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Ontology-Based Semantic Modeling of Coal Mine Roof Caving Accidents

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Abstract: The frequency of roof-caving accidents ranks first among all coal mine accidents. However, the scattered knowledge system in this field and the lack of standardization exacerbate the difficulty of analyzing roof fall accidents. This study proposes an ontology-based semantic modeling method for roof fall accidents to share and reuse roof fall knowledge for intelligent decision-making. The crucial concepts of roof fall accidents and the correlations between concepts are summarized by analyzing the roof fall knowledge, providing a standard framework to represent the prior knowledge in this field. Besides, the ontology modeling tool Protégé is used to construct the ontology. As for ontology-based deep information mining and semantic reasoning, semantic rules based on expert experience and data fusion technology are proposed to evaluate mines' potential risks comprehensively. In addition, the roof-falling rules are formalized based on the Jena syntax to make the ontology uniformly expressed in the computer. The Jena reasoning engine is utilized to mine potential tacit knowledge and preventive measures or solutions. The proposed method is demonstrated using roof fall cases, which confirms its validity and practicability. Results indicate that this method can realize the storage, management, and sharing of roof fall accident knowledge. Furthermore, it can provide accurate and comprehensive experience knowledge for the roof fall knowledge requester.

Keywords: ontology; roof-caving accidents; knowledge representation; data fusion; semantic rules; reasoning mechanisms

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1. Introduction

Coal mining is a vital industry that plays a significant role in global energy production, but it also presents numerous hazards and risks, making it one of the most dangerous occupations. Among the frequent accident types in this industry, roof, gas, and fire accidents are the most common. As shown in Figures 1 and 2, these statistics highlight the proportion of accidents and deaths in coal mine accidents in China between 2003 and 2021 [1]. Among all kinds of coal mine accidents, the roof-caving accident ranks first with a high frequency of occurrence, a large number of casualties, enormous scope of influence, accident rescue difficulties, and other characteristics [2].

Many scholars have studied the roof fall accidents from different angles. One common approach is to predict the warning signs through manual observation. However, the accuracy of such predictions is often influenced by professionals' level of knowledge reserve. In addition, sensor-based monitoring methods such as microseismic and electromagnetic radiation methods are also widely used to infer the stability of surrounding rock [3–6]. With the continuous development of artificial intelligence technology, more researchers are paying attention to techniques such as artificial neural networks [7] and deep learning [8]. These intelligent technologies can help researchers more accurately warn and take measures to avoid roof fall accidents before they occur. However, these methods have limitations in knowledge sharing, reuse, and management. In other words, due to the lack of comprehensive information and a unified management system, the degree of information sharing and utilization is low, which cannot meet the needs of large-scale data analysis and mining [8]. Therefore, it is a crucial problem to organize, research and manage information regarding roof falls. Furthermore, through the statistics and analysis of roof fall accidents in recent years, the staff does not have a deep understanding of the accidents and cannot accurately find and prevent the hidden danger of the accident that is the leading cause [9,10]. Therefore, it is necessary to strengthen the management and reuse of accident knowledge to improve the safety of coal mine production.

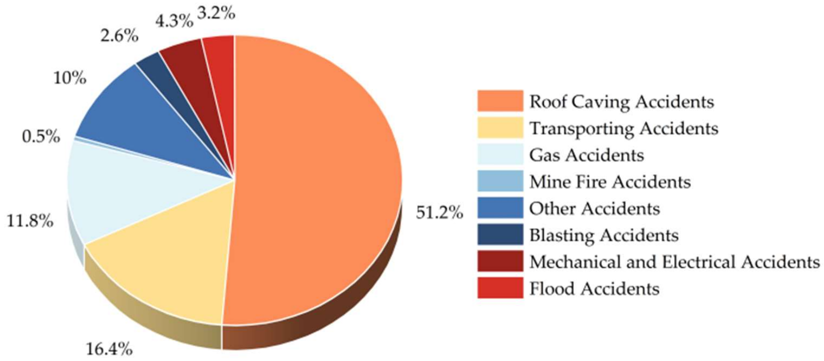

Figure 1. Proportion chart of various types of coal mine accidents.

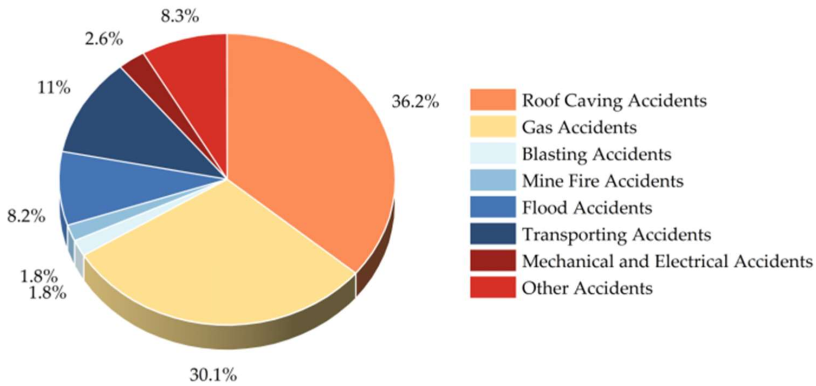

Figure 2. Proportion chart of the death toll in various coal mine accidents.

In order to cope with the significant challenges brought by roof fall accidents, researchers have considered early warning and prevention based on data fusion methods [11–13]. However, the lack of a unified knowledge organization has limited people's understanding of information, hindering the development of practical solutions. Therefore, this paper formalizes and integrates knowledge from different sources to comprehensively understand roof fall accidents and meanwhile, providing semantic rules based on prior knowledge and data fusion technology to assist roof fall decision-making. In this way, it can promote information sharing and knowledge reuse in this field, assist decision-makers in referring, and provide a basis for developing intelligent systems to prevent and control roof fall accidents.

This paper proposes an ontology-based knowledge modeling method for roof fall accidents. The purpose is to realize the sharing and effective management of roof fall knowledge and automatically generate solutions for risk information. This paper is structured as follows: Section 2 reviews risk management and ontological analysis of coal mining accidents. Section 3 explains the proposed framework of roof fall accident ontology. In Section 4, the classification structure and interpretation of the roof fall accident ontology are proposed in detail. Section 5 presents the method of defining the semantic rules of roof fall accidents based on prior knowledge and the data fusion method. Section 6 gives the reasoning mechanism and implementation of the roof fall accident ontology. Section 7 addresses study limitations, proposes future research directions, and concludes the paper.

2. Related Work

2.1. Risk Management of Coal Mines

Currently, researchers have conducted a lot of research on coal mine risk management. These studies aim to identify and evaluate potential hazards, develop strategies to minimize coal mine risks, and promote worker safety [14]. For example, Javadi et al. [13] proposed an evaluation framework based on a fuzzy Bayesian network, which can be used for roof fall risk assessment under uncertain conditions. Through this model, complex relationships in underground mining can be modeled to help people analyze problems more accurately. Based on prior knowledge and case collection, Meng et al. [15] proposed a data-driven Bayesian network model to reveal the priority of risk factors and provide emergency strategies for significant accidents. Li et al. [11] established an information fusion model of coal mine roof fall based on D-S theory and fuzzy mathematics theory, which can predict the risk level of mine roof fall, identify the characteristics of roof fall warnings, and provide a basis for roof fall accident prediction. Zhang et al. [16] utilized neural network technology to integrate multiple sources of information from coal mines, allowing for the deduction of accident states and providing auxiliary decision-making information for coal mine dispatchers.

The knowledge of coal mine accidents is mainly obtained from various sources in structured and unstructured forms (e.g., expert experience, accident case base, sensor data, etc.). However, the absence of a standardized framework for organizing such accidents impedes researchers' comprehensive understanding of the data, thereby hindering the reliable advancement of research and practical solutions. In this context, the further exploration of the formalization of accident information is necessary to achieve better accident analysis and management.

2.2. Ontology Technology

The term "ontology" originated from philosophy and primarily described the essence of things [17]. In recent years, researchers have applied ontology concepts to acquire and describe domain-specific knowledge, facilitating the interaction and reuse of knowledge. Ontology is a modeling tool that describes domain concepts at the semantic and knowledge levels [18]. It has significant advantages, such as solid logic, rigid structure, and machine interpretability. Specific domain ontologies can be organized by defining classes, properties, relationships, etc., reflecting the characteristics of the field. Existing ontology languages mainly include XML, RDF, RDFS, OWL, etc., which can convert knowledge into machine-recognizable symbols [19]. Moreover, ontology utilizes appropriate reasoning engines and query languages to facilitate knowledge reasoning and query functions of domain ontologies [20]. In this way, knowledge sharing, management, and reuse can be achieved better to promote the management and application of domain knowledge.

Ontology is increasingly used in the solution of practical problems. Liang et al. [21] constructed an electric security data integration framework based on ontology technology to integrate different data sources. Zhang et al. [20] developed the ontology-based semantic modeling of construction safety knowledge to organize, store, and reuse construction safety knowledge. Xing et al. [22] proposed a domain ontology of safety risk identification in metro construction, providing precise specifications for standardizing and formalizing safety risk knowledge.

2.3. Ontology for Accident Analysis in Coal Mines

Due to the ability of ontology to organize, represent and share knowledge, researchers began to seek to apply ontology technology to coal mining. Cheng et al. [23] involved the concept and theory of ontology in the coal mine field, providing a unified semantic framework for constructing digital mines. Zhang et al. [24] proposed an ontology-based knowledge construction method for mining equipment, which provides a new idea for knowledge management of mining equipment. Wu et al. [25] proposed the ontology construction and reasoning method of the main types of work in the coal mine system, which ensured the operation safety of the coal mine workers. Zhang et al. [26] designed a coal mine accident ontology based on the accident causation theory and realized the construction of the knowledge base and knowledge reasoning. Zhang et al. [27] used the improved evidence theory to integrate ontology reasoning rules and realized the comprehensive evaluation of the mine environment. Zhang et al. [28] analyzed the mechanism and influencing factors of water inrush accidents, constructed a warning knowledge base, and predicted the level of floor water inrush.

However, the current coal mine ontology is limited to a specific domain or fusing certain information. There is a lack of research on developing an ontology-based approach for roof fall accidents, which can support early warning and decision-making in this area. Moreover, there is a need for a comprehensive and unified knowledge system to mine the implicit domain knowledge and propose targeted measures deeply.

3. Overall Framework

Figure 3 illustrates the proposed ontology-based knowledge modeling method for roof fall accidents. Firstly, the ontology knowledge base of roof fall accidents is developed based on domain knowledge. Seven high-level classes are defined to represent the highest level of abstraction concepts, and subclasses are defined to subdivide more specific concepts. Then, the semantic rule base of roof fall accidents is constructed based on the relevant safety production regulations, expert experience, and the data fusion method. Finally, the data information in the actual mine production is collected and mapped to the ontology knowledge base to generate knowledge specific to the roof fall accident. The reasoning is based on the semantic rules of the roof fall accident. If the data information in the knowledge base meets the conditions, the semantic rules are activated to report the events and locations, and the activity intervention measures are given. The information is stored in the knowledge base to improve and update the knowledge base.

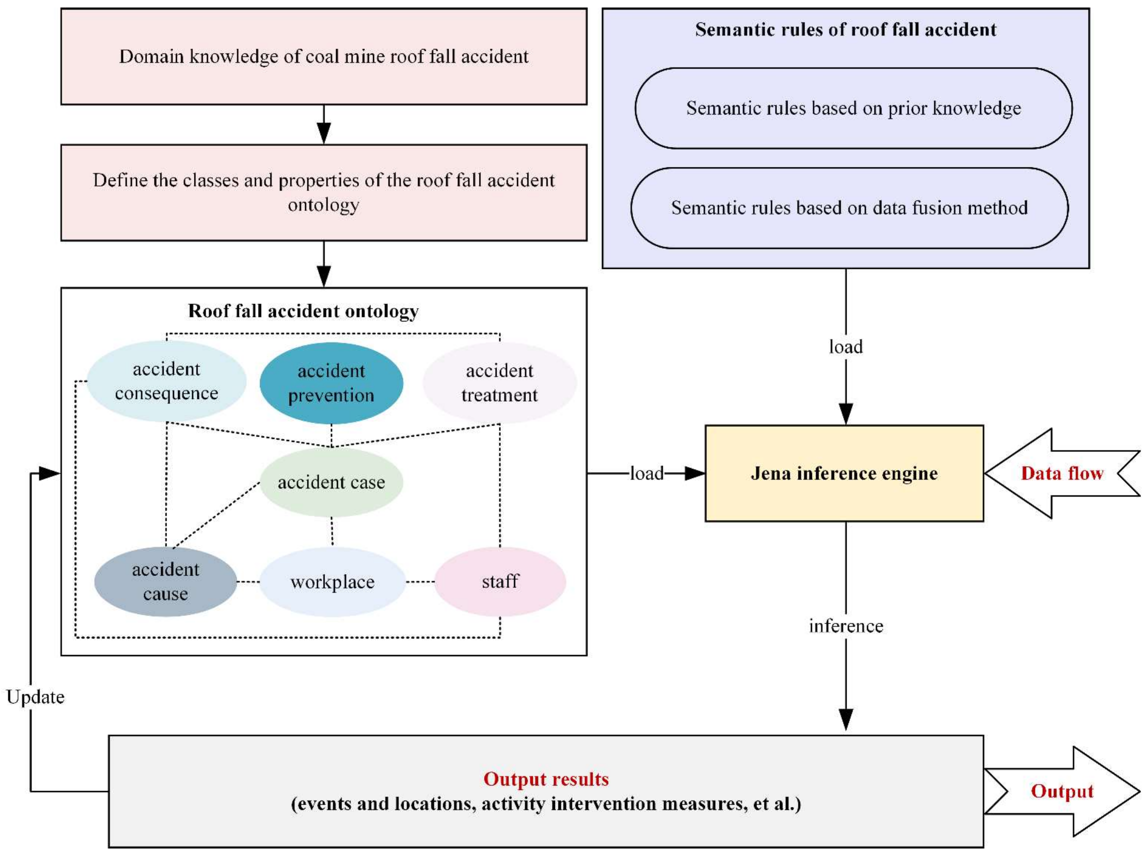

Figure 3. Flow chart of ontology-based semantic modeling of the roof fall accident.

4. Ontology for the Roof Fall Accidents

4.1. Ontology Construction Process

In the process of ontology construction, relevant standards and regulations should be followed. Common ontology construction methods include the TOVE, Skeleton, IDEF-5, and seven-step methods [29,30]. This section refers to the seven-step and skeleton methods to ensure a systematic and well-structured ontology construction process. The seven-step method facilitates the structured development of the ontology, while the skeleton method guarantees a well-organized and easily maintainable ontology structure. Moreover, the use of Protégé facilitates the ontology construction process [31]. The specific process is shown in Figure 4.

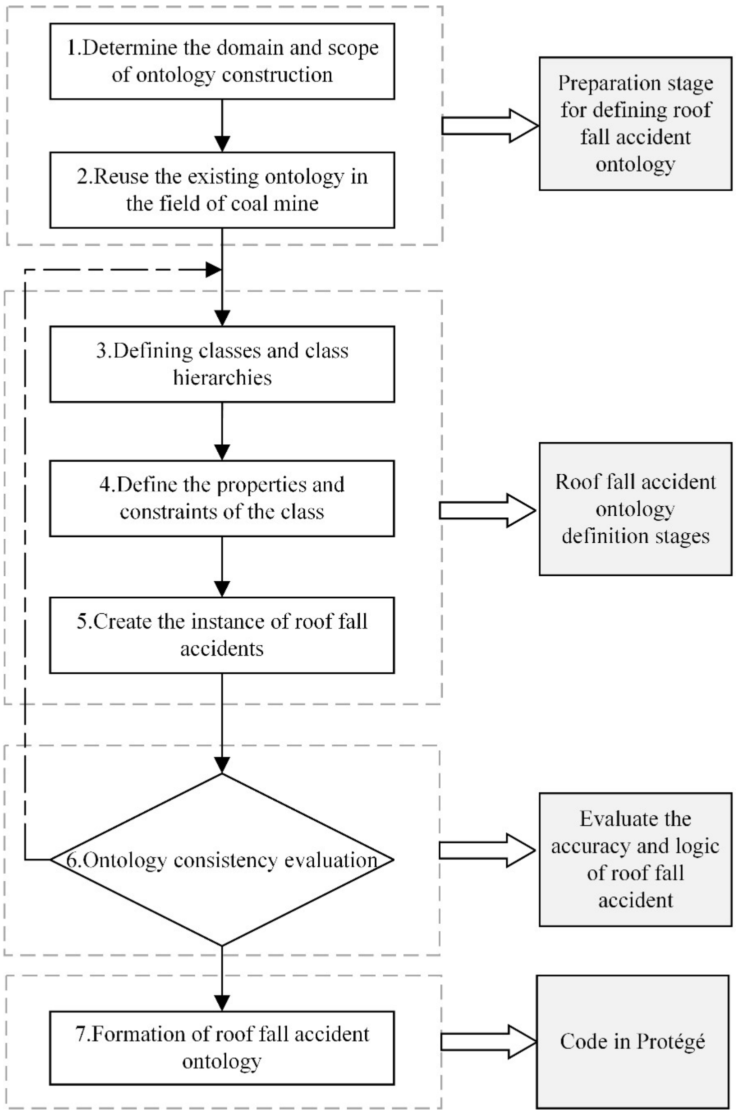

Figure 4. The construction process of the ontology for roof fall accidents.

Formalizing relevant knowledge is imperative to enable effective interaction and knowledge reuse in roof fall accidents. In this case, the applicable safety regulations, roof fall cases, expert experience and published literature can be used as the knowledge source of ontology. Moreover, the formalization of this knowledge aims to establish a clear and unified language to describe the domain-specific knowledge, thereby facilitating efficient information sharing and application.

The ontology can uniformly represent the conceptual knowledge related to the roof falls and realize the integration of heterogeneous knowledge. The main body of roof fall accidents consists of five essential elements:

$$O = \{C, R, F, A, I\} \tag{1}$$

where C is the set of roof fall accident classes or concepts, there is a hierarchical structure among the classes of the roof fall accident ontology. R is the relationship between classes. F is functions. A is axioms or inference rules. I is the instances of roof fall accidents, which is the concretization of the classes and has an indivisible nature.

4.2. Class Hierarchy

The construction of roof fall accident ontology should cover the knowledge and management chain of the roof fall accident field, including the cause, consequence, treatment, staff, workplace and other accident information. This paper uses top-down and bottom-up methods to collect knowledge related to roof falls by extensively consulting relevant literature, regulations, accident reports, books, etc. The roof fall accident ontology is divided into seven classes: accident prevention, accident cause, accident treatment, accident consequence, workplace, staff, and accident case. Additionally, the ontology has been optimized through expert review.

(1) Accident prevention class

The accident is causal, latent and preventable. Through the investigation and statistical analysis of roof fall accidents in recent years, the hidden danger of accidents is the direct cause. Therefore, correctly understanding the precursor information of the roof fall accident and taking reasonable and practical preventive measures can significantly reduce the roof fall accident. According to the characteristics of roof fall accidents, the accident prevention class is divided into accident omen, safety education strategies, safety management strategies, and engineering technology strategies.

(2) Accident cause class

The roof fall accident is the result of various factors that are interrelated and affect each other. According to the accident cause theory, the causes of roof fall accidents are summarized from the perspective of the man-machine loop. Moreover, the influence of mining technical factors such as the initial support force of the support, mining velocity, and roof stability on roof fall accidents is also considered. Finally, the accident causes in the roof fall accident ontology are divided into unsafe human behavior, the unsafe condition of things, mine environmental factors, management defects, and mining technologic factors.

(3) Accident consequence class

The consequences of roof fall accidents include casualties, production suspension, economic losses and equipment damage. Among them, casualties include injuries and deaths.

(4) Accident treatment class

Roof fall accident treatment is divided into accident investigation, emergency response, relief materials, and equipment maintenance.

(5) Workplace class

Through the statistics and analysis of roof fall accidents, the locations of roof fall accidents are gob area, coal mining face, auxiliary transportation lane, return airway, transportation gateway, excavation face, connection roadway, blind lane, and so on.

(6) Staff class

Researchers have constructed the ontology knowledge base for coal mine workers [25]. Referring to the constructed coal mine ontology, the ontology that can be reused for the roof fall accident ontology of the coal mine is extracted. The staff class of roof fall accidents is divided into four classes: emergency personnel, command personnel, coal mine types of work, and relevant experts.

(7) Accident case class

The construction of the knowledge base of roof fall accidents should include typical accident cases. The accident case class in roof fall accident ontology represents the abstract concept of all roof fall accidents, and the roof fall accident instance embodies the accident case class. For example, *the 1.12 Shenmu roof fall accident* is an instance of the accident case class.

4.3. Properties

Based on the classification of the roof fall accident ontology, it is also necessary to specify the properties to connect the related classes to realize the semantic interaction between the ontology knowledge. This paper identifies two properties, namely, object property and data property. Object property reflects the relationship between classes. For example, there is a correlation *hasReason* between *accident_case* and *accident_cause*, indicating the specific cause of the roof fall accident. Data property reflects the relationship between classes and values. For example, the data property *hasDeathToll* has a domain of *accident_case* and a range of *positiveinteger*. Table 1 presents some properties of the roof fall accident ontology.

Table 1. Some properties in roof fall accident ontology.

Name	Type	Domains	Ranges
hasMeasures	Object property	*accident_case*	*accident_prevention*
happenIn	Object property	*accident_case*	*workplace*
workIn	Object property	*staff*	*workplace*
hasReason	Object property	*accident_case*	*accident_cause*
hasAction	Object property	*staff*	*accident_treatment*
resultIn	Object property	*accident_cause*	*accident_consequence*
hasSafetyState	Object property	*staff*	*accident_consequence*
hasEnvironment	Object property	*workplace*	*accident_cause*
hasDeathToll	Data property	*accident_case*	*positiveinteger*
occurrenceTime	Data property	*accident_case*	*datetime*
hasInjuredToll	Data property	*accident_case*	*positiveinteger*

Semantic relations link the roof fall ontology classes to ensure that potential hazards and recommended solutions are generated for specific case events. Figure 5 shows the semantic relationship between the ontology classes of roof fall accidents.

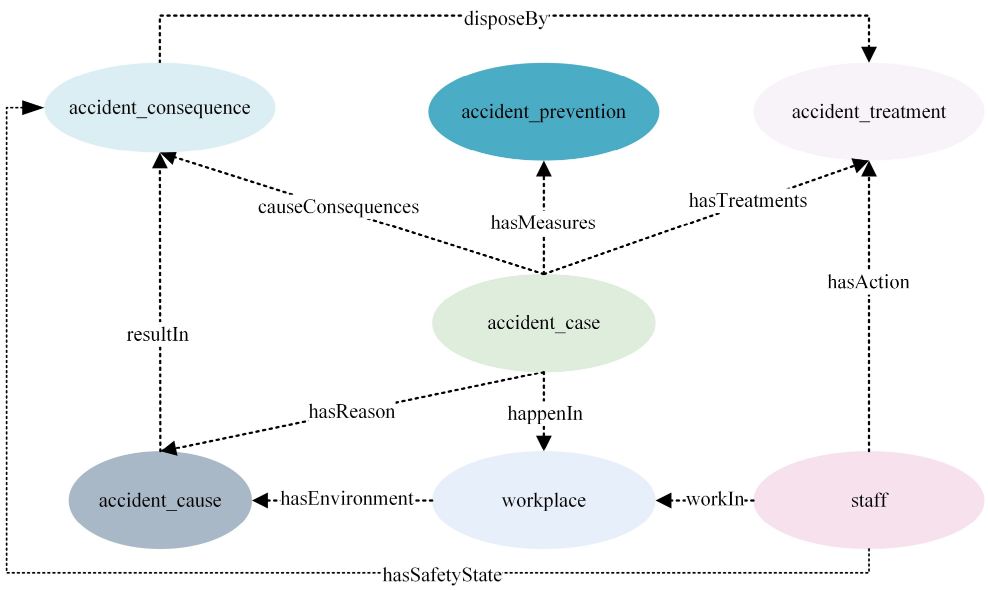

Figure 5. Relationship between the high-level classes of roof fall accidents.

4.4. Framework of Roof Fall Accident Instance

The roof fall accident ontology describes abstract information, properties, and axioms, and the instance layer represents the factual information of the class. For example, on 12 January 2019, a roof fall accident occurred in the Shenmu coal mine. The main causes of the accident include non-explosion-proof vehicles entering the mine, not exploring before digging, and the workers' lack of basic safety knowledge and other factors. The accident resulted in 21 deaths. A typical roof fall accident consists of multiple instances, including the location, cause, number of deaths, treatments, etc. Similar cases can be pushed through the creation, screening, matching and retrieval of roof fall accident cases, and experience reference can be realized.

Figure 6 illustrates the construction framework of roof fall accidents by taking *the 1.12 Shenmu roof fall accident* as an example.

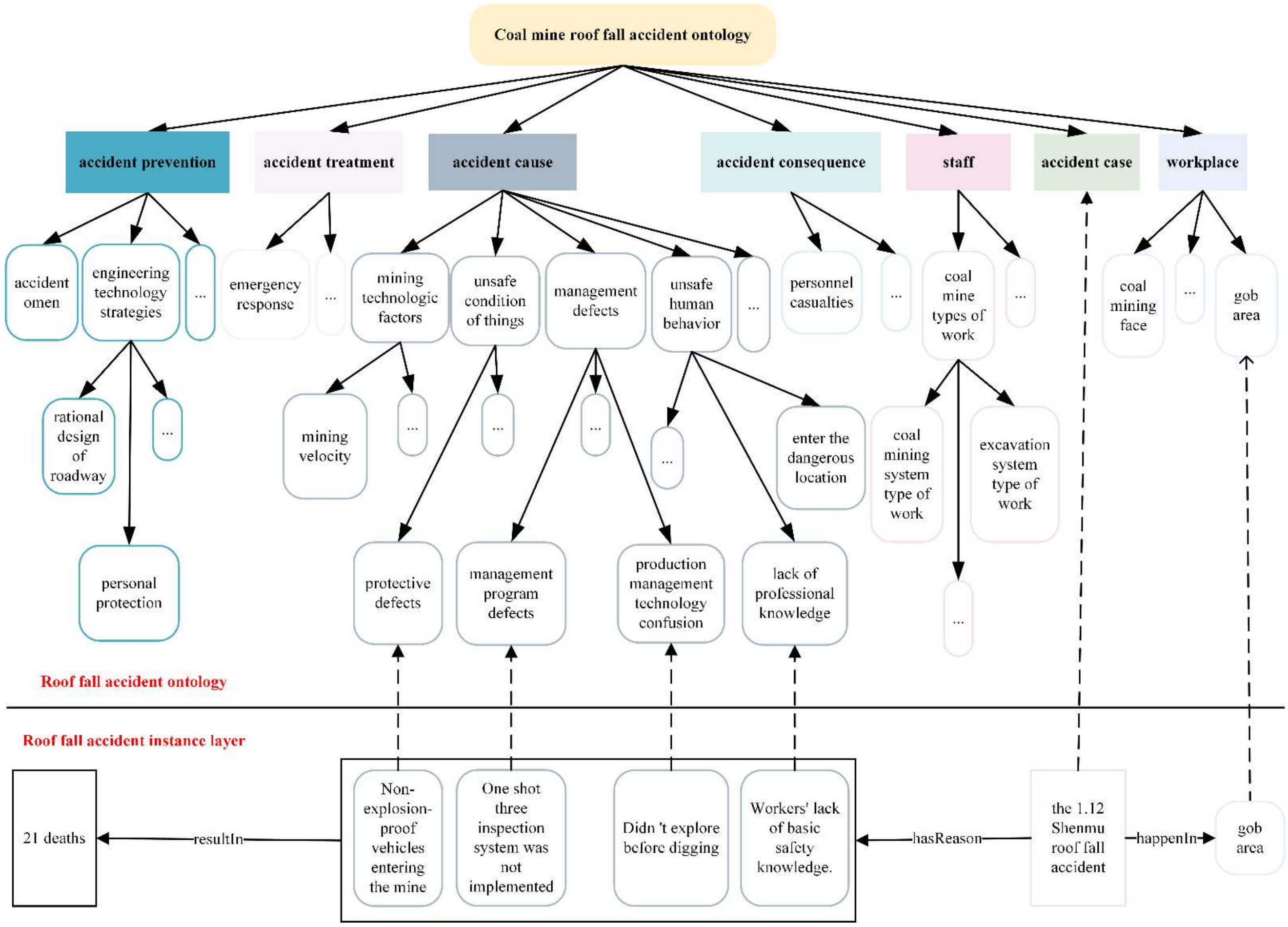

Figure 6. An integrated framework for mapping roof fall accident instances to ontology.

5. Semantic Rules of Roof Fall Accidents

Based on the constructed roof fall accident ontology, semantic rules should be set to deeply mine the information generated by the coal mine production to derive potential hidden dangers and specific measures related to roof fall accidents.

The definition of rules mainly includes the normalization and formalization of rules. The normalization of rules mainly adopts the expression of *if–then*, and the terms involved should be consistent with the classes and properties in the roof fall accident ontology. The formalization of rules converts natural language rules into computer-recognizable coding languages to facilitate inference. This paper uses the rule syntax of Jena to realize the formalization of rules. The formalized rule is: [*rule*: (*?X ?H ?Y*),(*?Y ?I ?Z*)→(*?X ?J*

?Z)] [32,33]. Where X, Y, and Z represent class or instance, H, I, and J represent the property. It represents that X and Y are connected by property H, Y, and Z are connected by property I, and it is inferred that X and Z are connected by property J. According to this definition rule, the natural language rules are formalized and finally constructed into a rule base.

5.1. Semantic Rules Based on Prior Knowledge

The semantic rules based on prior knowledge are constructed by referring to various sources, including coal mine regulations, standards, and expert experience. Firstly, the applicable prior knowledge regarding roof fall accidents is screened. Figure 7 selects some safety regulations related to roof fall accidents as examples.

Semantic regulations

Rule 1 : When the roof control distance of the excavation face does not meet the requirements of the operation procedures, or the support is damaged, or the canopy exceeds the requirements, the charge blasting is strictly prohibited.

Rule 2 : Empty roof operation is strictly prohibited in excavation face.

Rule 3 : When the shearer is mining, it must be moved in time, and when the distance exceeds the specified distance or the roof fall or spalling occurs, it must stop mining.

Rule 4 : Before and during the support, it is necessary to knock the top and remove the perilous rock in time.

Figure 7. Some safety regulations related to roof fall accidents.

Secondly, the screened knowledge content should be appropriately normalized in the expression of *if–then*, with terms consistent with the ontology's classes, properties, and instances. Finally, rule formalization is used to formalize and convert knowledge into a computer-recognizable language, and the resulting formalized rule is: [*rule*: (*?X ?H ?Y*),(*?Y ?I ?Z*)→(*?X ?J ?Z*)] [32,33]. Figure 8 is the formalization of the screened safety regulations.

Semantic rules

[**rule1**: (?x rdf:type untitled-ontology-30:excavation_face),(?y rdf:type untitled-ontology-30:staff),(?y untitled-ontology-30:workIn ?x),(?x untitled-ontology-30:hasEnvironment ?z),(?z rdf:type untitled-ontology-30:protective_defects) ->(?y untitled-ontology-30:hasSafetyState untitled-ontology-30:dangerous)]

[**rule2**: (?x rdf:type untitled-ontology-30:excavation_face),(?y rdf:type untitled-ontology-30:staff),(?y untitled-ontology-30:workIn ?x),(?x untitled-ontology-30:hasEnvironment ?z),(?z rdf:type untitled-ontology-30:stay_in_dangerous_area) ->(?y untitled-ontology-30:hasSafetyState untitled-ontology-30:dangerous)]

[**rule3**: (?x rdf:type untitled-ontology-30:shearer_driver),(?y rdf:type untitled-ontology-30:workplace),(?x untitled-ontology-30:workIn ?y),(?y untitled-ontology-30:hasEnvironment ?z),(?z rdf:type untitled-ontology-30:accident_omen) ->(?x untitled-ontology-30:hasSafetyState untitled-ontology-30:dangerous),(?x untitled-ontology-30:hasAction untitled-ontology-30:stop_mining)]

[**rule4**: (?x rdf:type untitled-ontology-30:bolt_support_workers),(?y rdf:type untitled-ontology-30:workplace),(?x untitled-ontology-30:workIn ?y),(?y untitled-ontology-30:hasEnvironment ?z),(?z rdf:type untitled-ontology-30:perilous_rock) ->(?x untitled-ontology-30:hasSafetyState untitled-ontology-30:dangerous),(?x untitled-ontology-30:hasAction untitled-ontology-30:remove_perilous_rock)]

Figure 8. The formalization of the screened safety regulations.

The construction of roof fall accident rules based on prior knowledge can reveal potential information that staffs are unaware of and make up for the requirements of personnel quality in roof fall accident analysis. Specifically, by importing the constructed ontology into the inference engine and utilizing corresponding rules to infer the existing knowledge, new knowledge can be derived, thereby revealing the underlying patterns and implicit knowledge in roof fall accidents.

5.2. Semantic Rules Based on Data Fusion Method

Although the semantic rules constructed based on empirical knowledge can infer some information regarding roof fall accidents, it is unable to thoroughly mine other potential data rules. In other words, to fully understand and analyze roof fall accidents, it is essential to integrate, analyze, and mine the semantic relevance of multiple data information. Thus, it is imperative to introduce data fusion technology to mine more profound semantic information about roof falls.

Data fusion methods commonly include evidence theory [34,35], neural networks [36], rough sets [37,38], fuzzy reasoning [39,40], etc. The rough set method is a kind of information fusion method, mainly used for describing and reasoning fuzzy and uncertain knowledge, and it does not need other prior knowledge [41,42]. This section introduces the rough set method to mine the data information and extracts the semantic rules of the roof fall accident.

5.2.1. Rough Set

(1) Decision table construction

The decision table is the basis of the rough set theory. Generally, the attributes in the decision table can be divided into conditional and decision attributes. Condition attributes describe the characteristics of decision objects, while decision attributes describe the decision results [43]. The decision table can accurately express and analyze complex logical relations and multi-condition combination problems, representing different condition combinations and corresponding operations or results. The rough set is defined as a decision table shown in Table 2.

Table 2. The general form of the decision table.

Object	**Condition Attribute**				**Decision Attribute**
U	v_1	v_2	$\ldots$	v_n	S
u_1	v_{11}	v_{12}	$\ldots$	v_{1n}	s_1
u_2	v_{21}	v_{22}	$\ldots$	v_{2n}	s_2
$\ldots$	$\ldots$	$\ldots$	$\ldots$	$\ldots$	$\ldots$
u_n	v_{n1}	v_{n2}	$\ldots$	v_{nn}	s_n

Where U = $\{u_1, u_2, \ldots, u_n\}$ is the universe of objects, V = $\{v_1, v_2, \ldots, v_n\}$ is a set of attributes, and S is the decision attribute.

(2) Data standardization and discretization

Data standardization and discretization is the pre-step of rough set reasoning, and the purpose is to map the values of different attributes to the same scale [44]. Discretizing the continuous characteristics typically involves using breakpoints to divide the attribute space into finite regions. To ensure data quality, the finite field division needs to be combined with the actual situation.

The discretization methods of continuous data can be divided into two types according to whether there is prior knowledge. One kind of method is based on equal distance division and equal frequency division. The method fails to consider the attribute characteristics of factors, and the data quality cannot be guaranteed after discretization. The second type of method includes the Naïve Scaler algorithm, entropy algorithm, and boolean reasoning algorithm [45].

(3) Attribute reduction of rough set

Attribute reduction is one of the core steps of rough set reasoning. In a rough set framework, the set of condition attributes $V = \{v_1, v_2, \ldots, v_n\}$ are considered responsible for the occurrence of a particular result S. An attribute v_i is considered redundant or unnecessary if v_i is removed from the set of attributes and does not affect the classification results [41]. The attribute reduction of the rough set is the process of removing unnecessary knowledge from the knowledge base. The commonly used attribute reduction algorithms are the genetic algorithm, the Johnson greedy algorithm, dynamic reduction, exhaustive calculation, etc.

(4) Software based on the rough set

Due to a large amount of manual calculation and inaccurate results, this paper uses ROSETTA software to realize attribute reduction, data discretization, data completion, upper and lower approximation set estimation, rule generation, and other functions.

5.2.2. Semantic Rule Example Based on the Rough Set Method

Take roof stability analysis as an example which is a critical technical measure to prevent roof accidents. By constructing the semantic rules of roof stability, hidden dangers can be eliminated before the formation of roof fall accidents.

(1) Data acquisition

The primary data sources of roof fall accidents are automatic perception data and manual input data. There are many factors that lead to roof falls. Roof stability is one of the influencing factors. Once the coal seam roof falls, it will not only cause damage to underground equipment but also may harm workers. Therefore, by referring to relevant research [46,47], this paper takes the roof stability classification data as an example to show the construction process of roof fall accident semantic rules based on the rough set method.

The original data are shown in Table 3. Yang et al. [46] selected five factors affecting roof stability: uniaxial compressive strength of the immediate roof, rock quality designation, coal compressive strength, mining velocity, and roof hydrological conditions. There are one discrete index and four continuous indexes. According to the influence time of roof accidents, roof stability is divided into four categories: unstable, medium stable, stable, and extremely stable. Among them, the medium stable and unstable roofs belong to the disastrous roof, which must be managed and maintained during mining to prevent roof accidents. The extremely stable and stable roofs belong to the safe roof, and the caving work must be carried out in time according to the technical requirements of the mining process.

Table 3. Working face observation information.

No.	Uniaxial Compressive Strength of Immediate Roof (MPa)	Rock Quality Designation	Coal Compressive Strength (MPa)	Mining Velocity (m/month)	Roof Hydrological Conditions	Roof Stability
1	30.5	65	1.2	72	water gushing	medium stable roof
2	30.5	65	1.2	72	water gushing	medium stable roof
3 *	30.5	85	2.5	105.5	water spraying	stable roof
4	30.5	85	2.5	102.5	humidity	stable roof
5	30.5	85	1.5	84.5	humidity	stable roof
6	53.1	85	1.2	97.5	humidity	stable roof
7	53.1	81	1.2	101	humidity	stable roof
8	53.1	81	1.2	98	humidity	stable roof
9	75.4	81	0.8	85.5	humidity	medium stable roof
10 *	75.4	77	1.2	125	humidity	extremely stable roof
11	75.4	65	0.8	81	humidity	medium stable roof
12	75.4	65	0.6	28	humidity	unstable roof
13	75.4	65	0.6	81	humidity	medium stable roof
14	75.4	65	0.6	60.5	humidity	unstable roof
15	75.4	65	0.8	95.5	humidity	stable roof
16	75.4	65	0.8	92	humidity	stable roof
17	45.2	75	0.8	93	humidity	stable roof
18	45.2	75	0.8	120.5	humidity	extremely stable roof
19	45.2	85	1	93.5	humidity	stable roof
20 *	45.2	85	1	99.5	humidity	stable roof

Table 3. *Cont.*

No.	Uniaxial Compressive Strength of Immediate Roof (MPa)	Rock Quality Designation	Coal Compressive Strength (MPa)	Mining Velocity (m/month)	Roof Hydrological Conditions	Roof Stability
21	45.2	85	0.8	105.5	humidity	stable roof
22	45.2	85	0.8	101	humidity	stable roof
23	85.4	70	0.6	43	water spraying	unstable roof
24	85.4	70	0.6	37	water spraying	unstable roof
25 *	85.4	70	0.6	42.5	water spraying	unstable roof
26	95.1	85	1	70	humidity	medium stable roof

Note:"*" is the test sample.

(2) Discretization of continuous data

The rough set software ROSETTA is used to discretize the continuous data. In this paper, different discretization methods are compared with the actual mine. Finally, the entropy-based method is selected for discretization.

(3) Attribute reduction

After using ROSETTA software to discretize the data, the next step is attribute reduction.

Attribute reduction can eliminate redundant factor attributes to simplify the decision table and maintain classification accuracy. This step can eliminate irrelevant data and improve the efficiency of the decision-making process. This section uses the genetic algorithm to reduce the data. Table 4 displays the result of data reduction using ROSETTA software.

Table 4. Data reduction results with ROSETTA.

No.	Reduction Results	Length
1	{rock quality designation, coal compressive strength (MPa), mining velocity (m/month), roof hydrological conditions}	4
2	{uniaxial compressive strength of immediate roof (MPa), rock quality designation, mining velocity (m/month), roof hydrological conditions}	4
3	{uniaxial compressive strength of immediate roof (MPa), coal compressive strength (MPa), mining velocity (m/month), roof hydrological conditions}	4

Rule generation

After attribute reduction processing, the generated attribute subsets can be used for effective classification and decision-making. In the end, 32 inference rules are generated. Rules appear in the form of *if-then*. In principle, the rules should include all possible situations. Table 5 shows some inference rules.

Table 5. Partial inference rules about coal mine roof stability.

No.	Rules
1	uniaxial compressive strength of immediate roof (MPa)([*, 80.4)) AND coal compressive strength (MPa)([*, 1.4)) AND mining velocity (m/month)([*, 85.0)) AND roof hydrological conditions(water gushing) => roof stability(medium stable roof)
2	uniaxial compressive strength of immediate roof (MPa)([*, 80.4)) AND coal compressive strength (MPa)([1.4, *)) AND mining velocity (m/month)([88.8, 113.0)) AND roof hydrological conditions(humidity) => roof stability(stable roof)
3	uniaxial compressive strength of immediate roof (MPa)([*, 80.4)) AND coal compressive strength (MPa)([1.4, *)) AND mining velocity (m/month)([*, 85.0)) AND roof hydrological conditions(humidity) => roof stability(stable roof)
4	uniaxial compressive strength of immediate roof (MPa)([*, 80.4)) AND coal compressive strength (MPa)([*, 1.4)) AND mining velocity (m/month)([88.8, 113.0)) AND roof hydrological conditions(humidity) => roof stability(stable roof)
5	uniaxial compressive strength of immediate roof (MPa)([*, 80.4)) AND coal compressive strength (MPa)([*, 1.4)) AND mining velocity (m/month)([85.0, 88.8)) AND roof hydrological conditions(humidity) => roof stability(medium stable roof)

Table 5. *Cont.*

No.	Rules
6	uniaxial compressive strength of immediate roof (MPa)([*, 80.4)) AND coal compressive strength (MPa)([*, 1.4)) AND mining velocity (m/month)([*, 85.0)) AND roof hydrological conditions(humidity) => roof stability(medium stable roof) OR roof stability(unstable roof)
7	uniaxial compressive strength of immediate roof (MPa)([*, 80.4)) AND coal compressive strength (MPa)([*, 1.4)) AND mining velocity (m/month)([113.0, *)) AND roof hydrological conditions(humidity) => roof stability(extremely stable roof)
8	uniaxial compressive strength of immediate roof (MPa)([80.4, 90.3)) AND coal compressive strength (MPa)([*, 1.4)) AND mining velocity (m/month)([*, 85.0)) AND roof hydrological conditions(water spraying) => roof stability(unstable roof)
9	uniaxial compressive strength of immediate roof (MPa)([90.3, *)) AND coal compressive strength (MPa)([*, 1.4)) AND mining velocity (m/month)([*, 85.0)) AND roof hydrological conditions(humidity) => roof stability(medium stable roof)

Finally, it is necessary to formalize the inference rules generated so that the machine can recognize and understand them. The formalized style of rule is: [*rule*: (*?X ?H ?Y*),(*?Y ?I ?Z*)→(*?X ?J ?Z*)] [32,33]. Take the first rule in Table 5 as an example to illustrate how the generated inference rules are formalized into machine-readable semantics. The formalized rules are presented in Figure 9. Then the formalized rules are added to the knowledge rule base of the roof fall accident.

Take test data in Table 4 to verify the reliability and accuracy of the semantic rules. It is found that the data mining results using the rough set method are consistent with the actual values, which can meet the actual discrimination of roof stability in mine roof fall accidents. In addition, with the increase of information factors in the knowledge base, the accuracy of rules will be further improved, and the uncertainty of knowledge will be reduced.

Semantic rules

[**rule**: (?x rdf:type untitled-ontology-30:accident_case),(?x untitled-ontology-30:has_uniaxial_compressive_strength ?a), lessThan(?a, 80.4),(?x untitled-ontology-30:has_coal_compressive_strength ?b), lessThan(?b, 1.4),(?x untitled-ontology-30:has_mining_velocity ?c), lessThan(?c, 85.0),(?x untitled-ontology-30:has_roof_hydrological_conditions ?d),equal(?d, "water_gushing") ->(?x untitled-ontology-30:roof_stability untitled-ontology-30:medium_stable_roof)]

Figure 9. Example of semantic rules for coal mine roof stability through data fusion.

6. Implementation of Ontology Reasoning Mechanism

6.1. Implementation Environment

Based on the roof fall accident ontology and semantic rules developed above, this section uses Protégé [48] and Apache Jena [49–51] software to implement the reasoning mechanism based on the roof fall accident ontology.

Protégé is a free ontology development environment widely used to construct domain knowledge models [22]. Protégé supports the creation of classes, properties, and instances of ontology and can transform knowledge into machine-understandable language and support visualization [48].

Apache Jena is an open-source Java framework for building semantic web and linked data applications, and it supports ontology models' storage, query, update, reasoning, and other functions [49,50]. Jana can realize the query and modification of the roof fall accident ontology and trigger the reasoning engine according to the predefined roof fall accident-related knowledge rules to realize the roof fall accident query and reasoning function.

The components used in this study include TDB, Jena inference engine, and Fuseki. TDB is a built-in storage mode officially recommended by Jena; Jena provides RDFS, OWL, and general rule inference engine; and Fuseki is a SPARQL server provided by Jena [51].

The Apache Jena version used in this article is 3.8.0, and the Java environment configuration is 1.8. Figure 10 shows the system architecture.

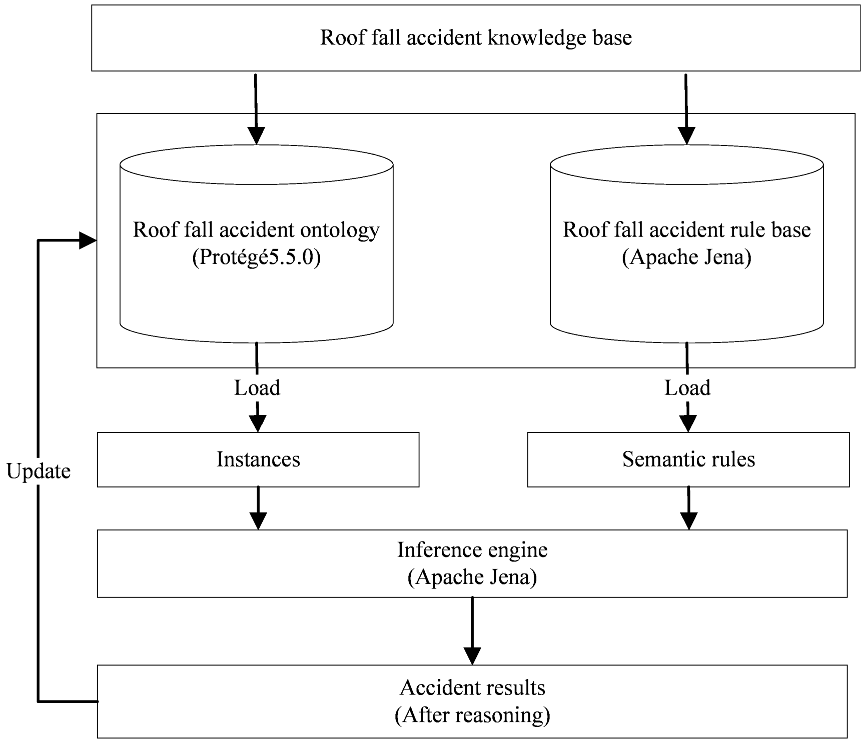

Figure 10. The system architecture of roof fall accident knowledge base.

6.2. Implementation of Roof Fall Accident Reasoning Using Inference Engineer

6.2.1. Case 1: Accident Omen Reasoning

There are usually some omens before the occurrence of roof falls, such as falling debris, roof cracks, and thunderous sounds from roof fractures in the goaf area. However, due to differences in staff experience, perceptions of these omens may vary, making it difficult to detect roof fall omens on time. The deployment of the ontology model can facilitate personnel decision-making. For example, before the roof fall accident, *staff_A* found that the gob area continuously cracks and thunks, representing the omen of the roof fall accident. This situation triggers the semantic rules for detecting accident omens. The system intelligently infers the current dangerous state and treatment measures. The reasoning process is as follows: *staff_A* is a *staff* individual who works in the *gob_area*, and *the_gob_area_cracks_and_thunks* is an *accident_omen* individual. The *staff_A* is associated with the *gob_area* through the object property *workIn*, while the *gob_area* is linked to the *the_gob_area_cracks_and_thunks* via the object property *hasEnvironment*. In this case, semantic rules are activated, *staff_A* is inferred to be *dangerous*, and the event's specific location and activity interventions are reported. Figure 11 shows the inference chain based on semantic rules.

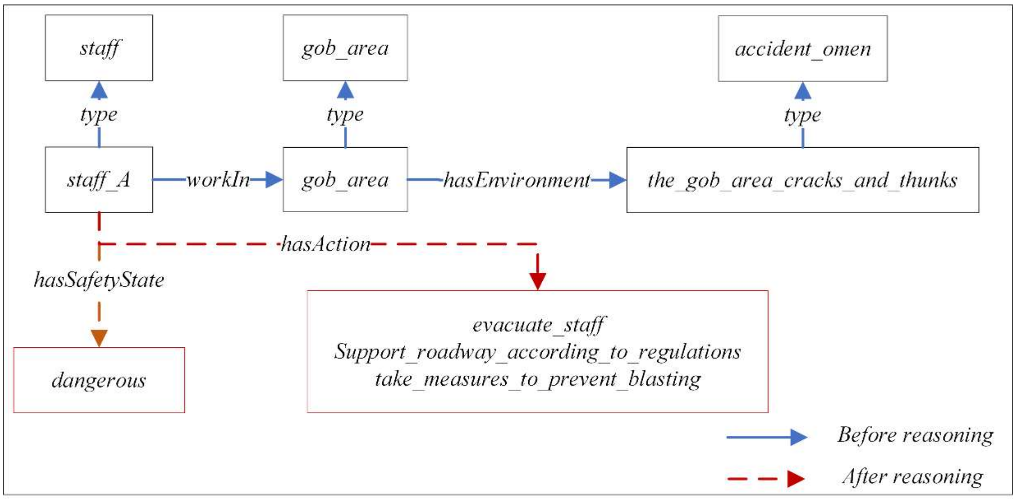

Figure 11. Semantic rule-based inference chain for accident omen.

6.2.2. Case 2: Judgment of Personnel Risk

The working place of *staff_B* is the *excavation_face*1. However, no support measures are taken on the roof during operation. This information triggers the semantic rules for detecting whether the operator's work is compliant. The reasoning chain is as follows: *staff_B* is a *staff* individual, and *excavation_face*1 is an *excavation_face* individual. According to the object property *workIn*, *staff_B* is associated with the *excavation_face*1, while the *excavation_face*1 is connected to the *empty_roof_operation* through the object property *hasEnvironment*. In this case, *staff_B* is in a dangerous state and needs to take emergency measures to evacuate personnel. Figure 12 shows the reasoning chain to judge the personnel risk. This approach can potentially improve the safety of coal mines and help prevent the recurrence of similar tragedies.

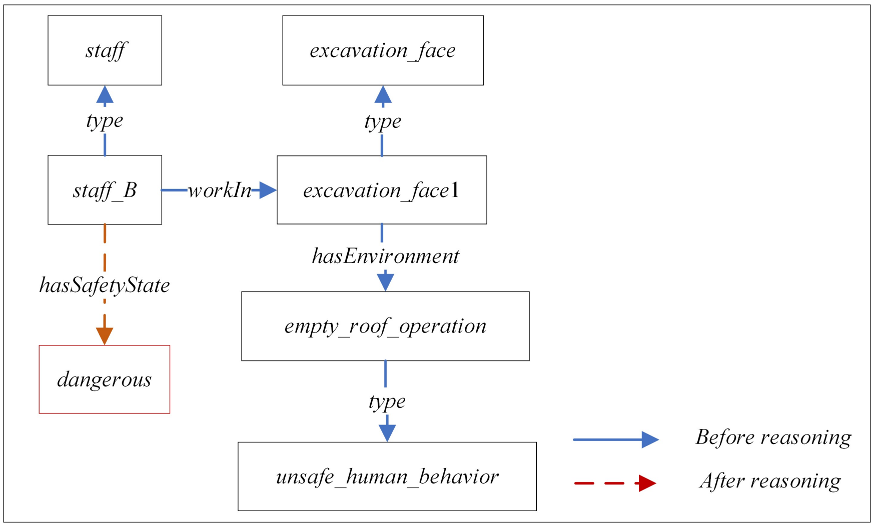

Figure 12. The reasoning chain to judge the personnel risk.

6.2.3. Case 3: Reasoning of Roof Stability

Roof stability is one of the indexes to judge roof fall. The data in Table 3 is used as input to trigger semantic rules about roof stability. According to the reasoning chain, *Case*1 is considered an individual case of *accident_case*. The properties of *Case*1 are connected to data information through the data properties such as *has_uniaxial_compressive_strength*, *has_coal_compressive_strength*, *has_roof_hydrological_conditions* and *has_mining_velocity*. Figure 13 shows an example of roof stability reasoning. The result shows that *Case*1 is related to the *unstable_roof* with the object property *roof_stability*, and it is necessary to take measures to reduce the risk before the formation of roof caving accidents.

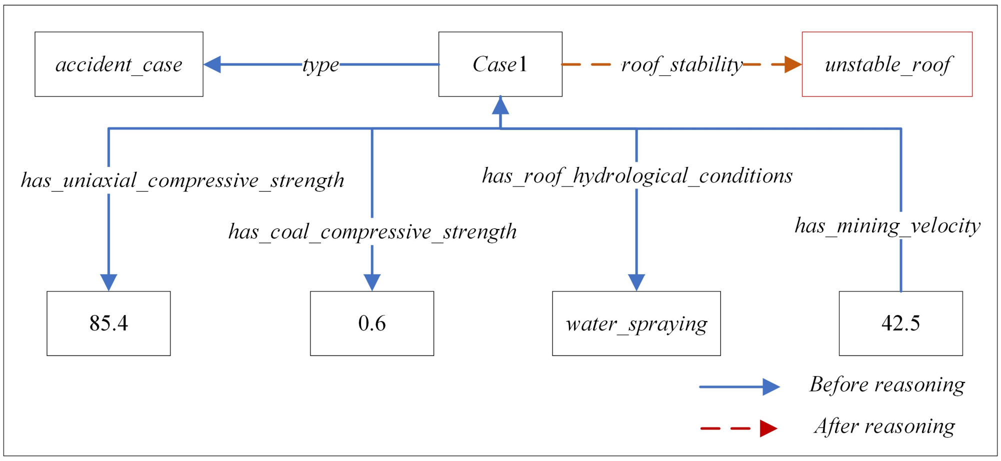

Figure 13. Inference chain for roof stability.

The above examples can trigger the relevant rules of the roof fall accidents and obtain the reasoning results, which reflect the feasibility of the roof fall accident ontology and rule base. In short, the knowledge representation and reasoning model of roof fall accidents based on ontology can infer implicit knowledge and realize the mining of new knowledge, which can effectively guarantee the smooth progress of production activities and support the early warning of roof falls.

7. Discussions and Conclusions

7.1. Limitations and Future Study

Preliminary practice and test results show that ontology-based technology can be unified management of roof fall accident knowledge. However, there are some potential limitations in this study. Firstly, this study only focuses on roof fall accidents, which leads to the limitation that the constructed ontology and semantic rules lack information from other domains. Additionally, this study is based on a large amount of textual data from roof fall accident cases, primarily focusing on textual case analysis. It is necessary to conduct the comprehensive testing of the constructed ontology framework and apply it to coal mine accidents to further help validate the model's compatibility. Furthermore, the existing roof fall accident ontology relies on manual construction and the exploration of automatic acquisition functions is still required.

Future research will focus on deploying the ontology and semantic rules on a visualized platform in coal mines and integrating domain experts and knowledge from different fields to support cross-disciplinary accident analysis and decision-making. Moreover, with the development of natural language processing and deep learning, it is possible to utilize appropriate techniques to automate the acquisition and construction of ontology knowledge, providing more accurate, comprehensive, and flexible semantic modeling capabilities in practice.

7.2. Conclusions

This study proposes an ontology-based semantic modeling method for roof fall accidents, which aims to share and reuse roof fall knowledge for intelligent decision-making in coal mines. It provides a unified framework for sharing, storing, and managing knowledge to assist research progress, enhance safety management, and minimize accidents. For the problem of poor organization and reusability of accident knowledge, a domain ontology of roof fall accidents is developed based on the analysis of many roof fall accident cases and combined with expert opinions to optimize, which provides a standard framework to represent the prior knowledge in this field. Semantic rules based on expert experience and data fusion technology further improve the ontology knowledge system. In addition, the formal processing of roof-falling rules based on the Jena syntax is used to make the ontology uniformly expressed in the computer, facilitating subsequent inference engine processing. Data information in mine production is collected and mapped to the ontology knowledge base. If the information meets semantic conditions, the semantic rules are activated to report events, locations, and interventions and detect hazards in real-time. Further research could extend this framework to other types of accidents in coal mines while considering the adoption of automatic acquisition and construction of ontology knowledge. This approach could lead to the intelligent construction and reasoning of ontology models, promoting the development of intelligent systems.

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