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Review

Ontologies and Knowledge Graphs for Railway Safety

Marzia De Bartolomeo [1,†] and Antonio De Nicola [2,*,†]

[1] Independent Researcher, 84124 Salerno, Italy; marzifacio@gmail.com
[2] Agenzia nazionale per le nuove tecnologie, L'energia e lo sviluppo economico sostenibile (ENEA), Via Anguillarese 301, 00123 Rome, Italy
* Correspondence: antonio.denicola@enea.it
† These authors contributed equally to this work.

Abstract

Semantic technologies based on ontologies and knowledge graphs are increasingly recognized for their potential to enhance safety, risk, and emergency management in railway systems. This paper presents a systematic literature review aimed at identifying how ontologies, knowledge graphs, and the technologies based on them are applied within the domain of railway safety and assessing their contributions. A total of 53 relevant papers were analyzed using a structured review process, covering four main areas: risk management, safety management, emergency management, and accident analysis. The results reveal that ontologies and knowledge graphs support proactive hazard identification, formalization of safety knowledge, intelligent emergency response, and detailed accident causation modeling. Moreover, they enable semantic interoperability, reasoning, and automation across complex socio-technical railway systems. Despite their benefits, challenges remain regarding data heterogeneity, scalability, and the lack of semantic standardization. This study identifies the most relevant models and technologies, such as SRAC, SRI-Onto, and transformer-based graph neural networks, highlighting their role in advancing intelligent railway safety solutions. This work contributes a detailed map of the current state of semantic applications in railway safety and offers insight into emerging opportunities for future development.

Keywords: knowledge graph; ontology; railway safety

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1. Introduction

The railway system can be considered as a cyber-socio-technical system because it involves a deeply integrated interplay between technological, physical, and human elements. As described by Patriarca et al. [1], such systems are characterized by their complexity and the dynamic nature of interactions across different levels of activity, perception, and control. In the case of railways, digital and automated technologies, such as intelligent monitoring tools, real-time control systems, and knowledge-based safety platforms, form the cyber dimension of the system. These tools not only process data but actively influence decision making and operational performance. At the same time, the physical infrastructure, including trains, tracks, stations, and signaling systems, remains central to the functioning of the railway system. However, these physical components do not operate in isolation. Human actors, such as train drivers, maintenance personnel, control center operators, safety analysts, and even passengers, play an essential role in shaping and responding to the state of the system. Their actions, expertise, and interactions contribute to the system's behavior in ways that are often unpredictable or emergent. What makes the railway system distinctly cyber-socio-technical is the mutual dependency and co-evolution of these three layers. Human decisions are increasingly informed or guided by cyber systems, which in turn are designed to monitor and manage the physical domain. These interactions are not linear but form a network of relationships that must be understood holistically. Moreover, the railway system continuously adapts to changes, such as disruptions, accidents, or maintenance needs, by relying on both human judgment and computational support. This makes it a prime example of a system in which safety, performance, and resilience can only be ensured through the integrated management of cyber, social, and technical knowledge and behavior.

Safety is a critical concern in railway systems, where the complexity of the interaction among humans, cyber infrastructure, and physical infrastructures introduces significant risks and potential for disruption. Traditional safety analysis methods, while valuable, often fall short in capturing the dynamic, interconnected nature of hazards, especially as digital systems generate increasingly diverse and unstructured data. In recent years, semantic technologies, including ontologies, knowledge graphs, and associated reasoning methods, have emerged as promising tools to coping with the complexity of cyber-socio-technical systems by formalizing, integrating, and exploiting safety-related knowledge [2].

According to De Nicola and Missikoff [3], an ontology is a conceptual model of a fragment of an observed reality, consisting of a repository of interlinked concepts related to a specific application domain. Ontologies provide structured vocabularies and conceptual models that allow for consistent representation of domain knowledge, while knowledge graphs enable linking and reasoning over heterogeneous information sources. Indeed, a knowledge graph is a graph of data designed to accumulate and represent real-world knowledge, where nodes correspond to entities and edges denote diverse relationships between them, enabling integration, reasoning, and inference over complex, interconnected data sources [4]. These technologies are particularly well suited to railway systems, where understanding risk propagation, responding to emergencies, and analyzing accidents require a comprehensive and adaptable knowledge framework exploiting data collected by diverse sources, such as IoT devices and video cameras.

Despite their potential, the application of semantic technologies in the field of railway safety remains fragmented and far from unleashing its potential. To address this gap, this paper presents a systematic literature review that investigates how these technologies are currently being applied, what value they bring, and which models and methods are most relevant. The review aims to answer four key research questions, covering areas of application, added value, current challenges, and leading technologies, thereby contributing to a clearer understanding of the role of semantics in advancing railway safety.

The rest of the paper is organized as follows: Section 2 outlines the phases of the methodology employed in the systematic literature review, including the planning and design of the research process, the collection and semantic analysis of the papers, and the identification of key insights that inform the subsequent analysis and discussion. Section 3 presents a multidimensional perspective on how ontologies and knowledge graphs have been used to enhance railway safety, focusing on risk management, safety management, emergency management, and accident analysis. The answers to the four key research questions are provided in Section 4. Finally, Section 5 concludes the article with key takeaways and suggestions for future research in this field.

2. The Systematic Literature Review Methodology

The primary objective of this systematic literature review was to identify and analyze the most significant publications concerning the application of ontologies and knowledge graphs in the context of railway safety. This effort aimed to address a set of research questions focused on the current adoption and impact of semantic technologies within the sector. The review methodology follows the structured approach proposed by De Nicola and Villani [5], and is organized into the following three main phases:

- *Planning and design*;
- *Papers collection and semantic analysis*;
- *Takeaways*.

Each phase encompasses a series of steps that were executed either automatically or through manual examination of the retrieved publications.

The specific steps involved are elaborated in the following subsections.

2.1. Planning and Design

This phase aims at defining the aim of this study and at designing a rigorous methodological approach to be followed for the review. It consists of two steps, which are described as follows:

Define research questions. This initial step focuses on formulating the research questions that guide the literature review. These questions serve two primary objectives: first, to analyze and categorize existing research on the application of ontologies and knowledge graphs in railway safety; second, to identify emerging topics where semantic technologies could play a significant role in the near future. The four guiding research questions are listed below.

RQ1. In which areas of the railway safety domain have ontologies, knowledge graphs, semantic methods, and semantic technologies been applied so far?
RQ2. Do ontologies, knowledge graphs, semantic methods, and semantic technologies provide significant added value in this domain?
RQ3. What are the main challenges encountered?
RQ4. Which ontologies, knowledge graphs, semantic methods, and semantic technologies are most relevant?

Design systematic literature review process. This step involves developing a rigorous and adaptable methodological framework for conducting the review. The goal is to ensure objectivity through automation in the selection of scientific literature while allowing enough flexibility to manually include relevant studies that may not have been captured automatically.

2.2. Papers Gathering and Semantic Analysis

This phase consists of six steps and has two primary goals. The former is to define the scope of the analysis by automatically collecting a set of papers from SCOPUS (SCOPUS url: https://www.scopus.com), which is Elsevier's abstract and citation database. The latter is to make a partially automated semantic analysis to classify the sectors and technological areas they address.

SCOPUS query formulation. This step establishes the foundation for defining the scope of the analysis. We identified a set of "seed terms", i.e., keywords representing both the railway-related sectors of interest and the semantic technologies under investigation. The selected seed terms were railway, railroad (to collect also the papers using American English terminology), ontology, and knowledge graph. At this stage, we deliberately opted for a broad search scope to avoid prematurely excluding papers that might indirectly pertain to safety-related issues. We recognize that natural language processing (NLP) represents an important set of techniques, particularly in the construction of ontologies and knowledge graphs. However, in this study, our primary focus is not on the NLP techniques themselves, but rather on how ontologies and knowledge graphs are used to support safety, risk, and emergency management in railway systems. Therefore, our query strategy prioritized terms like ontology, knowledge graph, and related concepts in order to capture literature that specifically explores the application and integration of these semantic tools.

SCOPUS query

```
(TITLE-ABS-KEY (("railway" OR "railroad") AND ("ontology" OR
"knoweldge graph" )))
```

Query execution and papers retrieval. The SCOPUS database was queried on 3 February 2025 and on 14 July 2025, resulting in the retrieval of 236 publications related to railways (or railroads) and semantic technologies. For each paper, metadata such as authors, title, publication type (e.g., journal article, conference paper, workshop contribution, or book), year of publication, citation count, and additional details including DOI, URL, number of pages, volume, and issue number were collected. Figure 1 illustrates the distribution of these papers over time. The trend clearly indicates a growing interest in this area within the scientific community.

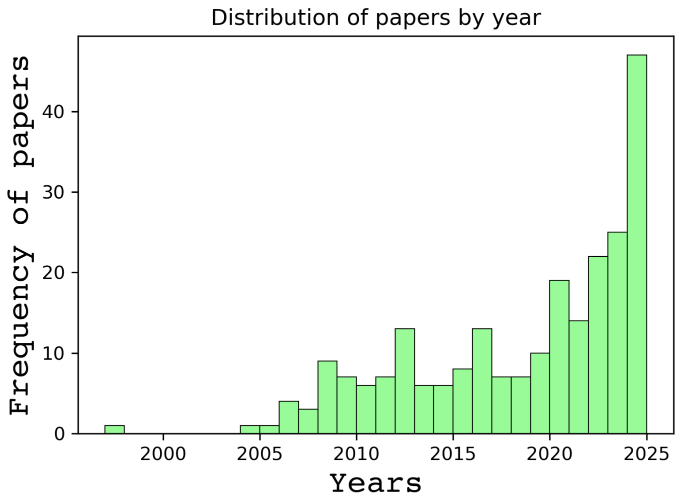

Figure 1. Distribution of retrieved papers addressing railway and semantic technologies by year.

Keywords extraction. In this step, we extracted the keywords assigned to the papers by both SCOPUS and the original authors. Of the total 236 papers, 28 did not include any authors' keywords. In total, 1370 keywords were collected using a Python application (version 3.x) specifically developed for this purpose.

Keywords pruning. To focus on the most relevant topics, we retained only those keywords that appeared more than once across the dataset. Following an additional manual evaluation, the final set was refined to 311 keywords.

Subsectors identification. This step addresses research question RQ1. We analyzed the set of 311 keywords and divided them into two categories: the first included keywords related to specific railway sectors, while the second encompassed methodological and technological terms referring to constructs, models, methods, and technologies not tied to any particular sector. We then focused on the first category to identify keywords specifically related to safety and risk management. These keywords were subsequently organized into a structured taxonomy through manual classification. Figure 2 illustrates an excerpt from the taxonomy derived from the keyword classification process. It organizes safety and risk management concepts into a hierarchical semantic framework composed of key domains and subdomains such as safety management, emergency management, accident analysis, and risk management. Each node represents a concept identified during the review, with subcategories capturing more specific topics, such as accident causation, railway safety risks, or emergency response. This taxonomy not only guided the systematic identification and classification of relevant papers but also serves as a conceptual structure for mapping how semantic technologies are applied across different aspects of railway safety.

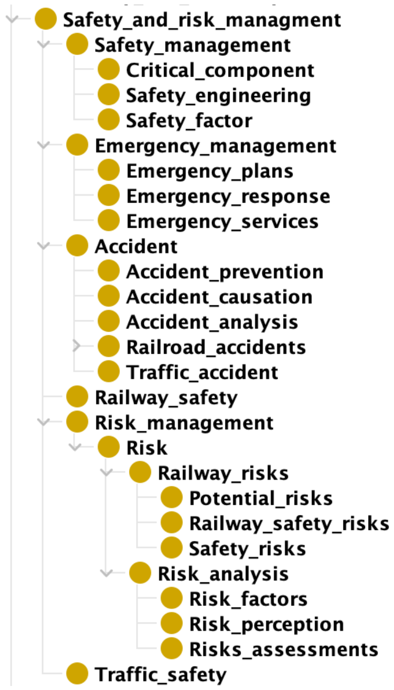

Figure 2. Excerpt from the taxonomy of keyword topics on safety and risk management.

Papers selection. In this step, we selected all papers associated with the keywords classified under the safety and risk management taxonomy. This process resulted in a final set of 53 papers. To maintain conciseness, the following sections highlight the most relevant and representative papers from the final selection. For completeness, however, all 53 selected papers were categorized by four subsectors of interest for our analysis: risk management [6–15], safety management [16–38], emergency management [39–41], and accidents [42–58].

2.3. Takeaways

Papers analysis and reporting. In this step, we conducted a detailed analysis of the selected papers with the aim of identifying key issues, the ontologies and knowledge graphs developed, and the services and technologies applied within each sector. The findings of this analysis are presented in the following section.

Answering research questions. This step involves formulating responses to the defined research questions. The corresponding answers are presented in Section 4.

3. Findings from the Multidimensional Analysis of Ontologies and Knowledge Graphs for Railway Safety

This section presents the results of the literature review aimed at understanding how ontologies and knowledge graphs have been applied across key dimensions of railway safety. The analysis is structured around four core subdomains, risk management, safety management, emergency management, and accident analysis, each of which plays a critical role in ensuring the reliability, resilience, and safety of railway operations. Within each domain, the section outlines the main issues faced by the railway sector, reviews the ontologies and knowledge graphs proposed to address these challenges, and highlights the services and technologies developed using semantic approaches. These findings offer a multidimensional perspective on the evolving role of semantic technologies in enhancing railway safety through improved knowledge representation, reasoning, and decision-making support.

3.1. Risk Management

Risk management refers to the systematic process of identifying, assessing, and mitigating potential hazards that could negatively impact the safety, performance, or continuity of operations [59]. In the context of railways, it involves analyzing complex cyber-socio-technical systems to anticipate accidents, manage uncertainties, and implement strategies that minimize the likelihood and consequences of risks. Effective risk management not only enhances operational resilience but also supports informed decision making through proactive planning and the use of formalized knowledge.

3.1.1. Issues in Risk Management

Risk management in the railway domain involves identifying, analyzing, predicting, and mitigating potential hazards to ensure system safety and performance continuity. In many railway systems, particularly those involving large-scale construction or operations under complex environments (e.g., subways, high-speed rail, and heavy haul freight lines), accidents often result from complex chains of interrelated risk factors. Traditional risk analysis techniques (e.g., fault trees, expert judgment) lack the ability to model dynamic interrelationships, update over time, or scale with growing data complexity. As previously demonstrated in environmental systems modeling, integrating climate and environmental hazards into risk assessments via semantic representations allows for more holistic and anticipatory safety planning [60]. Additionally, there are gaps in integrating multi-source knowledge and formalizing domain understanding in a way that enables automated reasoning and proactive mitigation strategies. For example, the integration of knowledge on signaling systems, train schedules, track conditions, and human factors in complex railway networks remains a challenge in conventional risk models.

3.1.2. Ontologies and Knowledge Graphs for Risk Management

The following works focus on identifying, analyzing, and managing risk, often proactively, using formal knowledge models.

In [6], Huo et al. introduced a data-driven knowledge graph-based model to analyze the coupling mechanism of risk hazards in subway construction. By collecting 231 accident reports, they built the Subway Construction Safety Accident Knowledge Graph (SCSAKG), a multidimensional complex network that models entities such as hazards, types, frequencies, consequences, and occurrence times. Their work emphasized the use of topological indicators to reveal the structure and interrelations within the graph, offering a novel method for understanding complex system risks and enabling the design of targeted prevention strategies.

In [7], Cao et al. developed the SRAC (Scenario-Risk-Accident Chain) ontology to model accident causation in heavy haul railway systems. The paper presented a method for ontology evolution and concept evaluation that incorporates knowledge discovery and semantic similarity to update risk ontologies dynamically. Their approach allows the system to evolve by introducing new concepts (e.g., device status data, train component failures), assess risk concept relevance, and perform accident level assessments via maximum flow analysis [61].

In [8], Li et al. explored rule-based reasoning using contextual ontologies for analyzing railway accidents. Their method models accident chains by tracing how risk factors are interrelated in specific operational scenarios. This approach enables inference over potential risk propagation pathways and supports proactive accident prevention, including scenarios such as railway signaling failures and human errors.

In [9], Cui et al. proposed an ontology-based probabilistic framework for seismic risk evaluation of subway stations. The framework integrates Monte Carlo simulation with an ontology model and semantic web rules, enabling multi-objective seismic risk assessments that include factors like economic loss, casualties, and recovery time. The ontology supports automated reasoning and decision support for urban transit systems and urban infrastructure resilience.

In [10], Wang et al. presented a domain-specific model for risk relation extraction using transformer-aware Graph Convolutional Networks (GCNs), specifically for the railway sector. By training on accident and risk-related texts, the model identifies latent semantic links between entities and relations, providing an intelligent and scalable method for constructing knowledge graphs for railway safety-critical systems. This approach enhances safety-critical systems by analyzing railway textual data, such as railway accident reports and operational manuals.

3.1.3. Services and Technologies for Risk Management

The reviewed works have demonstrated a variety of services and technological frameworks that leverage ontologies and knowledge graphs for effective risk management in the railway domain. As summarized in Table 1, these services span from probabilistic modeling and semantic reasoning to data-driven hazard analysis and machine learning-based relation extraction.

As mentioned, the seismic risk evaluation service proposed by Cui et al. [9] integrates Monte Carlo simulations with ontological reasoning to conduct multi-objective seismic risk assessments for subway stations. This allows for a comprehensive understanding of seismic impacts, considering variables like economic loss and recovery time, and the structural integrity of critical railway infrastructure, including bridges, tunnels, and stations, which are particularly vulnerable in seismic zones.

Huo et al. [6] contribute a hazard coupling analyzer, which is based on a domain-specific knowledge graph developed from real-world subway construction accident reports. The graph reveals complex interdependencies among hazards, and the system supports the development of preventative strategies through network topology analysis.

In terms of knowledge model maintenance, Cao et al. [7] developed an ontology evolution tool that enables dynamic updates to the ontology using semantic similarity and rule-based mappings. This service ensures that risk models remain adaptive to new data sources and operational contexts, such as the introduction of new high-speed rail technologies, changes in freight transport volumes, or the integration of autonomous train systems. This tool allows for continuous learning in the risk management process, ensuring that models evolve in response to emerging technologies and operational practices. It supports the development of preventive strategies through network topology analysis, enabling the prioritization of safety measures for high-risk segments of the railway network by accounting for factors such as train malfunctions, track conditions, and operational errors.

Finally, Wang et al. [10] introduce a risk relation extractor that uses transformer-aware Graph Convolutional Networks (GCNs) to extract latent semantic relationships from unstructured safety documents. This method automates the construction of risk knowledge graphs and improves the scalability and intelligence of safety analysis systems. By processing accident reports, maintenance logs, and operational protocols from various railway companies, the extractor creates a more comprehensive database for risk management, improving decision making and incident prevention strategies across regional and national rail networks.

Together, these services exemplify how semantic technologies can support advanced reasoning, automated knowledge updates, and intelligent risk inference, thereby enhancing the resilience and safety of railway systems, ensuring that critical operations such as train scheduling, infrastructure monitoring, and real-time hazard detection are continuously optimized for safety. Furthermore, the integration of ontologies and knowledge graphs with advanced technologies such as the Internet of Things (IoT) and machine learning is radically transforming railway safety management. The use of intelligent sensors distributed along the railway network allows for real-time data collection on track conditions, train speeds, rail wear, and structural integrity of infrastructure. These data are then integrated into predictive models powered by machine learning algorithms that identify risk patterns and predict failures or anomalies before they occur, minimizing the risk of accidents. For example, an integrated monitoring system could detect a damaged cable or brake overheating condition in real time, immediately alerting maintenance staff and enabling timely interventions. Additionally, the use of ontologies specific to railway safety allows for the standardization of response protocols, improving the efficiency of preventive maintenance and repairs. The intelligent management of data from various sources, such as autonomous trains and advanced signaling systems, can further enhance operational safety and ensure that resources are used as efficiently as possible, optimizing operational flexibility and the resilience of the railway system. This approach is consistent with other semantic-based systems that incorporate both spatiotemporal modeling and structured ontologies for urban risk assessment, such as the TERMINUS ontology and the CIPCast system developed for urban crisis management contexts [62].

Table 1. Ontology and knowledge graph-based services for risk management.

Service	Description
Seismic risk evaluation	It uses ontology and Monte Carlo for subway risk evaluation [9]
Hazard coupling analyzer	It analyzes interdependent hazards in subway works [6]
Ontology evolution tool	It allows dynamic evolution and evaluation of risk concepts [7]
Risk relation extractor	It extracts safety risk relationships using transformer-GCN [10]

3.2. Safety Management

Safety management [63] refers to the systematic processes and practices aimed at ensuring the safety of people, assets, and operations within complex systems such as railways and construction projects. It encompasses risk identification, hazard assessment, prevention strategies, and compliance with safety standards. As safety-related knowledge becomes increasingly complex and distributed, ontologies and knowledge graphs have emerged as powerful tools for formalizing, integrating, and reasoning over safety information. This subsection outlines the key issues in safety management, highlights recent developments in the use of ontologies and knowledge graphs, and presents services and technologies designed to support intelligent, proactive safety management.

3.2.1. Issues in Safety Management

Safety management in railway and construction domains involves ensuring operational integrity, minimizing risks to personnel and equipment, and maintaining compliance with safety standards throughout the system life cycle. However, several challenges persist. Safety information is often dispersed across unstructured documents, expert reports, and siloed data systems, which hampers its systematic reuse and integration. Furthermore, safety risk identification and mitigation are heavily reliant on expert judgment, which can vary widely and may not be scalable. New forms of interactive modeling, such as gamified approaches to safety data collection and the development of resilience indicators, have shown potential to address limitations of static assessments [64]. Another issue lies in the lack of standardization across different domains and regions, limiting semantic interoperability among safety management systems. As railway systems become increasingly complex, interweaving digital technologies, infrastructure, and human operators, there is an urgent need for formal, intelligent, and scalable solutions to support proactive safety management. For instance, the integration of real-time data from train sensors, signaling systems, and weather forecasts is critical to improving the prediction and prevention of accidents across large and interconnected railway networks. This necessitates the development of standardized, cross-platform ontologies and knowledge graphs that facilitate interoperability between different railway operators, regulatory bodies, and maintenance teams.

3.2.2. Ontologies and Knowledge Graphs for Safety Management

Recent advancements have demonstrated the potential of ontologies and knowledge graphs (KGs) in structuring, integrating, and reasoning over safety-related knowledge.

Kaindl et al. developed a unified core ontology to reconcile safety risk concepts across domains such as automotive and railway [16]. Their model aligns with international safety standards and provides a reusable reference structure for semantic consistency and reasoning in safety-critical systems.

Xing et al. proposed SRI-Onto, a domain ontology specifically for metro construction safety risk identification [17]. Their model formalizes diverse safety concepts, including risk factors, prevention measures, and consequences, into a structured representation, facilitating knowledge reuse and semantic interoperability across stakeholders and information systems. This ontology has applications in subway rail projects, where risks like track instability, passenger congestion, and system failures due to integration with urban transit networks must be proactively managed.

Jiang et al. combined ontology with improved case-based reasoning (CBR) to create a decision-support method for managing construction safety risks [18]. By incorporating similarity and correlation algorithms, their model enhances the retrieval of relevant risk scenarios, enabling proactive decision making for subway construction projects.

Wang et al. introduced a general knowledge graph-based framework for modeling railway safety risks [19]. Their approach emphasizes the integration of diverse hazard-related entities and relationships from operational data to support system-wide safety awareness and knowledge-driven analysis, helping, for instance, to identify vulnerabilities in railway signaling systems, train dispatching operations, and emergency response protocols across extensive rail networks.

Liu et al. developed a knowledge graph-based hazard prediction approach for operational railway accidents [20]. Their method constructs a railway operational hazard knowledge graph and applies translation-based embedding techniques for link prediction, enabling early identification of cascading hazards and guiding targeted control strategies. This approach is particularly useful in preventing railway accidents caused by chain reactions, such as signal system failures leading to train collisions or track defects causing derailments. Their model helps railway operators anticipate and mitigate the cascading impact of multiple risk factors, ultimately reducing the probability of catastrophic events across the network.

3.2.3. Services and Technologies for Safety Management

Table 2 summarizes key services and technologies developed using ontologies and knowledge graphs to enhance safety management in railway and construction contexts. These services address various stages of the safety management life cycle, including risk identification, evaluation, prediction, and decision-making support.

The safety risk assessment support service, based on the core ontology proposed by Kaindl et al. [16], offers a standardized semantic framework that aligns with international safety standards and enables formal reasoning across different safety-critical domains.

The automated safety checking service proposed by Li et al. [21] leverages building information modeling (BIM), ontology, and rule-based reasoning to automatically validate safety-related conditions and constraints during construction processes.

The ontology-based decision support system developed by Jiang et al. [18] integrates structured domain knowledge with an improved case-based reasoning mechanism, enabling more accurate and context-aware safety decision making in subway construction projects.

The hazard prediction tool proposed by Liu et al. [20] applies a knowledge graph embedding and link prediction approach to foresee potential operational hazards, providing a foundation for proactive hazard control and mitigation strategies.

Lastly, the integrated knowledge platform aims to unify safety, quality, and scheduling information within a coherent semantic framework, supporting intelligent management of complex construction scenarios such as railway tunnel projects [22].

Together, these services demonstrate the versatility and power of semantic technologies in structuring, analyzing, and applying safety knowledge in diverse and complex environments.

Table 2. Ontology and knowledge graph-based services for safety management.

Service	Description
Safety risk assessment support	It supports risk analysis via formal concept representation [16]
Automated safety checking	It automates safety checks using BIM, ontology, and rules [21]
Ontology-based decision support	It uses ontology and CBR for risk-based decisions [18]
Hazard prediction tool	It predicts potential hazards from accident patterns [20]
Integrated knowledge platform	It manages safety, quality, and schedule knowledge [22]

3.3. Emergency Management

Emergency management [65] refers to the coordinated processes and strategies aimed at preparing for, responding to, and recovering from unforeseen incidents or accidents that threaten the safety and continuity of operations. In railway systems and metro infrastructure, this involves structured planning, rapid response mechanisms, and knowledge reuse to mitigate risks and ensure passenger safety. As emergency scenarios are complex and time-sensitive, the integration of semantic technologies, based on ontologies and knowledge graphs, offers significant advantages by enabling formal modeling, intelligent retrieval, and automated reasoning over emergency plans and historical cases. This subsection explores the challenges in emergency response, summarizes recent developments using ontologies and knowledge graphs, and highlights services and technologies designed to support effective emergency management.

3.3.1. Issues in Emergency Management

Emergency management in railway systems is a critical function aimed at minimizing the impact of operational accidents and restoring safe, efficient service as quickly as possible. However, the complexity of railway infrastructures, the diversity of stakeholders, and the volume of unstructured safety documentation present major challenges. Emergency plans are often developed in heterogeneous formats and vary significantly in quality and detail, making it difficult to ensure rapid and consistent response across departments. Furthermore, due to the lack of semantic standardization, integrating and retrieving relevant emergency knowledge in real time remains a persistent obstacle. These challenges call for intelligent systems that can support real-time decision making, semantic interoperability, and case-based reasoning to improve preparedness and response efficiency. Furthermore, the dynamic nature of emergency scenarios in railway systems, such as train derailments, station evacuations, and signaling failures, demands highly adaptive and responsive management frameworks. The use of ontologies and knowledge graphs can significantly enhance the ability to model these dynamic situations, enabling the system to retrieve historical case data, identify patterns, and recommend optimal response strategies. By integrating real-time data from sensors and operational systems, these technologies can also predict potential escalation of incidents and guide emergency teams with actionable insights. This approach improves coordination across multiple stakeholders, such as train operators, emergency responders, and traffic control centers, while ensuring a swift, coordinated response that minimizes disruption to the network and guarantees passenger safety.

3.3.2. Ontologies and Knowledge Graphs for Emergency Management

Ontologies and knowledge graphs have increasingly been used to enhance the modeling, retrieval, and reasoning capabilities of emergency management systems in railway and urban transit contexts.

In [39], Hongliang and Zhenhai developed an ontology-based framework for modeling subway emergency plan knowledge. Their system is based on the Onto-EPMO ontology, which incorporates concepts regarding fault characterization, emergency response, and post-disposal measures.

In [40], Zhu proposed an ontology-based emergency response system for metro operations, where events and decision flows are semantically modeled to facilitate real-time, structured response actions across different emergency scenarios.

3.3.3. Services and Technologies for Emergency Management

Table 3 outlines the ontology and knowledge graph-based services that support enhanced emergency management in the railway and metro domains. These services aim to address key challenges such as fragmented emergency knowledge, inconsistent plan structures, and the need for rapid response under uncertainty.

The emergency plan modeling service developed by Hongliang and Zhang [39] is based on a semantically structured representation of subway emergency knowledge and incorporates case-based reasoning, allowing for efficient retrieval and reuse of past emergency cases based on similarity analysis. Complementary to these retrieval and reuse systems, other semantic frameworks have been proposed to support the creative modeling of emergency scenarios, enabling the generation of conceptual structures for simulation and preparedness exercises [66].

The metro emergency platform proposed by [40] enables real-time access to structured plan information and improving cross-departmental coordination during incidents.

The digital emergency assistant proposed by Wang et al. [41] integrates ontology modeling with deep learning to automate the adaptation and retrieval of high-speed rail emergency plans, enhancing the responsiveness and scalability of emergency management systems.

Finally, the emergency case reuse system proposed by Zhao et al. [67] employs a two-layer ontology and a case knowledge base to simulate emergency scenarios and guide decision making during real operations or training exercises.

Collectively, these services demonstrate how semantic technologies can streamline emergency preparedness, promote knowledge reuse, and support intelligent decision making under time-critical conditions. The integration of real-time operational data and sensor networks into ontology-based emergency systems is crucial in modern railway and metro environments. By incorporating dynamic data streams from infrastructure monitoring systems, such as track sensors, train location data, and signal statuses, ontologies and knowledge graphs can support adapting to ongoing incidents in order to provide more accurate, context-aware responses. This allows for predictive modeling and early warnings of potential accidents, enabling proactive intervention before incidents escalate. The combination of ontological reasoning and AI-based prediction tools further enhances decision making by offering tailored emergency protocols based on real-time conditions and historical patterns, optimizing response time, and minimizing disruptions. These intelligent systems not only improve the safety of passengers and staff but also help reduce operational downtime, which is crucial in maintaining service reliability.

Table 3. Ontology/knowledge graph-based services for emergency management.

Service	Description
Emergency plan modeling	It models emergency scenarios using ontologies to structure plan knowledge and support reasoning [39]
Metro emergency platform	It captures and links metro emergency entities, scenarios, and workflows semantically [40]
Digital emergency assistant	It combines ontologies with AI techniques to support digitized, responsive emergency plans [41]
Emergency case reuse system	It applies 2-layer ontology and case-based reasoning for rapid reuse of previous emergency responses [67]

3.4. Accidents

Accidents in the railway domain are unintended events that result in damage, injury, or loss of life, often due to complex interactions among technical, human, and environmental factors. Understanding how and why these accidents occur is essential for improving system safety and preventing future incidents. In recent years, ontologies and knowledge graphs have emerged as valuable tools for modeling accident causation, identifying interrelated hazards, and analyzing patterns across large datasets. This subsection explores the key challenges in accident analysis, highlights recent works that apply semantic technologies to model and reason over accident data, and presents services and tools designed to support advanced accident investigation and prevention.

3.4.1. Issues in Accident Analysis

Accidents in railway systems often result from complex interplays between human, technical, environmental, and organizational factors. Traditional accident analysis approaches tend to focus on isolated causal chains or single-factor explanations, which limits their ability to represent the multi-dimensional and interrelated nature of real-world incidents. Moreover, accident data are typically stored in unstructured textual reports, making systematic analysis and knowledge reuse challenging. The need for more holistic, data-driven, and semantically-rich approaches to model accident causation and hazard propagation is increasingly recognized, particularly as the volume and complexity of operational data grow.

3.4.2. Ontologies and Knowledge Graphs for Accident Analysis

Ontologies and knowledge graphs offer a structured way to model accident causation, interrelated hazards, and risk propagation paths, enabling more precise and proactive safety analysis.

In [42], Liu et al. developed a Railway Operational Accident Knowledge Graph (ROAKG), designed to reveal causation networks among hazards and accidents.

Yan et al. [43] focused specifically on railway fire incidents and proposed an ontology-based knowledge graph that models fire accident causation. Their framework emphasizes fire event characteristics, propagation paths, and emergency response measures, enabling targeted analysis and scenario-based risk evaluation.

Li et al. [44] introduced an ontology model that captures accident chains and infers multi-dimensional risk inter-relations. Their method demonstrates how different context instances (e.g., equipment failure, delayed response) can be semantically instantiated to detect the potential risk sources behind interconnected events.

Wang et al. [45] presented a real-world hazard correlation analysis based on a decade-long UK accident dataset. Using a Hazard Correlation Analysis Knowledge Graph (HCAKG), they modeled accident–hazard relationships, introduced new topology indices accounting for temporal dimensions, and developed prevention strategies by identifying and controlling key hazards.

In addition to the core literature reviewed in this section, several complementary studies deepen the understanding of how ontologies and knowledge-based systems can support accident modeling in the railway domain.

Maalel et al. [46] propose an integrated knowledge management approach that combines domain ontologies with case-based reasoning (CBR) to analyze and reuse prior accident scenarios in railway transport. Their method enables the formalization and retrieval of experience-based knowledge, aiming to support domain experts in identifying analogies and patterns across accident cases.

Further expanding on this direction, Maalel et al. [47] present a CBR system architecture that uses ontologies to harmonize terminology and enhance the acquisition and reasoning processes. Their work illustrates the role of ontologies not merely as static knowledge structures, but as dynamic enablers for learning from past incidents.

Additionally, the modeling of accident scenarios using ontology-driven approaches is addressed in [48], where a knowledge model is developed to assist in the representation and analysis of safety-critical events. The focus here is on streamlining communication among experts and improving the reliability of safety assessments.

Building upon these foundations, Maalel et al. [49] introduce a decision support system, Adast, that couples ontologies with CBR to guide safety analysis and enhance the reuse of structured safety knowledge. This system supports security experts by formalizing historical accident information into actionable support for prevention and decision making.

In a more recent contribution, He et al. [50] examine the integration of temporal knowledge graphs and digital twins for situational awareness and traffic incident management. While not focused exclusively on rail transport, their system leverages predictive analytics and real-time monitoring to anticipate congestion and traffic anomalies, factors often implicated in accident dynamics. Their work exemplifies how knowledge graphs can be extended into dynamic, context-aware frameworks for operational safety enhancement.

These studies collectively highlight the growing maturity of ontology-based tools for accident analysis, supporting tasks from scenario representation and risk detection to decision support and predictive management.

3.4.3. Services and Technologies for Accident Analysis

Table 4 summarizes the key ontology and knowledge graph-based services that support the analysis and interpretation of railway accidents. These services provide structured, intelligent methods for understanding accident causation, identifying high-risk elements, and supporting proactive safety interventions.

In [51], Liu et al. presented an accident causation analyzer that leverages text mining and semantic technologies to extract entities from accident reports and build a knowledge graph. This enables the identification of hidden hazard relationships and provides a basis for quantitative risk evaluation.

In [42], Liu et al. introduced an accident exploration platform, which models operational accidents and associated hazards in a heterogeneous knowledge graph. The platform uses custom topological indicators to analyze causation networks, helping stakeholders uncover latent accident patterns and formulate targeted prevention strategies.

The fire accident modeling tool proposed by Yan et al. [43] focuses on railway fire events. It formalizes fire-related entities and their relationships in an ontology-based knowledge graph to support structured analysis of propagation mechanisms and emergency response.

Li et al. [44] contributed the contextual risk relation engine, which models accident chains and risk propagation based on ontological representations of context. This system infers complex interrelations among risk sources, allowing for deeper understanding and early detection of cascading risks.

Finally, Wang et al. [45] developed a hazard correlation visualizer that builds on 10 years of UK accident data to analyze the temporal and structural relationships among hazards. Their system identifies key hazards and uses topological metrics to support the design of data-informed prevention measures.

The reviewed works expand the range of technological services available for accident-related safety management. For example, the Adast system [49] demonstrates how ontology-guided CBR can inform both retrospective analysis and proactive decision making. Similarly, the temporal knowledge graph approach proposed by He et al. [50] enables predictive modeling of accident-prone conditions within complex urban traffic systems. These efforts collectively reinforce the strategic role of ontologies in encoding domain expertise, harmonizing safety data, and supporting intelligent reasoning across all stages of accident management.

Together, these services highlight the power of semantic modeling in transforming unstructured accident data into actionable safety knowledge. To enhance accident analysis in the railway sector, integrating real-time monitoring from railway infrastructure and train systems into ontology-based models could enable a more proactive approach to accident prevention. For example, track sensors, train telemetry data, and signal system information could be continuously monitored to detect potential hazards, such as equipment failure or track conditions, before they lead to accidents. Coupling these data with predictive analytics could help forecast potential derailments, collisions, or signal failures. Additionally, the inclusion of real-time communication systems for railway operators and incident reporting networks from train crews and passengers could provide valuable, immediate insights to refine safety protocols. This integration would enable quicker identification of safety risks and lead to faster decision making, enhancing the overall safety management and emergency response capabilities of railway systems.

Table 4. Ontology and knowledge graph-based services for accident analysis.

Service	Description
Accident causation analyzer	It uses NLP and ML to build a KG from accident reports for risk identification and propagation analysis [51]
Accident exploration platform	It reveals causation patterns through topological analysis of heterogeneous KG structures [42]
Fire accident modeling tool	Ontology-based knowledge graph for analyzing causes and responses in railway fire incidents [43]
Contextual risk relation engine	It models accident inter-relations through contextual ontology reasoning to identify risk chains [44]
Hazard correlation visualizer	It identifies key hazards and their influence through a real-world knowledge graph model [45]
Case-based accident retrieval system	It uses ontologies and CBR to retrieve and analyze past railway accidents [49].
Digital twin-based accident mitigation	It combines real-time digital twin models with semantic traffic prediction [50].

4. Discussion

In this section, we first address the research questions outlined in Section 2, followed by a discussion of the common themes and approaches identified in the analyzed literature, as well as considerations related to the practical application of ontologies and knowledge graphs in safety-critical systems.

4.1. Addressing the Research Questions

***(RQ1)* In which areas of the railway safety domain have ontologies, knowledge graphs, semantic methods, and semantic technologies been applied so far?**

Ontologies, knowledge graphs, and related semantic technologies have been applied across the following four key areas in the railway safety domain:

- Risk Management: Ontologies, knowledge graphs, and semantic technologies were applied to model hazard interdependencies, update evolving risk knowledge, infer accident chains, and support probabilistic assessment of events such as seismic risks. Examples include the SCSAKG for hazard coupling analysis [6], SRAC ontology for dynamic risk concept evaluation [7], and transformer-based models for extracting risk relations from text [10].
- Safety Management: Ontologies, knowledge graphs, and semantic technologies were used for formalizing safety concepts, structuring safety procedures, supporting automated checks, and predicting potential hazards. Works include the domain-crossing

safety ontology by Kaindl et al. [16], the metro-specific SRI-Onto [17], and Liu et al.'s KG-based hazard prediction system [20].
- Emergency Management: Ontologies, knowledge graphs, and semantic technologies were used to support modeling and reuse of emergency plans, real-time response reasoning, and intelligent plan digitization. For example, Onto-EPMO by Hongliang and Zhang enables semantic case retrieval [39], and Wang et al. integrate deep learning with ontologies for emergency plan adaptation [41].
- Accident Analysis: Ontologies, knowledge graphs, and semantic technologies focused on constructing accident knowledge graphs, identifying causation patterns, and analyzing hazard propagation chains. Tools include the ROAKG for operational accident mapping [42], a fire accident knowledge graph [43], and the HCAKG from UK data for hazard correlation analysis [45].

***(RQ2)* Do ontologies, knowledge graphs, semantic methods, and semantic technologies provide significant added value in this domain?**

Yes, semantic technologies provide substantial added value across all studied areas of railway safety, as follows:

- They enable the formalization and integration of complex, multi-source, and unstructured knowledge (e.g., accident reports, safety standards, operational logs), addressing the fragmentation common in legacy safety systems.
- They support intelligent reasoning and decision making, as demonstrated in rule-based inference systems for accident causation [8], or ontology-enhanced Monte Carlo frameworks for seismic risk analysis [9].
- They improve knowledge reuse and update through ontology evolution mechanisms [7] and embedding-based prediction models that anticipate cascading hazards [20].
- They enhance automation and scalability, notably in automated safety checks [21], case retrieval in emergencies [39], and machine learning-driven risk relation extraction [10].
- Ultimately, they contribute to resilience and safety, enabling timely, informed, and coordinated responses across domains.

***(RQ3)* What are the main challenges encountered?** Several key challenges have been identified across the application of semantic technologies in the railway safety domain.

- Data fragmentation and heterogeneity remain major obstacles. Safety-related knowledge is often distributed across multiple formats, unstructured reports, procedural documents, and operational logs, making consistent integration and analysis difficult [31].
- Scalability and adaptability are also limited in traditional risk and safety approaches, which frequently depend on static models and expert judgment. These methods often lack the ability to evolve dynamically in response to new operational contexts or hazards [12].
- Semantic inconsistency across domains, organizations, and projects hinders interoperability. Different terminologies, data structures, and safety standards can complicate the sharing and reuse of safety knowledge across systems [15].
- Timeliness and real-time applicability are often compromised due to manual processes in emergency response and risk evaluation. Rapid access to structured, context-aware knowledge is critical in high-pressure scenarios such as operational disruptions or accident recovery [55].

***(RQ4)* Which ontologies, knowledge graphs, semantic methods, and semantic technologies are most relevant?**

To address these challenges, several ontologies have proven particularly effective. Core ontologies that align with international safety standards offer reusable and domain-agnostic frameworks. Domain-specific ontologies, such as those designed for metro construction [13] or accident chain modeling [54], enable detailed semantic representation of risks, hazards, and their relationships. Contextual ontologies support reasoning over accident scenarios and the inference of hidden risk pathways [12].

Knowledge graphs have also become instrumental, especially those built from historical accident data [56] or operational hazard records. These graphs provide structured, relational views of safety knowledge [22], enabling pattern detection [68], hazard prediction, and interdependency analysis. They are often constructed using natural language processing, embedding techniques, or expert-guided schema development.

Among semantic methods, rule-based reasoning [12] and ontology alignment [54] have shown value in modeling causation, inferring accident chains, and maintaining concept coherence. In more advanced applications, deep learning techniques, such as transformer-aware graph neural networks, enhance the extraction of semantic relations from unstructured texts [68].

Technologies like Monte Carlo simulation combined with ontological reasoning enable probabilistic risk assessments [12], while case-based reasoning engines allow the retrieval and reuse of relevant emergency response plans. These solutions contribute to more resilient, adaptive, and intelligent safety and emergency management in railway systems.

4.2. Common Themes and Approaches in the Analyzed Literature

Our review reveals several recurring themes and methodological trends across the analyzed literature. A central commonality is the widespread use of semantic artifacts, including ontologies and knowledge graphs, to formalize, integrate, and reason over safety-related information in railway systems [12,15,54]. In parallel, domain-specific ontologies, targeting metro construction, tunnel engineering, or heavy-haul operations, are frequently used to capture nuanced risk factors, model accident chains, and represent localized safety procedures [13,22,52].

A number of studies leverage knowledge graphs constructed from operational data, accident reports, or maintenance logs. These structured semantic models enable key safety-related tasks such as pattern discovery, hazard correlation analysis, and causal inference, and are often applied in support of both retrospective analysis and proactive risk mitigation [20,42,56].

Methodologically, a common approach involves rule-based reasoning, which remains a dominant strategy for modeling risk propagation and accident causation [12,58]. At the same time, more recent work incorporates machine learning techniques, such as graph neural networks and embedding-based models, to enhance scalability and automate semantic relation extraction from unstructured texts [37,42].

Across the literature, a shared emphasis is placed on the following four key capabilities:

1. Formal representation of safety knowledge;
2. Integration of heterogeneous and distributed data sources;
3. Intelligent reasoning over complex safety contexts; and
4. Predictive analysis for risk forecasting [27,28,32].

These commonalities underscore a growing consensus that semantic technologies are increasingly essential for supporting robust, adaptive, and intelligent safety and risk management in the railway domain.

4.3. Considerations on Safety-Critical Railway Systems

In the railway domain, safety-critical systems represent the core functional elements of the most sensitive operations, including subsystems for signaling, interlocking, supervision, and train control. Their design and validation are governed by stringent standards such as EN 50126 [69], EN 50128 [70], and EN 50129 [71], which, for instance, define requirements for reliability, availability, maintainability, and safety (RAMS), as well as for the development and certification of high-integrity software and electronic systems.

Although the systematic review presented in this work identified numerous applications of semantic technologies in risk management, operational safety, and accident analysis, no cases were found in which these technologies were directly integrated into certified environments compliant with safety-critical standards. Nonetheless, ontologies and knowledge graphs hold significant potential for supporting the implementation and harmonization of railway safety and quality standards.

Indeed, as demonstrated by [36], ontologies can bridge conceptual gaps between domains by providing a formalized and shared vocabulary of safety-related concepts. This capability is particularly valuable in the railway sector, where standards are complex, interrelated, and often interpreted differently across organizations.

EN 50126 focuses on the Specification and Demonstration of Reliability, Availability, Maintainability, and Safety (RAMS) for railway applications. Ontologies can support this standard by enabling consistent definition, tracking, and analysis of RAMS parameters throughout the system life cycle. Through a shared semantic model, ontologies facilitate the reuse of hazard and risk assessments, thereby improving traceability and comparability across different projects and subsystems.

For EN 50128 and EN 50129, which pertain to software and safety-related electronic systems in signaling, ontologies provide a structured framework to represent functional and safety requirements, failure modes, and mitigation strategies. They can enhance requirements engineering, formal verification, and compliance documentation by embedding standard-specific terminology directly into the development workflow. Ontologies also enable automated reasoning over safety constraints, allowing engineers to identify inconsistencies and ensure comprehensive coverage of critical system properties.

ISO/TS 22163 [72] extends the principles of ISO 9001:2015 to the railway sector, emphasizing quality and business management systems. Here, ontologies can map and align business processes, quality objectives, and compliance requirements, supporting integrated audits and continuous improvement initiatives. They help ensure that quality management practices are not only standardized but also contextually aligned with railway-specific constraints and expectations.

Overall, the development of a common safety ontology, as proposed by [15], paves the way for interoperability between standards, enhanced knowledge sharing, and improved system assurance. By embedding domain-specific standards into formal knowledge structures, ontologies act as both enablers of digital engineering and custodians of regulatory fidelity in the safety-critical railway environment.

5. Conclusions

This systematic literature review has mapped the landscape of semantic technologies in railway safety, highlighting their growing importance across four main areas: risk management, safety management, emergency management, and accident analysis. Ontologies and knowledge graphs are increasingly used to model complex risk relationships, structure safety knowledge, support emergency planning, and analyze accident causation. These technologies contribute substantial value by enabling knowledge reuse, intelligent reasoning, and system-wide interoperability.

However, several challenges remain, including fragmented data sources, limited standardization, and the need for scalable, real-time solutions. To address these issues, the field is moving toward more dynamic and intelligent approaches, such as ontology evolution frameworks and machine learning-enhanced graph models. Key contributions identified in this review include core ontologies like SRAC and SRI-Onto, domain-specific knowledge graphs, and hybrid models that integrate probabilistic reasoning or deep learning.

The findings underscore the potential of semantic technologies to improve railway safety and resilience. They also suggest directions for future research, particularly in developing unified frameworks, enhancing semantic interoperability, and expanding the use of intelligent automation in safety-critical decision-making contexts.

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Abbreviations

The following abbreviations are used in this manuscript:

BIM	building information modeling
CBR	case-based reasoning
GCN	Graph Convolutional Network
IoT	Internet of Things
ROAKG	Railway Operational Accident Knowledge Graph
RQ	Research Question
SCSAKG	Subway Construction Safety Accident Knowledge Graph
SRAC	Scenario-Risk-Accident Chain

References

1. Patriarca, R.; Falegnami, A.; Costantino, F.; Di Gravio, G.; De Nicola, A.; Villani, M.L. WAx: An integrated conceptual framework for the analysis of cyber-socio-technical systems. *Saf. Sci.* **2021**, *136*, 105142. [CrossRef]
2. De Nicola, A.; Villani, M.L.; Sujan, M.; Watt, J.; Costantino, F.; Falegnami, A.; Patriarca, R. Development and measurement of a resilience indicator for cyber-socio-technical systems: The allostatic load. *J. Ind. Inf. Integr.* **2023**, *35*, 100489. [CrossRef]
3. De Nicola, A.; Missikoff, M. A lightweight methodology for rapid ontology engineering. *Commun. ACM* **2016**, *59*, 79–86. [CrossRef]
4. Hogan, A.; Blomqvist, E.; Cochez, M.; D'amato, C.; Melo, G.D.; Gutierrez, C.; Kirrane, S.; Gayo, J.E.L.; Navigli, R.; Neumaier, S.; et al. Knowledge Graphs. *ACM Comput. Surv.* **2021**, *54*, 71. [CrossRef]
5. De Nicola, A.; Villani, M.L. Smart City Ontologies and Their Applications: A Systematic Literature Review. *Sustainability* **2021**, *13*, 5578. [CrossRef]
6. Huo, X.; Yin, Y.; Jiao, L.; Zhang, Y. A data-driven and knowledge graph-based analysis of the risk hazard coupling mechanism in subway construction accidents. *Reliab. Eng. Syst. Saf.* **2024**, *250*, 110254. [CrossRef]
7. Cao, T.; Mu, W.; Montarnal, A.; Barthe-Delanoë, A.M. A Method of Ontology Evolution and Concept Evaluation Based on Knowledge Discovery in the Heavy Haul Railway Risk System. *IFIP Adv. Inf. Commun. Technol.* **2019**, *568*, 220–233. [CrossRef]
8. Li, J.; Gou, J.; Mu, W.; Peng, L. Rules Reasoning of Inter-relation of Railway Potential Risks Based on Context of Accident Chain. *Tiedao Xuebao/J. China Railw. Soc.* **2017**, *39*, 8–14. [CrossRef]

9. Cui, C.; Xu, M.; Xu, C.; Zhang, P.; Zhao, J. An ontology-based probabilistic framework for comprehensive seismic risk evaluation of subway stations by combining Monte Carlo simulation. *Tunn. Undergr. Space Technol.* **2023**, *135*, 105055. [CrossRef]
10. Wang, Y.; Li, X.; Wu, Y.; She, W.; Ye, Y. Transformer-Aware Graph Convolution Networks for Relation Extraction of Railway Safety Risk. *Lect. Notes Electr. Eng.* **2024**, *1138*, 135–144. [CrossRef]
11. Xu, Y.; Liang, Y.; Li, K. A knowledge graph-based method for modeling and analyzing the disaster risks of railway construction in the mountainous area of Southwest China. In Proceedings of the 2021 4th International Symposium on Traffic Transportation and Civil Architecture (ISTTCA), Suzhou, China, 12–14 November 2021; Institute of Electrical and Electronics Engineers Inc.: New York, NY, USA, 2021; pp. 259–264. [CrossRef]
12. Cao, T.; Mu, W.; Gou, J.; Peng, L. A Study of Risk Relevance Reasoning Based on a Context Ontology of Railway Accidents. *Risk Anal.* **2020**, *40*, 1589–1611. [CrossRef]
13. Yan, Y.; Yan, W. Diagnosis of construction risks in railway tunnel engineering based on knowledge ontology basis. *Metall. Min. Ind.* **2015**, *7*, 232–238.
14. Parkinson, H.; Bamford, G. The potential for using big data analytics to predict safety risks by analysing rail accidents. In Proceedings of the Third International Conference on Railway Technology: Research, Development and Maintenance, Cagliari, Sardinia, Italy, 5–8 April 2016; Volume 110.
15. Hulin, B.; Kaindl, H.; Beckert, R.; Rathfux, T.; Popp, R. Towards a Common Ontology of Safety Risk Concepts for Railway Vehicles and Signaling. In *Computer Safety, Reliability, and Security*; Lecture Notes in Computer Science (including subseries Lecture Notes in Artificial Intelligence and Lecture Notes in Bioinformatics); Springer: Cham, Switzerland, 2018; Volume 11093, pp. 297–310. [CrossRef]
16. Kaindl, H.; Rathfux, T.; Hulin, B.; Beckert, R.; Arnautovic, E.; Popp, R. A core ontology of safety risk concepts: Reconciling scientific literature with standards for automotive and railway. In *Human-Centered and Error-Resilient Systems Development*; Lecture Notes in Computer Science (including subseries Lecture Notes in Artificial Intelligence and Lecture Notes in Bioinformatics); Springer: Cham, Switzerland, 2016; Volume 9856, pp. 165–180. [CrossRef]
17. Xing, X.; Zhong, B.; Luo, H.; Li, H.; Wu, H. Ontology for safety risk identification in metro construction. *Comput. Ind.* **2019**, *109*, 14–30. [CrossRef]
18. Jiang, X.; Wang, S.; Wang, J.; Lyu, S.; Skitmore, M. A decision method for construction safety risk management based on ontology and improved CBR: Example of a subway project. *Int. J. Environ. Res. Public Health* **2020**, *17*, 3928. [CrossRef]
19. Wang, Y.; Wang, Y.; Ye, Y. A Novel Method for Constructing Knowledge Graph of Railway Safety Risk. In Proceedings of the 6th International Conference on Computer Science and Application Engineering (CSAE '22), Virtual Event, China, 21–23 October 22022; pp. 1–6. [CrossRef]
20. Liu, J.; Chen, K.; Duan, H.; Li, C. A knowledge graph-based hazard prediction approach for preventing railway operational accidents. *Reliab. Eng. Syst. Saf.* **2024**, *247*, 110126. [CrossRef]
21. Li, X.; Yang, D.; Yuan, J.; Donkers, A.; Liu, X. BIM-enabled semantic web for automated safety checks in subway construction. *Autom. Constr.* **2022**, *141*, 104454. [CrossRef]
22. Zhu, Q.; Wang, S.; Ding, Y.; Zeng, H.; Zhang, L.; Guo, Y.; Li, H.; Wang, W.; Song, S.; Hao, R.; et al. A Method of Safety-Quality-Schedule Knowledge Graph for Intelligent Management of Drilling and Blasting Construction of Railway Tunnels. *Wuhan Daxue Xuebao (Xinxi Kexue Ban)/Geomat. Inf. Sci. Wuhan Univ.* **2022**, *47*, 1155–1164. [CrossRef]
23. Hadj-Mabrouk, H. A literature review on the applications of artificial intelligence to European rail transport safety. *IET Intell. Transp. Syst.* **2024**, *18*, 2291–2324. [CrossRef]
24. Sedghi, M.; Kauppila, O.; Bergquist, B.; Vanhatalo, E.; Kulahci, M. A taxonomy of railway track maintenance planning and scheduling: A review and research trends. *Reliab. Eng. Syst. Saf.* **2021**, *215*, 107827. [CrossRef]
25. Liu, X.; Zhu, H.Y.; Lu, Y.; Liu, Z.G. Construction and Application of a Knowledge Graph in the Field of Fully Automated Metro Train Degraded Operation. In Proceedings of the 24th COTA International Conference of Transportation Professionals, Shenzhen, China, 23–26 July 2024; American Society of Civil Engineers (ASCE): Reston, VA, USA, 2024; pp. 1174–1183. [CrossRef]
26. Kyriakidis, M.; Majumdar, A.; Ochieng, W.Y. Data based framework to identify the most significant performance shaping factors in railway operations. *Saf. Sci.* **2015**, *78*, 60–76. [CrossRef]
27. Kyriakidis, M.; Majumdar, A.; Grote, G.; Ochieng, W.Y. Development and assessment of taxonomy for performance-shaping factors for railway operations. *Transp. Res. Rec.* **2012**, *2289*, 145–153. [CrossRef]
28. Ghaboura, S.; Ferdousi, R.; Laamarti, F.; Yang, C.; Saddik, A.E. Digital Twin for Railway: A Comprehensive Survey. *IEEE Access* **2023**, *11*, 120237–120257. [CrossRef]
29. Smith, P.; Kyriakidis, M.; Majumdar, A.; Ochieng, W. Impact of european railway traffic management system on human performance in railway operations. *Transp. Res. Rec.* **2013**, *2374*, 83–92. [CrossRef]
30. Lindner, T.; Milius, B.; Schwencke, D.; Lemmer, K. Influential factors on human performance in railways and their interrelations. In *Safety, Reliability and Risk Analysis*; CRC Press: Boca Raton, FL, USA, 2014; pp. 435–442.

31. Figueres-Esteban, M.; Hughes, P.; van Gulijk, C. *Ontology Network Analysis for Safety Learning in the Railway Domain*; CRC Press/Balkema: Leiden, The Netherlands, 2017; p. 479.
32. Bugalia, N.; Maemura, Y.; Ozawa, K. Organizational and institutional factors affecting high-speed rail safety in Japan. *Saf. Sci.* **2020**, *128*, 104762. [CrossRef]
33. Klockner, K.; Toft, Y. Railway accidents and incidents: Complex socio-technical system accident modelling comes of age. *Saf. Sci.* **2018**, *110*, 59–66. [CrossRef]
34. Zheng, G.; Chen, J. Software redundancy design for a Human-Machine Interface in railway vehicles. In *WIT Transactions on The Built Environment*; WIT Press: Billerica, MA, USA, 2010; Volume 114, pp. 221–232. [CrossRef]
35. Chenariyan Nakhaee, M.; Hiemstra, D.; Stoelinga, M.; van Noort, M. The Recent Applications of Machine Learning in Rail Track Maintenance: A Survey. In *Reliability, Safety, and Security of Railway Systems. Modelling, Analysis, Verification, and Certification*; Lecture Notes in Computer Science (including subseries Lecture Notes in Artificial Intelligence and Lecture Notes in Bioinformatics); Springer: Cham, Switzerland, 2019; Volume 11495, pp. 91–105. [CrossRef]
36. Hulin, B.; Kaindl, H.; Rathfux, T.; Popp, R.; Arnautovic, E.; Beckert, R. Towards a Common Safety Ontology for Automobiles and Railway Vehicles. In Proceedings of the 2016 12th European Dependable Computing Conference (EDCC), Gothenburg, Sweden, 5–9 September 2016; Institute of Electrical and Electronics Engineers Inc.: New York, NY, USA, 2016; pp. 189–192. [CrossRef]
37. Ding, X.; Hu, H.; Hu, Y.; Jin, J.; Liu, Z.; Pan, H.; Shi, G. Identification and precise control of disaster-causing hazards in metro operation and maintenance: A new method for improving metro operation safety based on data mining. *Comput. Ind. Eng.* **2025**, *201*, 110899. [CrossRef]
38. Liu, C.; Yang, S. A two-stage clustering ensemble algorithm applicable to risk assessment of railway signaling faults. *Expert Syst. Appl.* **2024**, *249*, 123500. [CrossRef]
39. Hongliang, L.; Zhenhai, Z. Ontology modeling and case database construction of subway emergency plan knowledge. *IOP Conf. Ser. Earth Environ. Sci.* **2020**, *587*, 012076. [CrossRef]
40. Zhu, P. Research for the metro emergency based on the ontology model. *Adv. Mater. Res.* **2014**, *1030–1032*, 2087–2090. [CrossRef]
41. Wang, P.; Li, P.; E, R.; Yang, L. Method of Digitalization of High-speed Railway Emergency Plan Integrating Ontology and Deep Learning. *Tiedao Xuebao/J. China Railw. Soc.* **2020**, *42*, 29–36. Available online: https://cstj.cqvip.com/Qikan/Article/Detail?id=7102618577&from=Qikan_Search_Index (accessed on 12 October 2025).
42. Liu, J.; Schmid, F.; Li, K.; Zheng, W. A knowledge graph-based approach for exploring railway operational accidents. *Reliab. Eng. Syst. Saf.* **2021**, *207*, 107352. [CrossRef]
43. Yan, H.; Ma, X.; Chen, F.; Zhao, R.; Jia, L. Knowledge Modeling and Analysis for Railway Fire Accident Using Ontology-Based Knowledge Graph. In *Proceedings of the 5th International Conference on Electrical Engineering and Information Technologies for Rail Transportation (EITRT) 2021*; Lecture Notes in Electrical Engineering; Springer: Singapore, 2022; Volume 867, pp. 573–591. [CrossRef]
44. Li, J.; Mu, W.; Gou, J.; Peng, L. Modeling of railway risk inter-relation based on the study of accident context. In Proceedings of the 14th Information Systems for Crisis Response and Management, ISCRAM, Albi, France, 21–24 May 2017; pp. 328–340.
45. Wang, N.; Yang, X.; Chen, J.; Wang, H.; Wu, J. Hazards correlation analysis of railway accidents: A real-world case study based on the decade-long UK railway accident data. *Saf. Sci.* **2023**, *166*, 106238. [CrossRef]
46. Maalel, A.; Mejri, L.; Mabrouk, H.H.; Ben Ghezela, H. Toward a knowledge management approach based on an ontology and Case-based Reasoning (CBR): Application to railroad accidents. In Proceedings of the 2012 Sixth International Conference on Research Challenges in Information Science (RCIS), Valencia, Spain, 16–18 May 2012. [CrossRef]
47. Maalel, A.; Mejri, L.; Hadj-Mabrouk, H.; Ghézela, H.B. Towards a case-based reasoning approach based on ontologies application to railroad accidents. In *Data and Knowledge Engineering*; Lecture Notes in Computer Science (including subseries Lecture Notes in Artificial Intelligence and Lecture Notes in Bioinformatics); Springer: Berlin/Heidelberg, Germany, 2012; Volume 7696, pp. 48–55. [CrossRef]
48. Maalel, A.; Mejri, L.; Mabrouk, H.H.; Ben Ghezela, H. Towards an ontology of help to the modeling of accident scenarii: Application on railroad transport. In Proceedings of the 2012 6th International Conference on Sciences of Electronics, Technologies of Information and Telecommunications (SETIT), Sousse, Tunisia, 21–24 March 2012; pp. 1–6. [CrossRef]
49. Maalel, A.; Mejri, L.; Hadj-Mabrouk, H.; Ghézala, H.B. Towards a decision support system for security analysis application to railroad accidents. In *Information Systems for Crisis Response and Management in Mediterranean Countries. ISCRAM-med 2014*; Lecture Notes in Business Information Processing; Springer: Cham, Switzerland, 2014; Volume 196, pp. 46–56. [CrossRef]
50. He, F.; Bai, W.; Wang, Z. Investigating the synergistic effects of temporal knowledge graphs and digital twin technologies to enhance situational awareness decision-making in smart cities. *J. Comput. Methods Sci. Eng.* **2025**, *25*, 1793–1810. [CrossRef]
51. Liu, C.; Yang, S. Using text mining to establish knowledge graph from accident/incident reports in risk assessment. *Expert Syst. Appl.* **2022**, *207*, 117991. [CrossRef]
52. Liu, C.; Yang, S. A text mining-based approach for understanding Chinese railway incidents caused by electromagnetic interference. *Eng. Appl. Artif. Intell.* **2023**, *117*, 105598. [CrossRef]

53. Wright, L.; Van Der Schaaf, T. Accident versus near miss causation: A critical review of the literature, an empirical test in the UK railway domain, and their implications for other sectors. *J. Hazard. Mater.* **2004**, *111*, 105–110. [CrossRef]
54. Zhao, R.; Ma, X.; Dong, H.; Yan, H.; Chen, F.; Jia, L. Data-Driven Ontology Construction Method for Railway Derailment Accidents. In *Proceedings of the 5th International Conference on Electrical Engineering and Information Technologies for Rail Transportation (EITRT) 2021*; Lecture Notes in Electrical Engineering; Springer: Singapore, 2022; Volume 868, pp. 524–533. [CrossRef]
55. Meng, H.; Wang, X.; Gao, X. Design of Question Answering System for Railway Electricity Accidents. In Proceedings of the 2020 IEEE 11th International Conference on Software Engineering and Service Science (ICSESS), Beijing, China, 16–18 October 2020; IEEE Computer Society; pp. 216–219. [CrossRef]
56. Wang, X.; Wang, J.; Han, J. Knowledge graph construction for railway electrical accident analysis. In Proceedings of the 2019 International Conference on Machine Learning, Big Data and Business Intelligence (MLBDBI), Taiyuan, China, 8–10 November 2019; Institute of Electrical and Electronics Engineers Inc.: New York, NY, USA, 2019; pp. 214–219. [CrossRef]
57. Maalel, A.; Mejri, L.; Ben Ghézala, H. Adast: Intelligent support of decision making to improve security analysis. Application to railroad accidents. *Intell. Decis. Technol.* **2016**, *10*, 13–26. [CrossRef]
58. Maalel, A.; Mejri, L.; Ghézala, H.H.B. Adast: A decision support approach based on an ontology and CBR. Application to railroad accidents. *Int. J. Inf. Decis. Sci.* **2016**, *8*, 125–152. [CrossRef]
59. Aven, T. Risk assessment and risk management: Review of recent advances on their foundation. *Eur. J. Oper. Res.* **2016**, *253*, 1–13. [CrossRef]
60. Coletti, A.; De Nicola, A.; Villani, M.L. Building climate change into risk assessments. *Nat. Hazards* **2016**, *84*, 1307–1325. [CrossRef]
61. Cormen, T.H.; Leiserson, C.E.; Rivest, R.L.; Stein, C. *Introduction to Algorithms*, 3rd ed.; MIT Press: Cambridge, MA, USA, 2009.
62. Coletti, A.; De Nicola, A.; Di Pietro, A.; La Porta, L.; Pollino, M.; Rosato, V.; Vicoli, G.; Villani, M.L. A comprehensive system for semantic spatiotemporal assessment of risk in urban areas. *J. Contingencies Crisis Manag.* **2020**, *28*, 178–193. [CrossRef]
63. Hollnagel, E. *Safety-I and Safety-II: The Past and Future of Safety Management*; CRC Press: Boca Raton, FL, USA, 2018.
64. Patriarca, R.; Falegnami, A.; De Nicola, A.; Villani, M.; Paltrinieri, N. Serious games for industrial safety: An approach for developing resilience early warning indicators. *Saf. Sci.* **2019**, *118*, 316–331. [CrossRef]
65. Bullock, J.; Haddow, G.; Coppola, D. *Introduction to Emergency Management*; Butterworth-Heinemann: Oxford, UK, 2017.
66. De Nicola, A.; Melchiori, M.; Villani, M.L. Creative design of emergency management scenarios driven by semantics: An application to smart cities. *Inf. Syst.* **2019**, *81*, 21–48. [CrossRef]
67. Zhao, K.; Zhang, X.; Li, C.; Zhao, C.; Gai, Y. Case knowledge reuse method of railway train control system emergency plan; *China Saf. Sci. J.* **2022**, *32*, 217–224. [CrossRef]
68. Liu, J.; Cai, B.g.; Guo, Z.b.; Zhao, X.l. Constructing Knowledge Graph for Prognostics and Health Management of On-board Train Control System Based on Big Data and XGBoost. In *Big Data Technologies and Applications*; Lecture Notes of the Institute for Computer Sciences, Social-Informatics and Telecommunications Engineering, LNICST; Springer: Cham, Switzerland, 2021; Volume 371, pp. 3–16. [CrossRef]
69. *EN 50126-1:2017+A1:2019*; Railway Applications–The Specification and Demonstration of Reliability, Availability, Maintainability and Safety (RAMS)—Part 1: Basic Requirements, and Generic Process for RAMS. European Committee for Electrotechnical Standardization (CENELEC): Brussels, Belgium, 2017.
70. *EN 50128*; Railway Applications–Communication, Signalling and Processing Systems–Software for Railway Control and Protection Systems. European Committee for Electrotechnical Standardization (CENELEC): Brussels, Belgium, 2011.
71. *EN 50129*; Railway Applications–Communication, Signalling and Processing Systems–Safety-related Electronic Systems for Signalling. European Committee for Electrotechnical Standardization (CENELEC): Brussels, Belgium, 2018.
72. *ISO 22163*; Railway Applications–Quality Management System–Business Management System Requirements for Railway Organizations: ISO 9001:2015 and Particular Requirements for Application in the Railway Sector. International Organization for Standardization (ISO): Geneva, Switzerland, 2017.