans. The RSD graph has functionalities for adding, modifying, and deleting knowledge. Leveraging these functionalities, dynamic maintenance of emergency measures can be achieved. When new safety and control requirements need to be updated promptly, these requirements can be promptly added to the RSD knowledge repository.

4 RESULTS AND DISCUSSION

4.1 Application of the Proposed Method

RSD leverages graph theory to model risk control measures, with the overarching goal of achieving structured management and enhancing the feasibility of risk management practices. The primary focus of this study is the transformation of unstructured risk control plans into an RSD graph network. This transformation facilitates efficient decision-making and swift response in the realm of HSR operational risk control, thereby providing robust support for the safety of HSR operations. In the forthcoming sections, we will illustrate the construction method and process of RSD using a specific example.

The knowledge for constructing RSD mainly comes from the emergency management plans of railway operation departments at all levels. After a long period of accumulation, there are emergency response plans for all risks related to HSR operation safety. The following are some of the emergency plans: (1) Emergency Response Measures for Abnormal Situations in HSR Passenger Transport. (2) Emergency Response Measures for Derailment Accidents of High-speed train. (3) Emergency Response Measures for Abnormal Operation of High-speed train. (4) Emergency Response Measures for EMU Vehicle Failures. These documents are normative documents that must be followed for HSR risk prevention and handling. In the specific implementation process, various business departments of the railway will further refine the risk prevention and control measures in combination with their own characteristics, forming more specific and practical risk response plans. The following emergency plan is chosen from these existing plans, outlining in an unstructured manner how HSR implements speed limit measures to mitigate risks during rainy weather conditions. Example 1: In the event of rainy weather, when the rainfall in key flood control areas reaches 45 mm or more per hour, the train speed is limited to 120 km/h; when the rainfall reaches 60 mm or more per hour, the train speed is limited to 45 km/h. When the rainfall falls to 20 mm or less per hour and lasts for more than 30 minutes, the speed limit can be gradually lifted.

According to the definition of RSD in this paper, the content of the above emergency plan can be organized into an RSD table, as shown in Tab. 5. Tab. 5 represents a structured representation of emergency plans, providing a clear description of the internal structure of RSD. The following section discusses the RSD extraction method proposed in this paper. By incorporating the data from Example 1 into the input data section of Tab. 3, the extraction prompt for RSD is obtained. This prompt is then submitted to the LLM to leverage its natural language processing capabilities for extraction, yielding the following results.

Table 5 Tabular representation of RSD

<table>
<tr><th>Risk</th><th>S</th><th>D</th></tr>
<tr><td rowspan="3">Name: excessive rainfall
Warning Source: [...]
Risk Type: [...]
Risk Level: [...]
Warning Time: [...]
Occurrence Location: [...]
Warning Scope: [...]</td><td>S_1: When the 1-hour rainfall reaches 45 mm or above, the train speed is restricted to 120 km/h.</td><td rowspan="2">D_1: Speed Restriction
Subject: Train Driver
Execution: Speed Restriction
Object: Train
Parameters: speed</td></tr>
<tr><td>S_2: When the 1-hour rainfall reaches 60 mm or above, the train speed is restricted to 45 km/h.</td></tr>
<tr><td>S_3: After s_1 or s_2 occurs, when the 1-hour rainfall decreases to 20 mm or below and persists for more than 30 minutes, normal operations can be resumed.</td><td>D_2: Resume Operations
Subject: Train Driver
Execution: Remove Speed Limit
Object: Train</td></tr>
</table>

Note: The content enclosed in [...] in the table needs to be determined by an external system.

Table 6 RSD Extraction Example Based on LLM

Name	Type	Structure	Relationship
Event 1: Rainy Weather	Risk Event	Heavy rainfall, reaching 45 mm per hour or 60 mm and above	Conditional relationship with other events
Event 2: Train Speed Limit 120 km/h	Response Event	Subject (Train Driver), Action (Speed Limit), Object (120 km/h), Trigger Condition (Hourly rainfall reaching 45 mm and above)	Conditional relationship with Event1
Event 3: Train Speed Limit 45 km/h	Response Event	Subject (Train Driver), Action (Speed Limit), Object (45 km/h), Trigger Condition (Hourly rainfall reaching 60mm and above)	Conditional relationship with Event1
Event 4: Gradual Speed Release	Response Event	Subject (Train Driver), Action (Gradual Release), Object (Speed Limit), Trigger Condition (Hourly rainfall drops to 20 mm or below and continues for 30 minutes or more)	Conditional relationship with Events 2 and 3

Note: The contents in the table are derived from the output of the Baichuan LLM.

Since the purpose of RSD is to achieve automated risk management, it is essential to define the agents and objects of each action. For example, in the case of speed limit operations due to excessive rainfall, the dispatcher initiates the action by issuing speed limit commands to the train driver, who then executes the speed limit operation. Each action has a clear initiator and executor. Based on this analysis, the RSD in Tab. 6 can be represented by the graph structure shown in Fig. 5.

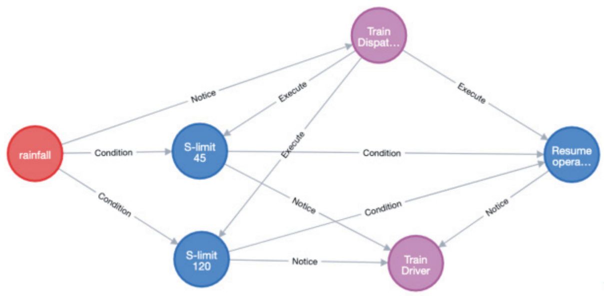

Figure 5 RSD graph for HSR rainfall risk handling

As can be seen from Fig. 5, railway risk emergency response is a complex process involving multiple participants and multiple measures. In accordance with the definition of subgraphs, Fig. 5 can be considered as a subgraph. $G(R, S, D)$ can be regarded as a complex network composed of multiple g, then G can be expressed as: $G = \{g_1, g_2, g_3, \ldots, g_n\}$. Multiple RSD subgraphs merged together form a complex network, as depicted in Fig. 6. The five red nodes in Fig. 6 represent five different risks, indicating that Fig. 6 is composed of five subgraphs.

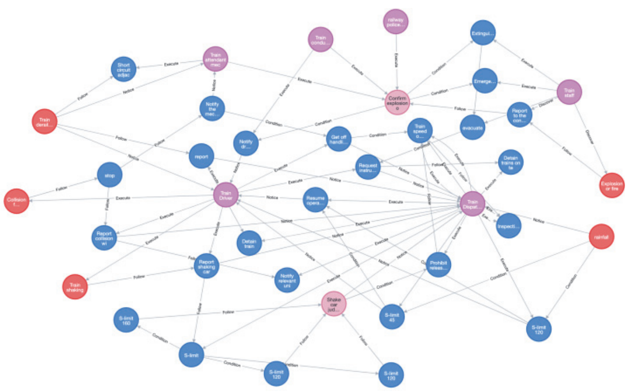

Figure 6 General form of RSD graph

In the above analysis, we provided a detailed exposition of various steps in constructing RSD, including knowledge acquisition, prompt formulation, knowledge extraction, and knowledge graph integration. By employing a specific example, we further validated the feasibility of the method proposed in this paper, which is based on the utilization of LLM for RSD construction. However, it is worth noting that LLM exhibits certain limitations during the RSD extraction process, with issues related to incomplete or inaccurate extractions. Supplementary external knowledge is often required to enhance the results. At present, it is evident that the construction of RSD still necessitates the active involvement of domain experts to ensure the quality and reliability of the final knowledge graph and extraction results.

4.2 Discussion in Practical Scenarios

In the context of RSD application, our research explores four distinct scenarios that collectively contribute to the enhancement of HSR risk management and control. These scenarios serve as pivotal components in our study, each addressing specific aspects of HSR safety. Let us embark on an exploration of these scenarios:

(1) Automation of high-speed rail risk management and control decision-making. Traditional risk management methods rely on human judgment and manual operations, which often lead to delayed responses and are constrained by the operators' experience and knowledge. To address these issues, the RSD model structures the risk management process into a graphical decision support system, enabling a highly automated decision-making process that improves decision-making efficiency and accuracy. 1) Automated Risk Response Generation through Feature Matching. When the system detects a risk alert, the RSD model automatically generates a compliant risk response by matching the detected features with an existing risk database. This automation significantly shortens response times, enhances processing efficiency, and reduces the risk of escalation caused by human delays. 2) Automated Multi-Department Collaborative Response. The RSD model generates collaborative responses for multiple departments, ensuring that all departments can rapidly coordinate under unified command. This mechanism prevents incomplete risk mitigation or secondary incidents due to poor coordination between departments. 3) Enhanced Response Speed and Decision Quality. By automating decision-making, the RSD model accelerates emergency response, ensuring that response measures are executed swiftly and accurately, reducing the decision errors that can result from human intervention.

(2) Management of key nodes in high-speed rail risk management and control. By analyzing the characteristics of the RSD graph, the degree (in-degree and out-degree) of nodes can be assessed, allowing for the identification of critical nodes within the network. Generally, a higher

degree indicates a node's greater importance within the RSD network. Nodes with higher degrees have a more significant impact on the entire network in the event of issues. For example, in the RSD subgraph shown in Fig. 4, Neo4j's Cypher query language facilitates the calculation of the degree values for various nodes. The first two nodes, "Train Driver" with a degree of 17 and "Dispatcher" with a degree of 11, have the highest degrees, highlighting their crucial role in the five risk-handling scenarios depicted in the graph. Therefore, these nodes should be prioritized for enhanced management in emergency situations to bolster their risk-handling capabilities.

(3) Simulation exercises for HSR risk handling plans. One of the key features of the RSD model is its ability to transform previously unstructured emergency plans into structured knowledge systems, represented in a graphical format. This transformation allows for the evaluation of the effectiveness and rationality of emergency plans through computerized simulations. The implementation of the RSD model for risk management and control exercises involves the following steps: 1) Preparation of Risk Simulation Data: Construct various potential risk scenarios based on existing risk data, covering different risk types and levels, to ensure comprehensive simulation exercises. 2) Simulation of Risk Control Decision-Making: Generate risk handling plans by randomly generating risk characteristics using the RSD graph network. This step verifies whether the RSD model correctly addresses various risk features and ensures consistency with manually formulated plans. 3) Simulation of Control Measures Execution: Simulate the execution process, involving the participation of action-executing entities. The simulation system receives instructions and feedback from these entities. Through interactions between the simulation system and the executing entities, risk control plan exercises are conducted. 4) Simulation Effect Evaluation and Feedback: After completing the simulation exercises, evaluate the results, including the correctness of control measures and response times. Based on the evaluation, feedback is provided for optimization, continuously improving and refining risk management and control plans. Through these simulation exercises, the RSD model helps railway departments better understand risk management and control processes and strategies. Additionally, it validates the reasonableness and effectiveness of risk plans.

(4) Optimization Strategies for HSR Risk Management and Control. The optimization of risk management and control decision-making through the RSD model is reflected in the following aspects: 1) The RSD model converts risk scenarios into quantifiable decision rules, reducing reliance on human judgment and significantly enhancing response speed. In the case of managing severe rainfall risks, the RSD model can automatically trigger speed-limit measures. Compared to traditional manual decision-making, which typically takes 2 minutes, the RSD model can complete risk identification and decision-making responses in just seconds, drastically reducing the processing time. 2) The RSD model enables parallel processing of tasks across multiple departments, avoiding delays associated with serial processing and optimizing the efficiency of emergency responses. 3) RSD enhances the efficiency and consistency of updating risk control measures by standardizing control measure nodes. For instance, when updating a "speed-limit" control measure, it is sufficient to update the "speed-limit" node within the RSD graph, which automatically applies the change to all relevant scenarios. By automating, parallelizing, and standardizing risk management, the RSD model significantly improves decision-making efficiency, response speed, and safety in high-speed rail operations.

4.3 Analysis of the Limitations of RSD

Despite its potential, RSD faces several challenges in practical applications. First, computational complexity can become a bottleneck when managing large-scale risk events and multi-department collaboration, especially in high-frequency railway environments. Optimizing algorithms and system processing is crucial for efficient performance. Second, integrating RSD with existing railway management systems is difficult due to differences in data structures and protocols. Developing interfaces for seamless integration is necessary to ensure compatibility between old and new systems. Lastly, real-time data processing is a major constraint. The large and dynamic volume of real-time monitoring data makes it challenging to update the RSD graph quickly. Adopting stream processing and edge computing can improve real-time response and ensure timely updates to the RSD graph. These limitations highlight areas for improvement, guiding the future development and application of RSD.

5 CONCLUSIONS

This study conducted a comprehensive and in-depth exploration of the management of high-speed rail operational risk control plans. The research began by introducing the background, current situation, and main issues, clearly defining the core problems to be addressed and the scope of the research. The paper then introduced the RSD model and provided a detailed analysis of its definition and functional characteristics. By comparing event graphs with RSD graphs, the paper highlighted the uniqueness and advantages of RSD. The focus of the study was on the construction of RSD, proposing methods such as LLM-based knowledge extraction and knowledge alignment, with feasibility verified through test data. Finally, the study examined the functions of RSD in automated decision-making, key point management, simulation drills, and optimization strategies in high-speed rail operational risk control, emphasizing the application value and practical significance of RSD in railway safety management.

Future research can be expanded in several areas: First, larger and more diverse real-world datasets can be used for validation to assess the robustness and scalability of the RSD model across different practical scenarios. Second, exploring RSD architectures suitable for edge computing can enhance real-time data processing and risk analysis capabilities at the edge of the high-speed rail system, improving response speed and accuracy. Additionally, integrating the RSD model with existing risk identification models will enable seamless coordination between risk detection and mitigation, further enhancing the collaborative effect and risk prevention capabilities in high-speed rail safety management.

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