Journal of
Marine Science and Engineering

MDPI

Article

Construction of Knowledge Graph for Flag State Control (FSC) Inspection for Ships: A Case Study from China

Langxiong Gan [1,2], Qiaohong Chen [1,2], Dongfang Zhang [3], Xinyu Zhang [4], Lei Zhang [1,2], Chengyong Liu [1,2] and Yaqing Shu [1,2,*]

1 School of Navigation, Wuhan University of Technology, Wuhan 430063, China
2 Hubei Key Laboratory of Inland Shipping Technology, Wuhan 430063, China
3 Suzhou Port and Shipping Development Center, Suzhou 215000, China
4 Navigation College, Dalian Maritime University, Dalian 116026, China
* Correspondence: y.shu@whut.edu.cn

Abstract: The flag state control (FSC) inspection is an important measure to ensure maritime safety. However, it is difficult to improve ship safety management efficiency using data mining due to the scattered and multi-source ship inspection knowledge. In this paper, the emerging knowledge graph technology is used to integrate multi-source knowledge for the FSC inspection. Firstly, an ontology model is built to systematically describe the knowledge and guide the construction of the data layer of the knowledge graph. Then, the BERT-BiGRU-CRF model is used to extract entities from the unstructured data of the FSC inspection. The extracted results are associated with structured and semi-structured data and stored in the graph database Neo4j to construct the knowledge graph. In addition, a case study of the FSC inspection knowledge graph of Dafeng Port in Yancheng, China, is conducted to verify the strength of the proposed method. The results show that the knowledge graph can correlate trivial knowledge and benefit the efficiency of the FSC inspection. Moreover, the knowledge graph can reflect the deficiency characteristics of ships and support the safety management of water transportation.

Keywords: maritime safety; flag state control inspection; knowledge graph; knowledge extraction; BERT-BiGRU-CRF model

check for updates

Citation: Gan, L.; Chen, Q.; Zhang, D.; Zhang, X.; Zhang, L.; Liu, C.; Shu, Y. Construction of Knowledge Graph for Flag State Control (FSC) Inspection for Ships: A Case Study from China. *J. Mar. Sci. Eng.* **2022**, *10*, 1352. https://doi.org/10.3390/jmse10101352

Academic Editors: Dracos Vassalos and Spyros Hirdaris

Received: 3 August 2022
Accepted: 17 September 2022
Published: 22 September 2022

1. Introduction

Shipping is an important method of transportation in international trade, bearing more than 80% of the world's total transportation volume and playing an irreplaceable role [1,2]. However, maritime traffic creates serious problems of navigation safety and ship pollution [3–5]. In both open sea and coastal waters, maritime traffic accidents occur frequently and could cause severe consequences, such as economic loss, environmental impact, and huge casualties [6]. Therefore, it is crucial to reduce ship navigation risk and prevent waterborne traffic accidents.

The flag state control (FSC) inspection is a powerful and effective measure adopted by maritime authorities to ensure ship navigation safety and to prevent marine environmental pollution from ships. The maritime administration authority takes corresponding measures for ships with deficiencies according to relevant laws, regulations, and professional knowledge [7]. In some serious cases, the ship will be "detained" and unable to leave the port. In the FSC inspection, the officers of maritime administrative inspection need to master multi-source information including ship information, laws, regulations, inspection requirements, and professional knowledge. Therefore, it is important to fuse knowledge from multiple sources to improve the efficiency of the FSC inspection.

As a result of the rapid development in information technology, knowledge management has been continuously updated in recent years. In 2012, the concept of a "knowledge graph" was first proposed to efficiently integrate useful knowledge and information from massive amounts of data [8]. The emerging knowledge graph technology uses entities as nodes and relations as edges to connect people and objects in the real world, resulting in a similar "multi-relation graph" of a huge semantic network [9,10]. It can be used to connect trivial knowledge and represent the complex relationship of professional knowledge to support multiple applications, such as knowledge retrieval and knowledge visualization. This provides a technique to solve the problem of knowledge dispersion in the field of ship inspection. Therefore, the research problem addressed in this paper is determining how to construct an FSC inspection knowledge graph, to realize the correlation of the knowledge and improve the efficiency of the FSC inspection.

To achieve this aim, a knowledge graph for the FSC inspection for ships is constructed and applied in this paper. Firstly, the relevant knowledge of the FSC field is integrated and an ontology model is designed with FSC inspection. Then, the Bidirectional Encoder Representations from Transformers-Bidirectional Gated Recurrent Units—Conditional Random Fields (BERT-BiGRU-CRF) model is used to extract the entity of text data, and the extraction results are associated with structured and semi-structured data. Finally, the graph database Neo4j is used to store multi-source heterogeneous data to construct and visualize the knowledge graph.

The remainder of this paper is organized as follows. A literature review on ship safety inspection and knowledge graph technology applications is conducted in Section 2. In Section 3, the construction method of the FSC inspection knowledge graph, including the ontology construction and the data layer construction, is introduced. In Section 4, a case study of the FSC inspection knowledge graph of Dafeng Port in Yancheng, China, is conducted, followed by a comprehensive discussion in Section 5. In Section 6, the conclusion is drawn.

2. Literature Review

According to the different inspection objects, ship safety inspection is generally divided into port state control (PSC) inspection and flag state control (FSC) inspection [11]. The former targets foreign ships [12], whereas the latter targets domestic ships [7]. As ship safety inspection is very important for maritime traffic safety, many studies have been conducted on ship safety inspections. Tsou [13] analyzed the relationship between ship detention deficiencies and external factors with the application of association rule mining technology under big data but did not consider internal factors. Based on previous studies that only considered the relationship between ship factors and inspection results, the main types of deficient ships were identified by optimizing the analytic hierarchy process (AHP) to predict ship detention probability [14]. Considering the internal relationship between ship critical defects and ship attributes, a hybrid model combining a feature selection scheme and support vector machine (SVM) was adopted to predict ship detention [15]. He et al. [7] proposed an interpretable decision-making model for ship detention based on machine learning, namely SMOTE-XGBoost-Ship Detention Model (SMO-XGB-SD). The model utilized the extreme gradient boosting (XGBoost) algorithm and Synthetic Minority Oversampling Technique (SMOTE) algorithm to judge whether a ship should be detained.

The research above constructed decision-making models to reduce ship navigation risks by analyzing the relationship between ship defects, ship attributes, and ship detention decisions. However, a large amount of knowledge including relevant laws, regulations, and professional knowledge is involved in the FSC inspection, but not limited to major defects that cause ship detention. It is a huge challenge to associate different knowledge and realize the correlation between the inspection elements to improve ship inspection efficiency.

In recent years, the knowledge graph has been gradually developed and successfully applied in many fields, such as medical treatment, medicine, and energy industries. In the field of transportation, Liu et al. [16] constructed the railway operational accident knowledge graph (ROAKG) by abstracting the knowledge entities as connected network nodes and performed the topological analysis of the ROAKG using new indicators to reveal the underlying rules of accidents. Tan et al. [17] adopted the TransD knowledge reasoning model based on the knowledge graph of the urban transportation system to excavate the hidden relationship between traffic entities and realize intelligent question answering of urban traffic services. A knowledge graph based on the travel chain model integrating multi-source public transport data was built to realize effective contact tracking of COVID-19 on a large-scale contact network [18].

Some achievements have also been made in maritime traffic. For example, Zhang et al. [19] constructed a knowledge graph for dangerous goods in waterway transport and correlated scattered dangerous goods knowledge to quickly query the knowledge of dangerous goods and automatically judge the stowage and isolation requirements of dangerous goods. Liu and Wang [20] used rules and dictionaries to extract knowledge of marine laws and regulations for the International Regulations for Preventing Collisions at Sea (COLREGS) and built a legal knowledge graph to realize intelligent retrieval of the related knowledge. Dong et al. [21] established the unified semantic representation of heterogeneous models through feature recognition and multi-strategy ontology mapping, and used semantic reasoning to realize the retrieval and reuse of existing knowledge. These results show that knowledge graph technology can relate trivial knowledge and mine the implicit relationship between sources of knowledge to realize the retrieval and full utilization of knowledge.

To conclude, most studies of knowledge graphs in maritime traffic have focused on the acquisition of maritime dynamic information, the association of maritime dangerous goods knowledge, and the query of ship information. However, little research on the knowledge graph has focused on the FSC inspection, which urgently needs a method to integrate multi-source knowledge to improve the efficiency of the FSC inspection.

3. Methodology

3.1. Research Framework

The framework of the construction of the FSC inspection includes data acquisition, construction of the ontology model, and construction of the data layer, as shown in Figure 1. Data acquisition is preparatory work for constructing a knowledge graph, as these data are the source of knowledge. The data types of the FSC inspection can be categorized into structured data, semi-structured data, and unstructured data. Structured data refers to data represented in a certain format, such as data stored in a relational database or object-oriented database, which can be directly used to construct knowledge graphs. Unstructured data are data having an irregular or incomplete structure, such as text, audio, and video, which require information extraction to further construct knowledge graphs. Semi-structured data lie between structured data and unstructured data, such as XML documents, HTML documents, and weblog files, which also need simple information extraction to construct knowledge graphs.

The construction of the FSC inspection knowledge graph includes the ontology model construction and the data layer construction. The ontology model is a combination of classes, and their attributes and relations, which represents the related concepts and hierarchical structure of the FSC inspection domain knowledge. The ontology model construction consists of knowledge representation, concept combing, attribute definition, and relation definition.

The data layer construction refers to the combination and filling of data based on the ontology, including knowledge extraction and knowledge storage. Knowledge extraction is a process of extracting available knowledge units from data of different sources and structures by automatic technology. The knowledge unit mainly includes three knowledge elements: entity, attribute, and relation. The entity is an individual in a conceptual classification, such as people's name and place name. The attribute is a further description of entity features, which is attached to entity existence. The relation is the semantic connection between different entities [22]. The entities, attributes, and relations obtained by knowledge extraction are represented in the form of (entity, relation, entity) or (entity, attribute, attribute value), namely a triple structure [23]. In a real inspection scenario, the FSC entity includes not only the contents and processing measures of each FSC inspection, but also the people, objects, and organizations involved in the inspection process. The entity attribute is the supplementary description of the inspected entity and exists in the form of attached text, whereas the FSC entity relation is a connecting bridge between different entities. Finally, knowledge storage is the process of storing triplet data obtained by knowledge extraction in the most popular graph database, Neo4j [24].

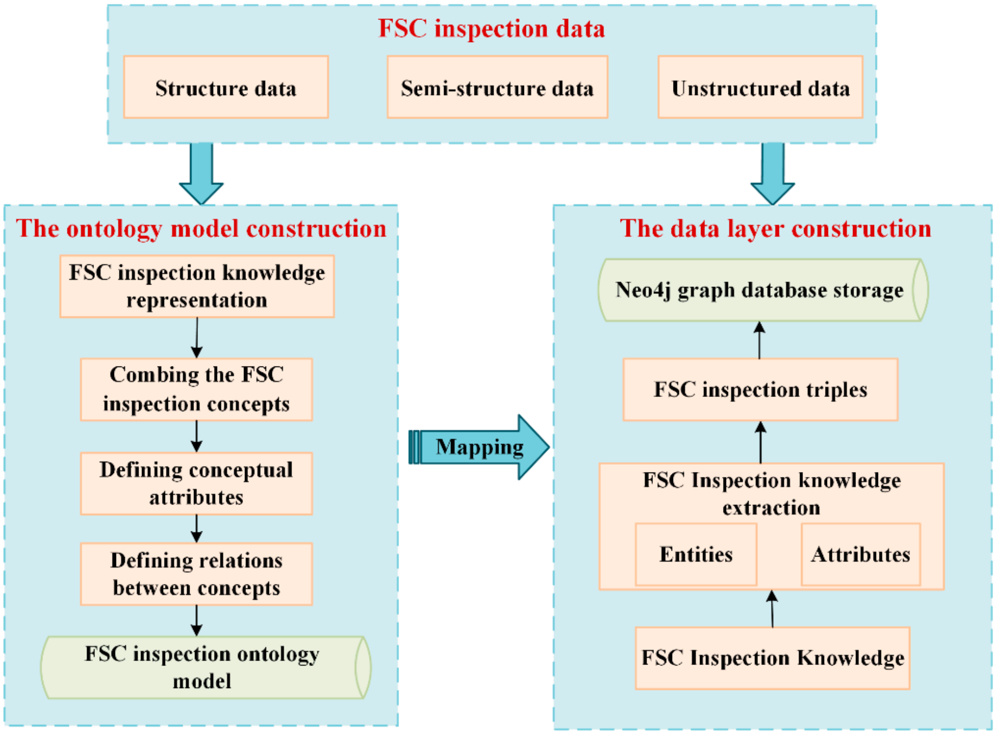


Figure 1. The framework of the FSC inspection construction.

3.2. Data Acquisition

In the task of constructing the FSC inspection knowledge graph, the data related to the FSC inspection should be collected. The data relating to the FSC inspection can be found from three sources: the structured historical inspection data from the collaborative management platform of the Maritime Safety Administration, the semi-structured ship static data from a maritime data supplier (www.shipxy.com, accessed on 3 November 2021), and the unstructured data from the official website and public account of the Maritime Safety Administration.

3.3. Construction of the Ontology Model

The ontology model of the FSC inspection knowledge graph is constructed to determine the entity types, relations, and attributes of the domain. The construction adopts the Protégé software developed by Stanford University [25]. Based on the seven-step method [26], the FSC inspection ontology construction process is determined, as shown in Figure 1. Firstly, it is necessary to determine the domain category and boundary described by ontology and fully understand the relevant knowledge system. On this basis, the core concepts and hierarchical structure between concept classes are combed. Then, the attributes of ontology concepts and the relations between concepts are defined to reflect the complete FSC inspection knowledge association system. Finally, the Protégé software is used to implement FSC inspection domain ontology representation.

3.4. Construction of the Data Layer

The construction of the data layer of the FSC inspection includes two parts: knowledge extraction and knowledge storage. Firstly, entity information and its semantic association are extracted based on different types of FSC inspection information. Then, the entities are associated and the FSC inspection knowledge network is established according to the FSC inspection ontology. Finally, the Neo4j graph database is used for knowledge storage.

3.4.1. Knowledge Extraction

The knowledge extraction is conducted to extract detailed information about entities and attributes from the FSC inspection data. Various types of relations between entities are defined by the constructed ontology model.

(1) Entity extraction based on the BERT-BiGRU-CRF model

In the FSC inspection, most entities exist in structured and semi-structured data and can be obtained directly after data preprocessing. However, entities including inspection items and contents mostly exist in unstructured texts such as laws and regulations, so they need to be identified by entity extraction technology. Entity extraction, also known as named entity recognition, is an important technology in natural language processing to identify entities with specific meanings from text statements, such as people's names, organization names, and proper nouns. There are three main types of entity extraction methods, namely, rule-based and dictionary-based methods, statistical model-based methods, and deep learning-based methods. With the development of the neural network, the neural network method based on deep learning has become the mainstream of entity extraction.

In entity extraction, each word first needs to be sequence-labeled. Sequence labeling refers to the task of labeling each element or part of elements in a sequence. This paper adopts the sequence-labeling method of BIO to annotate the text. The character at the beginning of the vocabulary is represented by "B-", whereas non-beginning characters of the vocabulary are represented by "I-" and other invalid characters are represented by "O-".

It is necessary to use a neural network model to train and learn the dataset obtained by sequence labeling to identify the needed entities from the new text. In this paper, the neural network model combining Bidirectional Encoder Representations from Transformers (BERT) [27], Bidirectional Gated Recurrent Units (BiGRU) [28,29], and Conditional Random Fields (CRF) [30] is used to identify entities in the FSC inspection. As shown in Figure 2, the structure of the BERT-BiGRU-CRF model is composed of three parts [29]. Firstly, the semantic representation of the input is obtained through the BERT layer pre-trained language model, and the word vector representation containing context information is obtained. Then, the word matrix composed of word vectors is used as the input of the BiGRU layer for semantic encoding. After feature extraction in the BiGRU layer, the label sequence with the highest probability of realizing named entity extraction for ship FSC inspection is obtained in the CRF layer.

To fuse the context on the left and right sides of the word, the bidirectional transformer is used as the encoder in the BERT. Two tasks, namely, Masked Language Model (MLM) and Next Sentence Prediction (NSP), are set in the BERT to capture word-level and sentence-level representations, respectively, and perform joint training. A paragraph of text based on the attention mechanism is modeled in BERT's transformer structure.

As a variant of Long Short-Term Memory (LSTM) [31], the Gated Recurrent Unit (GRU) [28] contains two gate structures: the reset gate for controlling information loss and the update gate for controlling information flow into the next moment. Compared to the LSTM, the scale of parameters is greatly reduced and the training speed of the network is improved. In entity extraction, it is necessary to mine the internal relationship of the context. However, the GRU model cannot encode information from back to front in the text. Therefore, the Bidirectional Gated Recurrent Unit (BiGRU) model containing the forward GRU and the backward GRU can be used to obtain the context information of the current word to make the prediction result more accurate.

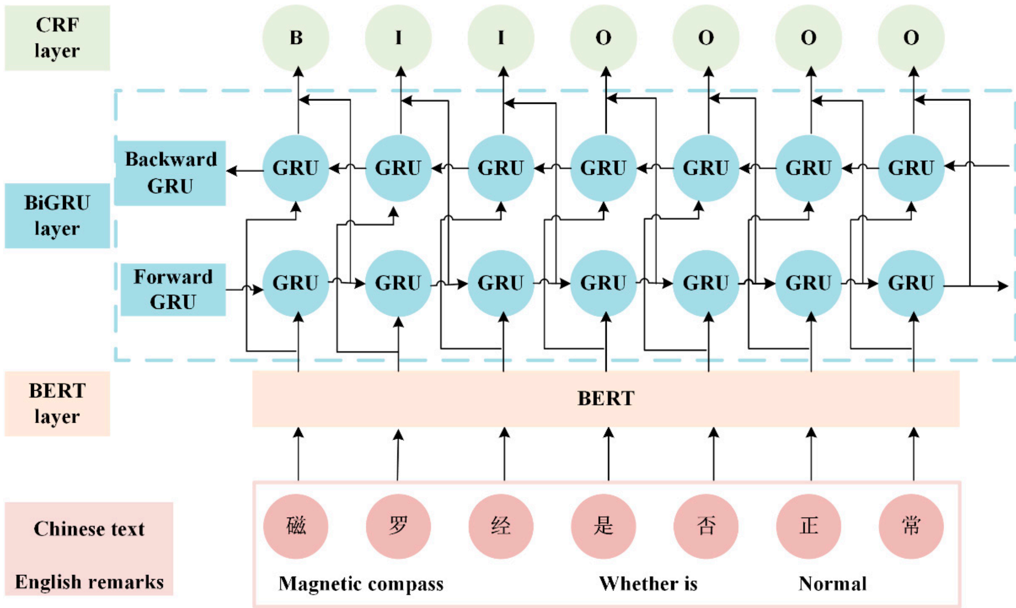


Figure 2. The BERT-BiGRU-CRF model structure [29]. The "Chinese text" part refers to the specific content of the obtained text data, which means "Whether magnetic compass is normal".

The BiGRU contains the forward and backward GRU for each input sequence, so the output results of the BiGRU network are obtained by the combined action of these two GRUs [29]. For each GRU, the initial input value is the word vector sequence $x = (x_1, x_2, \ldots, x_n)$ trained by the BERT layer and the hidden state h_{t-1} of the previous moment. In the GRU, the reset gate represents the information required at the current moment according to the current input, which can be obtained by Equation (1):

$$r_t = \sigma(W_r \cdot [h_{t-1}, x_t]) \tag{1}$$

where r_t denotes the vector for the update gate. σ denotes the sigmoid function, $x = (x_1, x_2, \ldots, x_n)$ is the input vector at the moment t, W_r is the weight matrix for the update gate. The reset gate data is spliced with x_t to obtain the candidate hidden state $\widetilde{h}_t$. The $\widetilde{h}_t$ can be calculated by the Equation (2):

$$\widetilde{h}_t = \tanh(W_c \cdot [r_t \cdot h_{t-1}, x_t]) \tag{2}$$

where W_c is the weight matrix for the candidate hidden state.

The vector for the update gate z_t is obtained by Equation (3) to control the information flowing into the next moment:

$$z_t = \sigma(W_z \cdot [h_{t-1}, x_t]) \tag{3}$$

where W_z is the weight matrix for the update gate.

Finally, the hidden state h_t of the current moment is obtained by the linear combination of the hidden state h_{t-1} of the previous moment and the candidate hidden state $\widetilde{h}_t$. The weight sum of h_{t-1} and $\widetilde{h}_t$ is 1. The weight of $\widetilde{h}_t$ is the output of the update gate, which represents the intensity of the information update. h_t is obtained by Equation (4):

$$h_t = (1 - z_t) \cdot h_{t-1} + z_t \cdot \widetilde{h}_t \tag{4}$$

Each BiGRU gets a forward hidden state $\overrightarrow{h}_t$ and a backward hidden state $\overleftarrow{h}$. A complete state sequence H_t in Equation (5) is obtained by splicing the two types of information received forward and backward:

$$H_t = \left[\overrightarrow{h}_t \oplus \overleftarrow{h}_t\right] \tag{5}$$

Although the GRU can well consider the long-term context relation, it cannot identify the dependencies between labels. For example, in the named entity recognition, some labels cannot appear consecutively, so it is necessary to add a CRF layer to the model to obtain the global optimal label sequence considering the adjacent relation between labels. For a given sequence $x = (x_1, x_2, \ldots, x_n)$, the corresponding prediction label sequence $y = (y_1, y_2, \ldots, y_n)$ can be obtained by using the linear chain conditional random field, and the prediction score can be calculated by Equation (6) [30]:

$$s(x,y) = \sum_{i=1}^{n} \left(W_{y_i-1,y_i} + P_{i,y_i}\right) \tag{6}$$

where $W_{i,j}$ represents the label transfer score, P_{i,y_i} denotes the score of the y_i-th label of the character. The definition of P_i is shown in Equation (7):

$$P_i = Wsh^{(t)} + b_s \tag{7}$$

where W denotes the transformation matrix, $h^{(t)}$ is the hidden state of the input data $x^{(t)}$ at the previous layer moment t.

Maximum conditional likelihood estimation is used for CRF training. For the training set $\{(x_i, y_i)\}$, the likelihood function is calculated by Equation (8):

$$L = \sum \log_a(p(y_i|x_i)) + \frac{\lambda}{2}\|\theta\|^2 \tag{8}$$

where the calculation of p can be calculated by Equation (9), which represents the probability corresponding to the original sequence to the predicted sequence:

$$p(y|x) = \frac{e^{x(x,y)}}{\sum\limits_{y \in Yx} e^{s(x,y)}} \tag{9}$$

In this paper, the evaluation indicators of entity extraction are precision rate P, recall rate R, and F_1 value, which are widely used as knowledge graph evaluation criteria [32,33]. The P value refers to the probability of actually being positive out of all predicted positive samples, which can be calculated by Equation (10). The R value refers to the probability of being predicted as a positive sample among the actual positive samples, which can be calculated by Equation (11). The F_1 value is used to comprehensively evaluate the precision and recall, which can be calculated by Equation (12):

$$P = \frac{TP}{TP + FP} \times 100\% \tag{10}$$

$$R = \frac{TP}{TP + FN} \times 100\% \tag{11}$$

$$F_1 = \frac{2PR}{P + R} \times 100\% \tag{12}$$

where TP is the number of correct entities identified by the model, FP is the number of irrelevant entities identified by the model, and FN is the number of related entities not detected by the model.

(2) Attribute extraction

Attributes are important information for the further semantic expression of entities, which can realize the complete description of entities. Its constituent elements generally include two parts: attribute name and attribute value. Attribute extraction refers to the data operation of extracting the corresponding attributes and attribute values from the target website according to the entity type and its attributes constructed by the FSC inspection ontology model.

3.4.2. Knowledge Storage

After the extraction, the knowledge needs to be stored to support the construction of the data layer. In this research, the graph database Neo4j is used to store triplet data extracted from knowledge. The entities in the triples are stored as nodes, while the relations are stored as edges and the properties are stored as attributes of the corresponding nodes. The Neo4j is used to realize the one-to-one correspondence between structured knowledge, nodes, and edges in the graph structure.

4. Case Study

In this paper, a case study is conducted to construct the FSC inspection knowledge graph for Dafeng Port in Yancheng, China, using the FSC inspection data from January 2018 to July 2021. Firstly, the FSC inspection knowledge is sorted and the FSC inspection ontology is constructed. Then, the FSC inspection corpus is constructed by obtaining the relevant text data of the FSC inspection from the official platform of the Maritime Safety Administration. The entity extraction is carried out using the BERT-BiGRU-CRF model based on corpus annotation. Finally, the FSC inspection knowledge graph is constructed and visualized.

4.1. Data Acquisition

The data used in this study include structured historical ship FSC inspection data, semi-structured ship static data, and unstructured FSC inspection text.

The structured data adopt the historical inspection data of ships in the collaborative management platform of the Maritime Safety Administration. The original dataset consists of 4363 FSC ship safety inspection samples and 11 features, including the ship's name, security inspection type, inspection date, inspection port, inspection authority, inspector, number of deficiencies, ship detention result, deficiency code, deficiency description, and handling opinion description.

The semi-structured data adopt the web crawler method. Static data of the ships involved in the historical inspection data are obtained from the maritime data provider (www.shipxy.com, accessed on 3 November 2021). Every piece of data includes the ship type, tonnage, length, width, height, port of registry, and the relevant information, such as organizations and personnel.

The unstructured data are the FSC inspection-related texts published on the Maritime Safety Administration's official website and the official public account. They are used to extract relevant entities of the ship inspection content. The size of the collected text is 248 KB.

4.2. The Ontology Construction

This paper uses the ontology editing tool Protégé to complete the construction of the ontology in the FSC inspection field. Protégé is ontology editing software, which can provide good support for knowledge visualization, query, and storage.

4.2.1. Knowledge Concepts and Attributes

In this research, the knowledge is categorized into factual knowledge and cognitive knowledge, according to the definition of the Organization for Economic Co-operation and Development (OECD) on the "knowledge-based economy" in 1996. The factual knowledge answers questions of what and who, whereas cognitive knowledge answers questions of why and how. To represent the structural level of FSC inspection domain knowledge concepts, the first and the second level concepts are designed under the classification of factual knowledge and cognitive knowledge. The factual knowledge includes all kinds of entities involved in FSC inspection, which can be divided into three categories: natural persons, objects, and institutions. Natural persons include officers and crew involved in the supervision and inspection process. Objects mainly refer to ships that are inspected by ship FSC. Institutions include maritime administration authorities and shipping companies. The cognitive knowledge in the FSC inspection field includes the legal basis, disposal decisions, inspection items, and deficiencies, which are usually expressed in words and symbols with various documents as the carrier.

In addition, the concept attributes are added to the knowledge as a supplement to accurately describe various types of knowledge. For example, attributes such as name, gender, title, and work unit are defined for the "Maritime officer" entity. Attributes such as name, gender, title, and eligibility information are defined for the "Crew" entity. Attributes such as type, ship identification number, length, width, and port of registry are defined for the "Ship" entity. Attributes such as subordination, responsibility, and scope of jurisdiction are defined for the "Maritime administration authority" entity. The details of the concepts and attributes are shown in Table 1.

Table 1. FSC inspection knowledge concepts and attributes.

Knowledge Category	The First-Level Concepts	The Second-Level Concepts	Attributes
Factual knowledge	Natural person	Maritime officer	Name, gender, position, work unit
		Crew	Name, gender, position, qualification information
	Object	Ship	Type, ship identification number, length, breadth, port of registry
	Institution	Maritime administration authority	Affiliation, Responsibilities, Jurisdiction
		Shipping company	Name, audit information, location
Cognitive knowledge	Documentation	Legal basis	Object-oriented, the scope of application, legal period, the content of articles
		Disposition decision	Decision codes, the scope of application
		Inspection item	Types, object orientation, bullet points
		Deficiency	Deficiency code, the scope of application

4.2.2. The Relations between Concepts

Based on the above-mentioned FSC inspection knowledge hierarchy design and its attribute division, the relations between FSC inspection knowledge are determined. The relations among FSC concepts include categorical relations, namely, upper–lower relations, and non-categorical relations reflecting semantic relations, as shown in Figure 3. The categorical relation reflects the logical level of the knowledge, such as crew and maritime officers under the natural person level, and legal basis, disposal decisions, deficiencies, and inspection items under the document level. The non-categorical relations represent semantic relations between different concepts, as shown in Table 2.

Table 2. Relations in the constructed knowledge graph.

Relation Label	Head Entity and Tail Entity	Description
Inspect	Maritime officer—Ship Maritime officer—Crew	Maritime officers inspect ships Maritime officers inspect the crew
Manage	Maritime administration authority—Shipping company Shipping company—Ship	The maritime administration authority manages the shipping company The shipping company manages the ship
Work	Maritime officer—Maritime administration authority Crew—Ship	A maritime officer works in a maritime administration authority Crew work on a ship

Table 2. *Cont.*

Relation Label	Head Entity and Tail Entity	Description
InspectItem	Crew—Inspection item Ship—Inspection item	The inspection item of the crew The inspection item of the ship
TakeFor	Deficiency—Disposition decision	Take disposition decisions for deficiencies
Exist	Inspection item—Deficiency	An inspection item exists deficiencies
BasedOn	Inspection item—Laws and regulations Deficiency—Laws and regulations Disposition decision—Laws and regulations	The inspection item is based on laws and regulations The deficiency is based on laws and regulations The disposition decision is based on laws and regulations

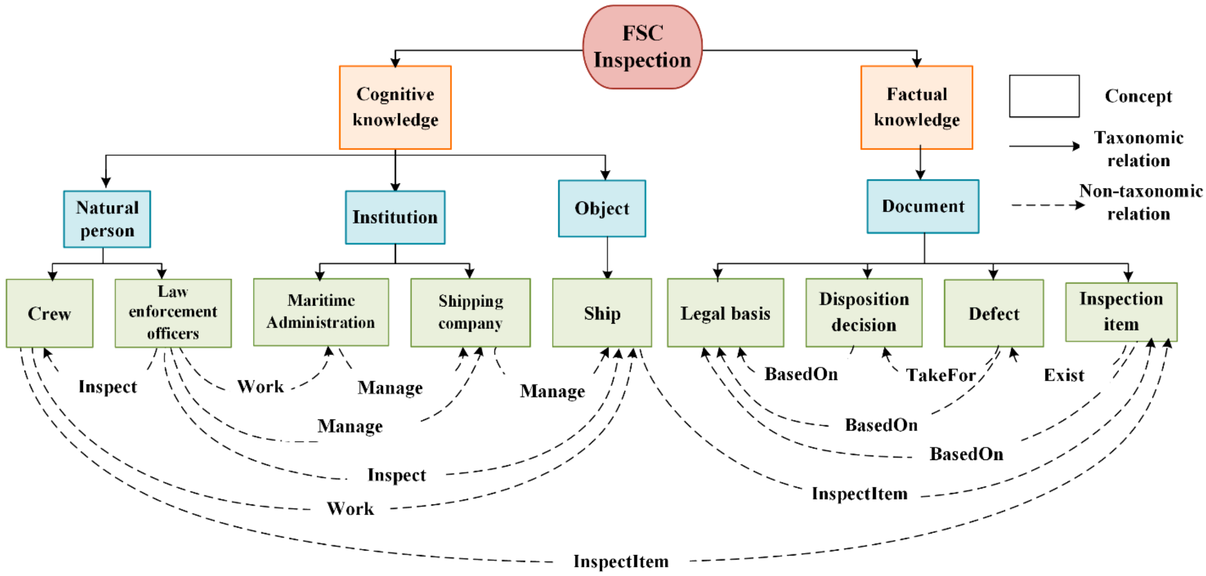


Figure 3. FSC inspection relations between different concepts.

Based on the above definition of concepts and their attributes and relations, the ontology model of the FSC inspection is constructed, as shown in Figure 4.

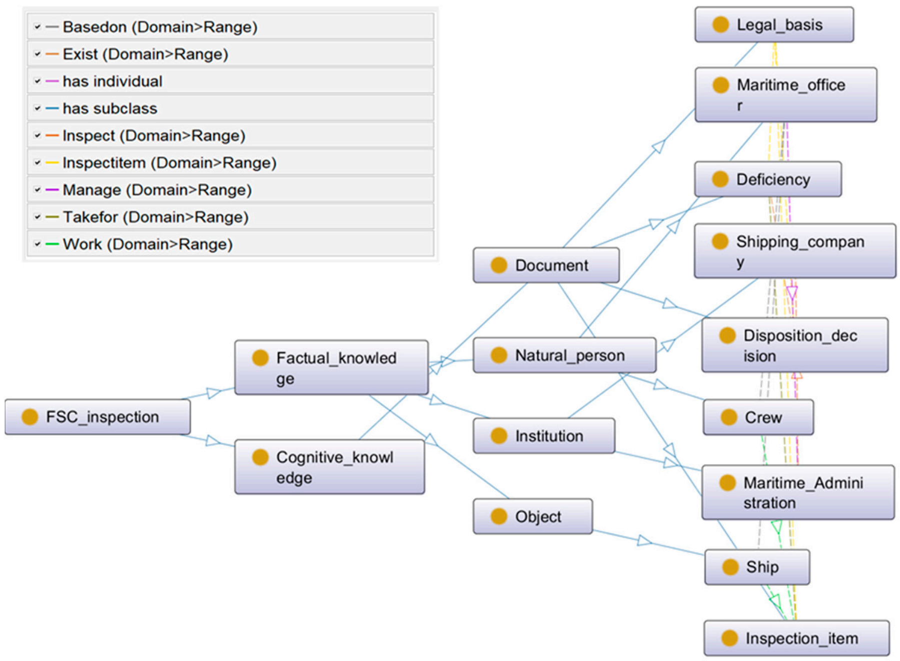


Figure 4. The ontology model of the FSC inspection.

4.3. The Knowledge Extraction Experiment

FSC historical inspection records of Dafeng Port in Yancheng, China, from January 2018 to July 2021 were collected, and 4363 structured data were obtained after preprocessing. Factual entities in historical ship inspection data were used as search terms, and attribute data were retrieved from ship websites such as the maritime data supplier (www.shipxy.com, accessed on 3 November 2021) and the official websites of each directly affiliated maritime bureau to complete attribute extraction. For relation extraction, the relation types are shown in Figure 3 and various entities are linked according to the relation defined by the ontology. For entity extraction, the entities of the inspection item class and inspection content class mostly exist in unstructured texts such as FSC inspection related procedure manuals and laws and regulations. In this research, the BERT-BiGRU-CRF model was used for entity extraction, and the specific experimental process is as follows.

4.3.1. Experimental Set-Up

The experimental environment for the FSC inspection entity extraction is Python 3.6.13 and the deep learning framework is Kashgari 1.1.5. The meanings and settings of various parameters in the entity extraction experiment are shown in Table 3.

Table 3. Experiment parameters' meaning and setting.

Experimental Parameters	Meaning	Value
Max_seq_len	Maximum sentence length in the BERT layer	100
Batch_size	The number of samples passed to the program for training in a single iteration	16
Epoch	The number of updates when all training data has been used once	50
BiGRU_units	The hidden unit of BiGRU	128
Dropout	The parameter used to prevent overfitting	0.5

4.3.2. Sequence Labeling Result

The sequence labeling method of BIO is used to annotate the text. To classify entities in text data, this paper defines six categories of labels: "CEDO", "PCT", "CMDP", "STR", "FAEQ", and "REQ". The representative entities and their specific meaning are shown in Table 4. Therefore, each word in the text is labeled as "B-CEDO", "I-CEDO", "B-PCT", "I-PCT", "B-CMDP", "I-CMDP", "B-STR", "I-STR", "B-FAEQ", "I-FAEQ", "B-REQ", "I-REQ", and "O". An example is shown in Figure 5 by converting the text "after the inspection of lifting equipment is qualified, ships should be equipped with the relevant 'lifting equipment certificate'" in Chinese into the sequence label.

Table 4. Six types of entities and their specific meaning.

Label	Entity	The Specific Meaning
CEDO	Certificate documents	The ship, crew provisioning, and holding of relevant statutory certificates and related materials
PCT	Passenger and cargo transportation	The ship's carrying of passengers, cargo, precautions, and cargo securing and lashing
CMDP	Crew staffing and duty performance	The situation of the crew on the ship, and the crew performing their duties, including the maintenance of facilities and equipment related to their duties, and the actual operation ability
STR	Ship structure	The internal and external structure of the ship, such as ship skeleton form, fire prevention structure and its corresponding requirements, the type of ship pipe system and layout requirements, etc.
FAEQ	Facility and equipment	The facilities and equipment used to complete the navigation, berthing and unberthing, loading and unloading of goods and other production operations of ships, and to ensure the safety of ships and personnel
REQ	Inspection requirements	The checkpoints and attention points required by FSC inspection

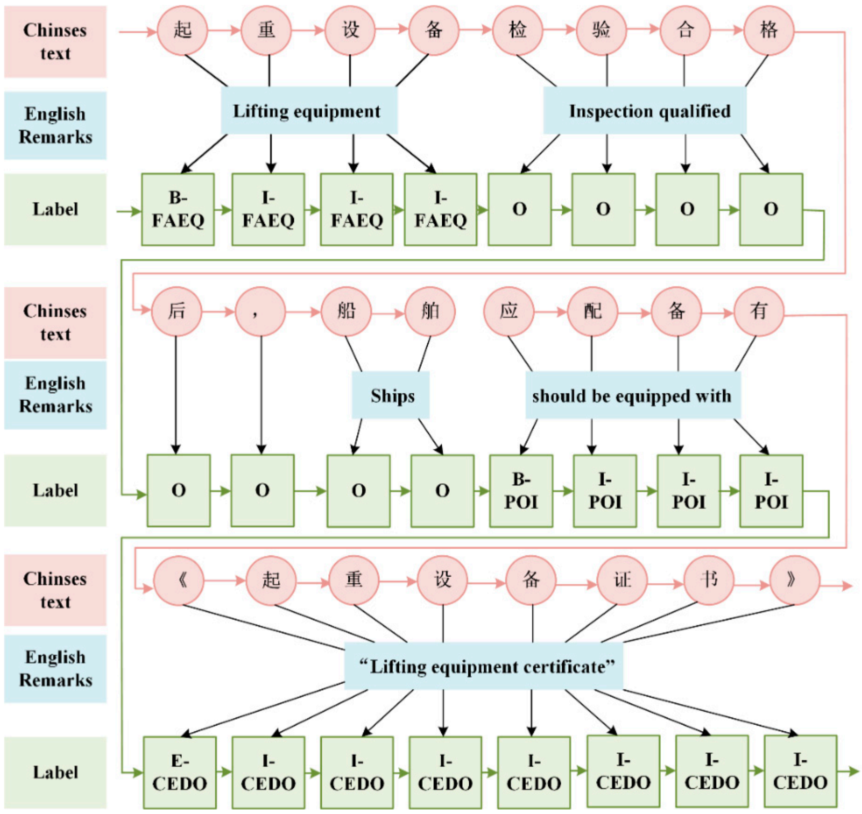


Figure 5. Sequence labeling example for the FSC inspection. The "Chinese text" part refers to the specific content of the obtained text data, which means “after the inspection of lifting equipment is qualified, ships should be equipped with the relevant ‘lifting equipment certificate’”.

4.3.3. Entity Extraction and Validation

In this research, the text content related to the FSC inspection was obtained by a web crawler. Then the corpus was constructed and annotated by the BIO to support the training, testing, and validating of the entity extraction model. The training set, test set, and validation set of the experiment were divided according to the ratio of 8:1:1. The precision rate, recall rate, and F_1 value of the BERT-BiGRU-CRF model for the labels of certificate documents, passenger and cargo transportation, crew manning and duty performance, ship structure, facility and equipment, and inspection requirements are shown in Table 5.

Table 5. Results of various types of FSC inspection entities (%).

FSC Inspection Entities	P	R	F_1
Certificate documents	100.00	73.33	84.62
Passenger and cargo transportation	83.33	90.91	86.96
Crew manning and duty performance	100.00	93.33	96.55
Ship structure	92.86	100.00	96.30
Facility and equipment	85.45	95.92	90.38
Inspection requirements	79.69	87.93	83.61

To verify the effectiveness of the BERT-BiGRU-CRF model in the FSC inspection entity extraction, comparison research was conducted between the BERT-BiGRU-CRF model and three other models: the BiGRU-CRF model, Word2vec-BiGRU-CRF, and BERT-CNN-LSTM model, which are the models of knowledge extraction used in knowledge graphs [29,34,35]. Moreover, the P, R, and F_1 values were used to evaluate the four mentioned models. Figure 6 shows the changes in the P, R, and F_1 values with the number of training epochs under different models. It can be seen that the P, R, and F_1 values of different models increase with the increase in training epochs, and the training results converge when the epoch is 50. The robustness of the model is validated using varying training epochs for different models. The BERT-BiGRU-CRF model used in this paper has always higher P, R, and F_1 values than other models when the epoch increases.

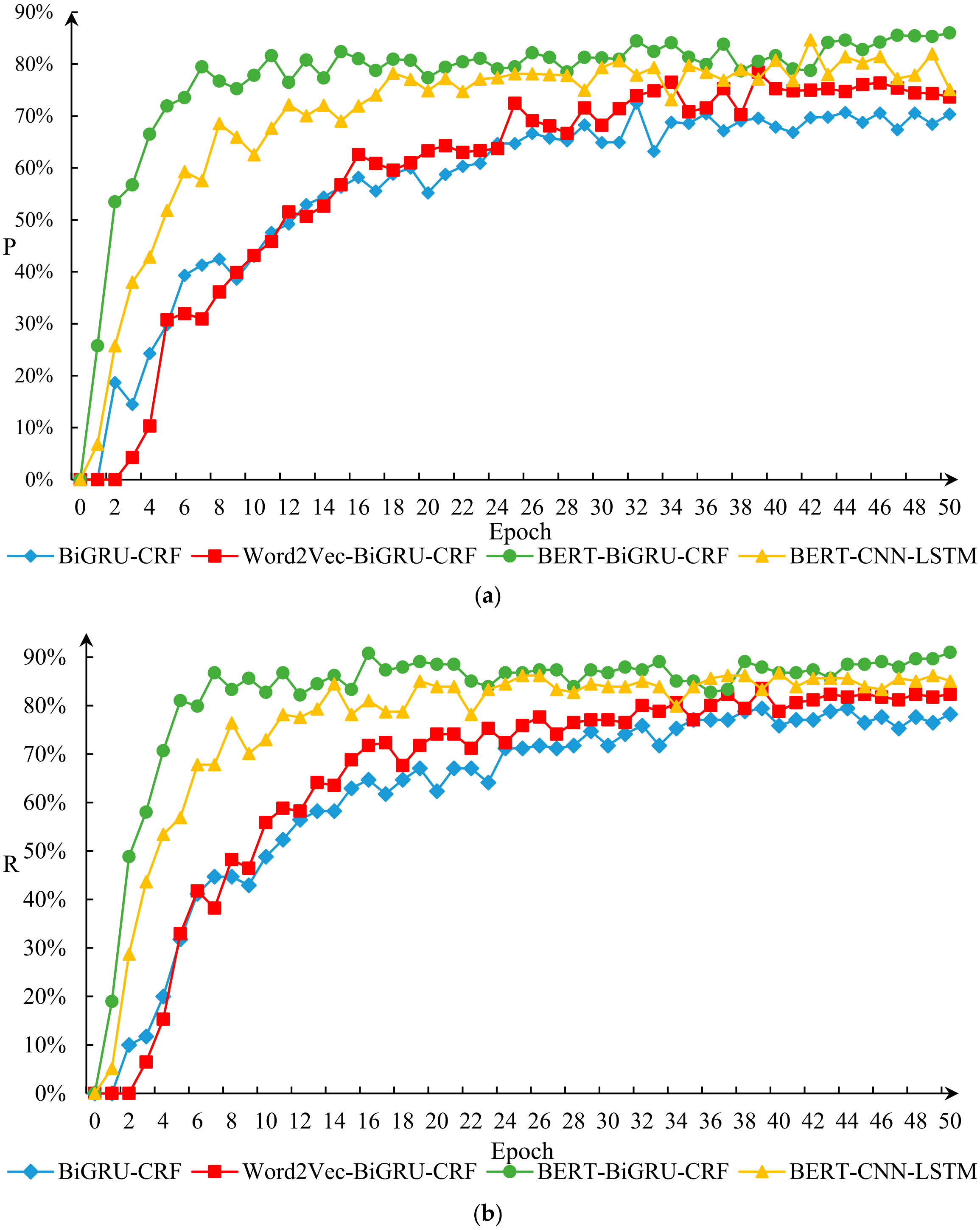
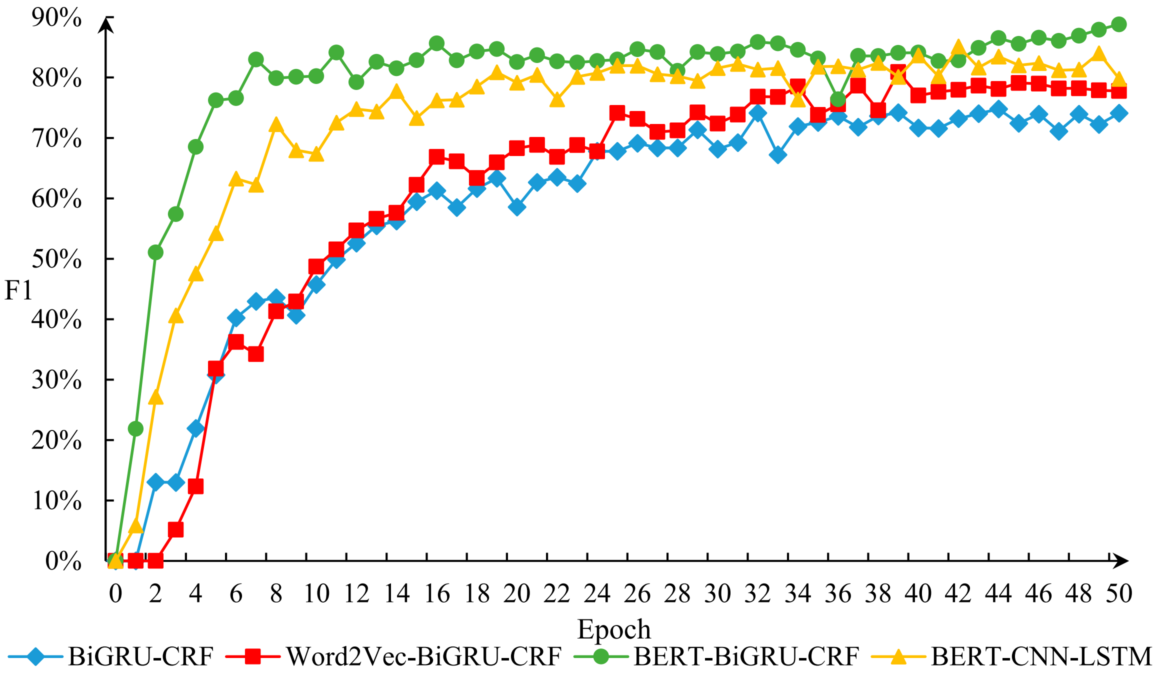


Figure 6. *Cont.*



(**c**)

Figure 6. The P, R, and F_1 values during the training process. (**a**) P values; (**b**) R values; (**c**) F_1 values.

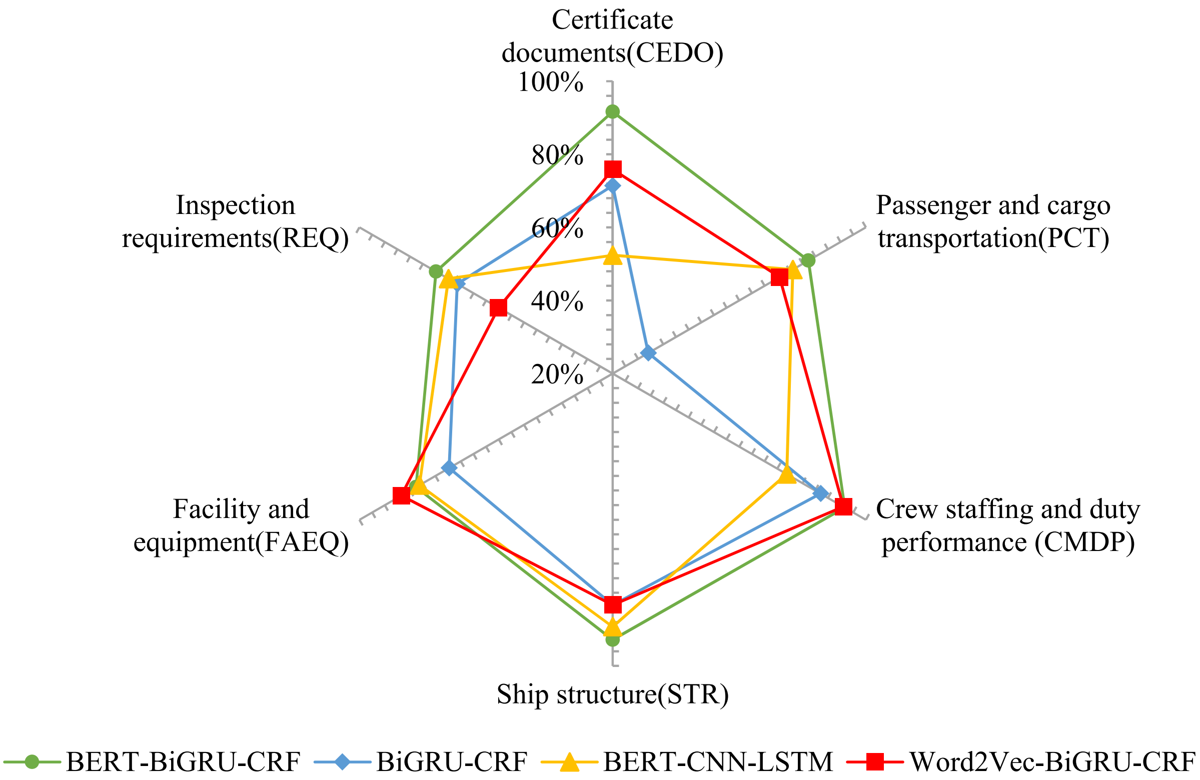
The results of the comparison at epoch 50 are summarized in Table 6. It can be seen that the P, R, and F_1 values of the BERT-BiGRU-CRF model are 86.41%, 91.38%, and 88.83%, respectively, at epoch 50, which are all higher than other models.

Table 6. Results of the entity extraction by different models (%).

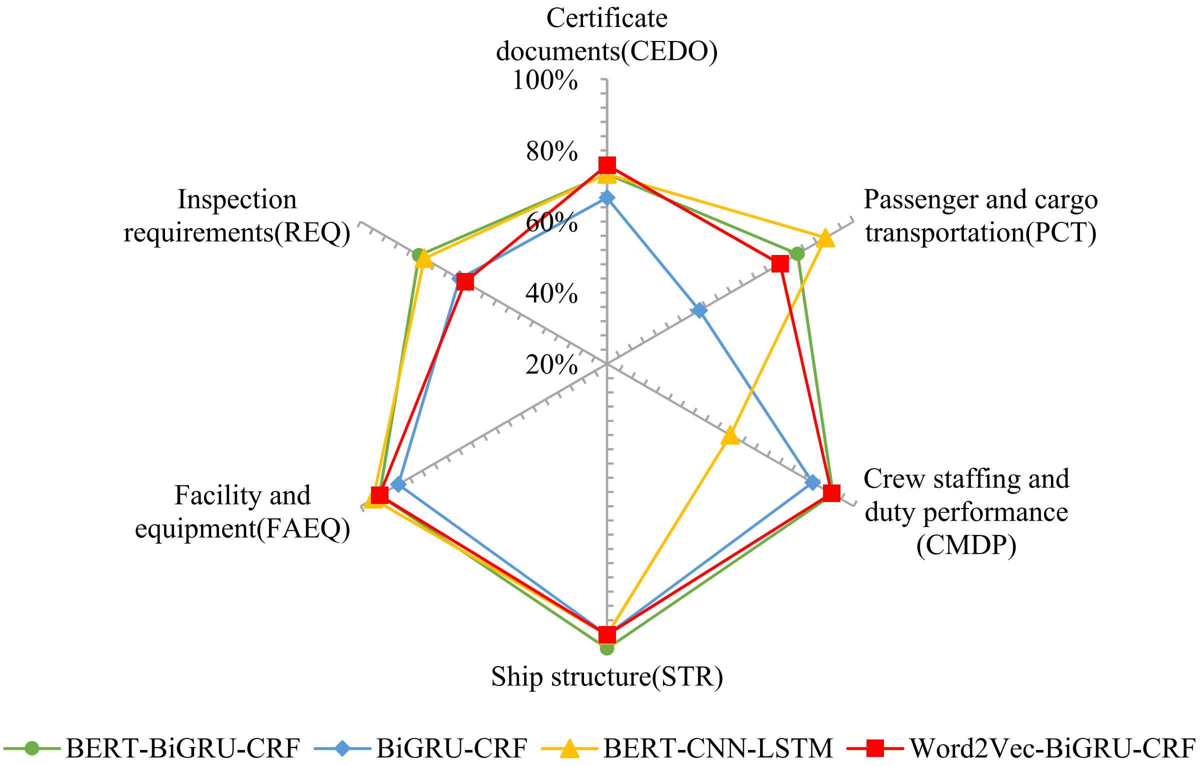
	P	R	F_1
BiGRU-CRF	70.37	78.24	74.09
Word2Vec-BiGRU-CRF	73.68	82.35	77.78
BERT-CNN-LSTM	75.13	85.06	79.78
BERT-BiGRU-CRF	86.41	91.38	88.83

The combination of Table 6 and Figure 6 shows that BERT-BiGRU-CRF has a strong feature extraction ability, and the extracted features are more precise than those of the BERT-CNN-LSTM model. Compared with the Word2Vec-BiGRU-CRF model, the BERT-BiGRU-CRF model has a great improvement in precision, recall rate, and F_1 value. This shows that the BERT pre-trained language model can better represent the semantic information of words because the word vector generated by BERT is context-dependent and can extract sentence features well.

In addition, the P, R, and F_1 values of different models for the labels of certificate documents, passenger and cargo transportation, crew manning and duty performance, ship structure, facility and equipment, and inspection requirements are shown in Figure 7. It can be seen that the P and R values of inspection requirements entities are lower than those of other entities in the BERT-BiGRU-CRF model. This may be because there is a large amount of interference information, such as noun nesting, abbreviations, and ambiguity in inspection requirements entities, which means, without other sufficient contexts, prediction errors can be easily made. Moreover, it can be seen that the P, R, and F_1 values of the BERT-BiGRU-CRF model in the six types of entities are at a high level, which indicates that the identification performance of the BERT-BiGRU-CRF model is higher than that of other models.

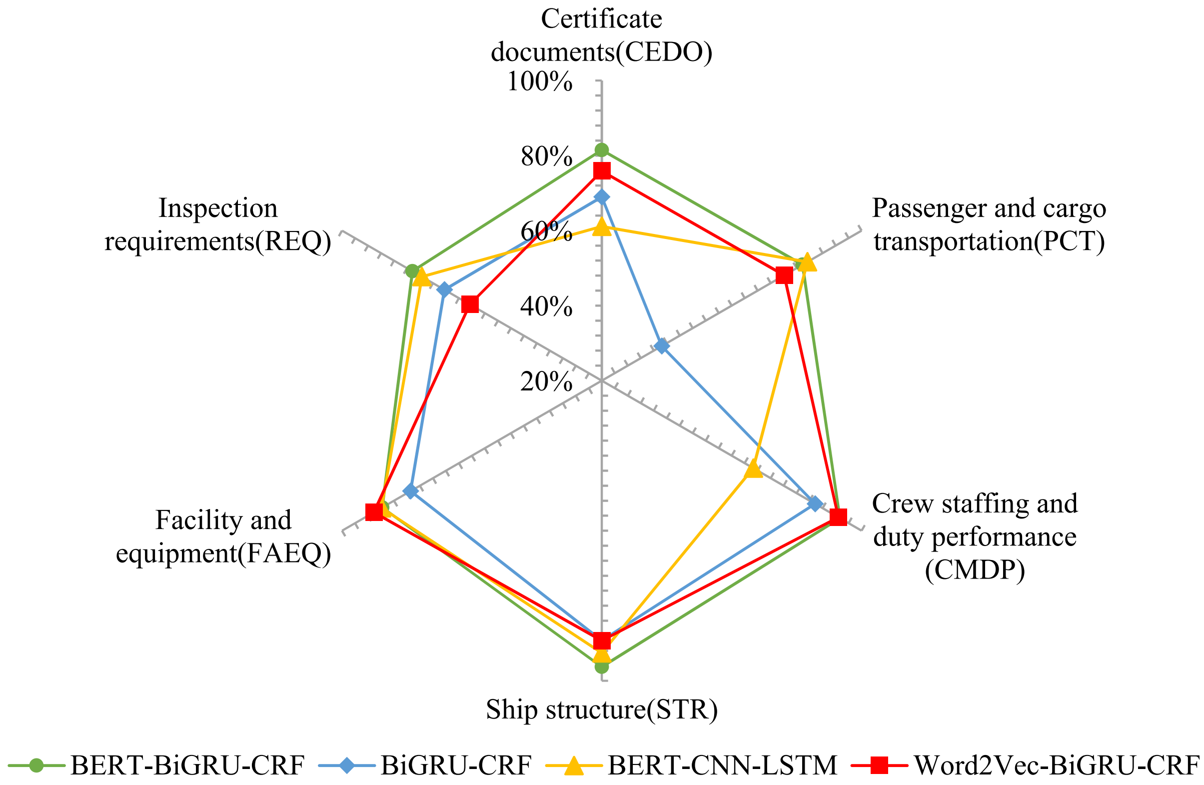


(**a**)



(**b**)

Figure 7. *Cont*.



(**c**)

Figure 7. P, R, and F_1 values of different entities in different models. (**a**) P values; (**b**) R values; (**c**) F_1 values.

4.4. Knowledge Storage and Visualization

In this paper, the Neo4j graph database was chosen for knowledge storage. As mentioned above, the FSC inspection knowledge graph data consist of structured, semi-structured, and unstructured data. Taking the ship FSC inspection data of Dafeng Port in Yancheng, China, from January 2018 to July 2021 as an example, the extracted triple data were imported into Neo4j using py2neo, which is a third-party library of Python. As shown in Figure 8, the circular nodes represent entities and the annotated edges represent the relations between entities in the FSC inspection knowledge graph. Then, the FSC inspection knowledge graph can integrate multi-source heterogeneous data, and utilizes the entity concepts and relations to develop the potential value of the FSC inspection system.

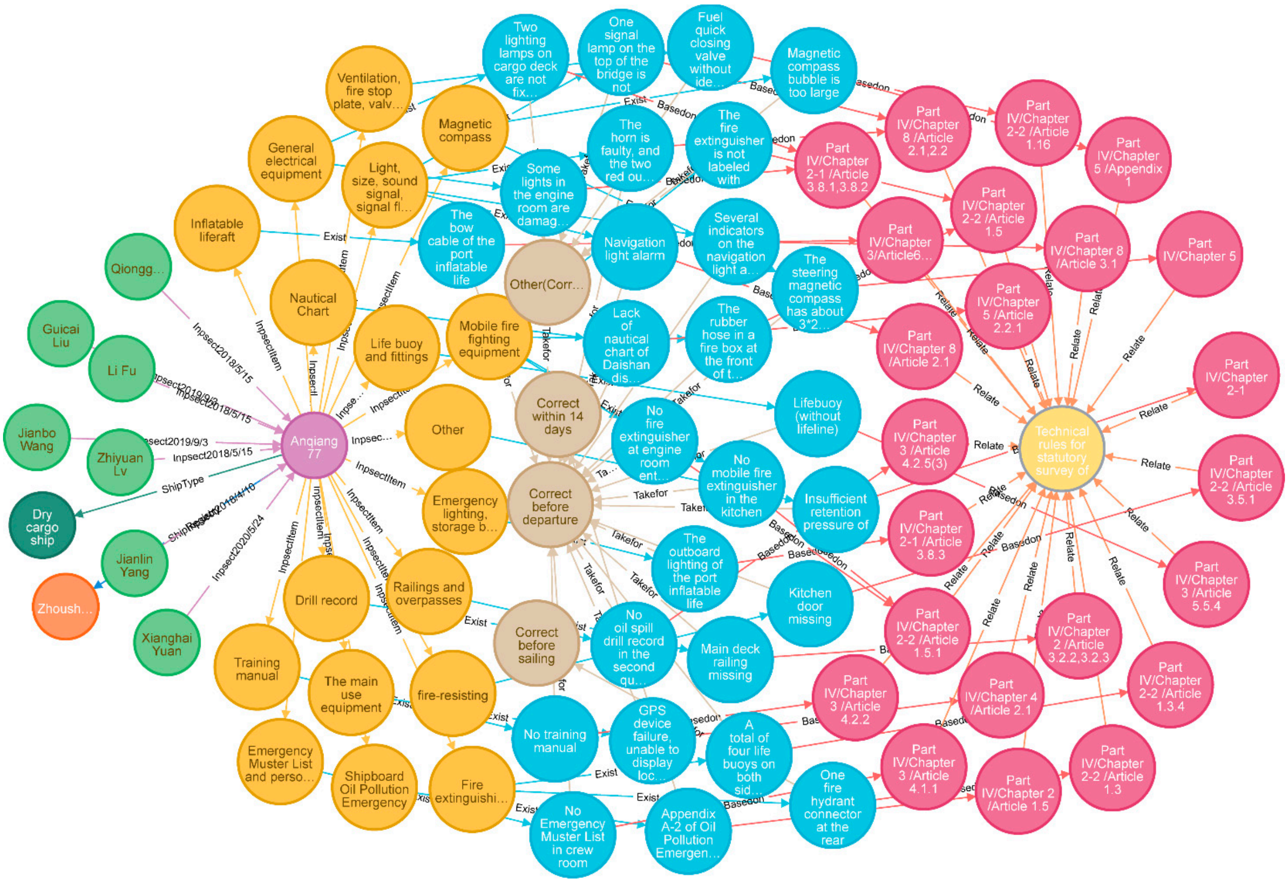


Figure 8. Ship FSC inspection knowledge graph (part).

5. Discussion

As a result of the rapid development of the world shipping industry and the continuous improvement in human awareness of marine environmental protection, people have paid increasing attention to the seaworthiness and safety of ships engaged in maritime transport [4,36,37]. Ship safety inspections are increasingly important for navigation safety. The flag state is the main body of ship safety administration and is responsible for ship safety management [38,39]. Therefore, the FSC inspection is a powerful and effective means to ensure navigation safety on the water and to prevent the pollution of the marine environment. Today, the FSC inspection heavily relies on the expertise and historical experience of maritime officers. This method of ship inspection based on experience cognition places high requirements on the ability of maritime officers and also introduces subjectivity into the inspection. In addition, the FSC inspection involves many laws and regulations, so maritime officers need to search for relevant information when inspecting ship deficiencies and making decisions accordingly in most inspections. These manual operations are time-consuming and affect inspection efficiency. Moreover, due to the disadvantages of data redundancy and low query efficiency in the traditional ship database [40], maritime officers need to query multiple databases before the FSC inspection to master the complete information of the inspected ship. Therefore, it is necessary to use advanced and intelligent technology to improve inspection efficiency and facilitate the maritime administration authorities to better manage ships.

Many studies on ship safety inspections have been conducted in the past decade because ship safety inspections are an essential part of ship navigation safety. Most of the research has focused on the major deficiencies that affect ship navigation safety [41,42]. These research methods are mainly statistical methods and machine learning methods. For example, association rules are used to study the relation between deficiencies and ship parameters, and the influence of different deficiency types on ship retention [41,43–45]. In addition, principal component analysis, Bayesian models, and grey correlation theory are normally used to analyze the influence of ship deficiencies and technical parameters on the retention results [46–49]. However, the above studies cannot be related to all aspects of ship inspection information. Based on this, it is of great significance to apply knowledge graph technology to ship FSC inspection. The knowledge graph technology can well associate different data resources and structures to realize the intelligent management of inspection data. At the same time, the query technology of Neo4j can be used to input keywords for associated retrieval according to the information to be used in the actual inspection, to realize the rapid query of information and improve the inspection efficiency [50].

The FSC inspection knowledge graph can be used to improve the efficiency and accuracy of ship inspections for maritime authorities. In the real FSC inspection process, maritime officers often need to query multiple databases to fully understand the relevant information about ships and inspections [40]. In the FSC inspection knowledge graph, maritime authorities can use a semantic search using the CYPHER query language of Neo4j to effectively obtain the relevant knowledge required for ship FSC inspection [24]. As shown in Figure 9, ship-related information can be obtained by retrieving a specific ship as a keyword and serves as an input into the FSC inspection. In addition, after adding the historical inspection activities and relevant elements of the inspection, the "ship" entity can be obtained by matching to obtain the historical inspection data of the ship. The historical inspection information includes deficiencies, inspectors, inspection locations, and the regulatory basis for each inspection deficiency [7], as shown in Figure 10. These are critical pieces of information, which may guide the next FSC inspection. Moreover, when maritime officers have doubts about the relevant content of laws and regulations, the obtained information can provide a timely legal basis for their on-site law enforcement to improve inspection efficiency and accuracy.

Figure 9. Ship association information retrieval for the ship "Anqiang77".

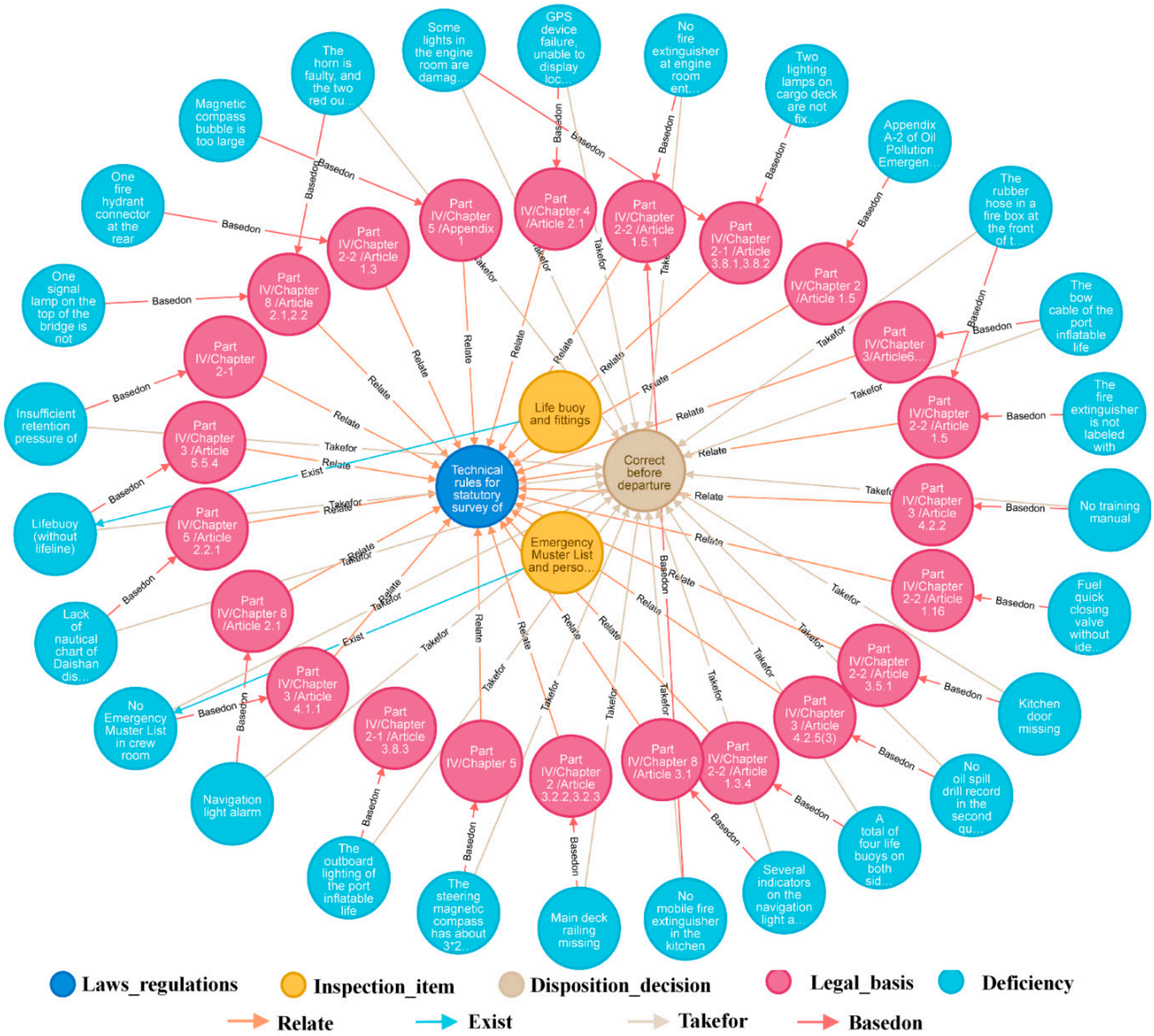


Figure 10. Ship inspection information retrieval.

The FSC inspection knowledge graph can well correlate with trivial FSC inspection knowledge to improve the efficiency of FSC inspection. However, this study has certain limitations. Due to limited data sources, this paper only took the ship history inspection of Dafeng Port in Yancheng, China from January 2018 to July 2021 as an example to construct the knowledge graph, and not all historical ship inspection data in China were included. Therefore, more data on the FSC inspection will be collected, and then semantic analysis and knowledge inference will be added in subsequent studies to study its inference function.

6. Conclusions

Knowledge graph technology is an emerging and important technical means of knowledge visualization and potential association combing, which provides a new research idea for knowledge management and ship intelligent supervision in the FSC inspection field. The main contribution of this research is to apply the knowledge graph in data fusion of multi-source and complex information in the FSC inspection. The FSC inspection knowledge graph was established to improve the efficiency of the FSC inspection. It can be seen that the knowledge graph can be used to show the potential relationship between the FSC inspection knowledge and the hierarchy of industry knowledge. Compared with traditional knowledge management technology, the FSC inspection knowledge graph can be used more intuitively to improve the efficiency and knowledge retrieval quality of the FSC inspection.

In future research, the application of the FSC inspection knowledge graph will be further studied based on enriching data sources. Based on the constructed FSC inspection knowledge graph and enriching data sources, semantic analysis and knowledge reasoning will be added to deeply mine the implicit relations between ship attributes, ship deficiencies, and detention decisions, and to explore the influencing factors of FSC examination results.

Author Contributions: Conceptualization, D.Z. and C.L.; methodology, Q.C. and Y.S.; validation, L.Z.; formal analysis, L.Z.; investigation, C.L.; data curation, X.Z.; writing—original draft, L.G.; writing—review and editing, Q.C. and Y.S.; visualization, D.Z. and X.Z.; funding acquisition, L.G. All authors have read and agreed to the published version of the manuscript.

Funding: This research was funded by the National Natural Science Foundation of China (NSFC) grant number 52271369.

Institutional Review Board Statement: Not applicable.

Informed Consent Statement: Not applicable.

Data Availability Statement: Not applicable.

Acknowledgments: The authors would like to thank the sponsor from the National Natural Science Foundation of China (NSFC) (No. 52271369).

Conflicts of Interest: The authors declare no conflict of interest.

References

1. Ojala, J. Maritime trade and merchant shipping: The shipping/trade-ratio from the 1870s until today. *SSRN Electron. J.* **2016**, *29*, 838–854. [CrossRef]
2. Zhang, G.; Thai, V.V. Expert elicitation and Bayesian Network modeling for shipping accidents: A literature review. *Saf. Sci.* **2016**, *87*, 53–62. [CrossRef]
3. Chen, Q.; Lau, Y.Y.; Ge, Y.E.; Dulebenets, M.A.; Kawasaki, T.; Ng, A.K.Y. Interactions between Arctic passenger ship activities and emissions. *Transp. Res. Part D Transp. Environ.* **2021**, *97*, 102925. [CrossRef]
4. Yu, Y.; Chen, L.M.; Shu, Y.Q.; Zhu, W.Y. Evaluation model and management strategy for reducing pollution caused by ship collision in coastal waters. *Ocean Coast. Manag.* **2021**, *203*, 105446. [CrossRef]
5. Shu, Y.Q.; Wang, X.Y.; Huang, Z.Q.; Song, L.; Fei, Z.Q.; Gan, L.X.; Xu, Y.M.; Yin, J.C. Estimating spatiotemporal distribution of wastewater generated by ships in coastal areas. *Ocean Coast. Manag.* **2022**, *222*, 106133. [CrossRef]
6. Chen, J.H.; Di, Z.J.; Shi, J.; Shu, Y.Q.; Wan, Z.; Song, L.; Zhang, W.P. Marine oil spill pollution causes and governance: A case study of Sanchi tanker collision and explosion. *J. Clean. Prod.* **2020**, *273*, 122978. [CrossRef]
7. He, J.; Hao, Y.; Wang, X.Q. An Interpretable Aid Decision-Making Model for Flag State Control Ship Detention Based on SMOTE and XGBoost. *J. Mar. Sci. Eng.* **2021**, *9*, 156. [CrossRef]
8. Abu-Salih, B. Domain-specific knowledge graphs: A survey. *J. Netw. Comput. Appl.* **2021**, *185*, 103076. [CrossRef]
9. Tan, Z.; Zhao, X.; Wang, W.; Assoc Comp, M. Representation Learning of Large-Scale Knowledge Graphs via Entity Feature Combinations. In Proceedings of the ACM Conference on Information and Knowledge Management (CIKM), Singapore, 6–10 November 2017; pp. 1777–1786.
10. Nickel, M.; Murphy, K.; Tresp, V.; Gabrilovich, E. A Review of Relational Machine Learning for Knowledge Graphs. *Proc. Ieee* **2016**, *104*, 11–33. [CrossRef]
11. Heij, C.; Bijwaard, G.E.; Knapp, S. Ship inspection strategies: Effects on maritime safety and environmental protection. *Transp. Res. Part D Transp. Environ.* **2011**, *16*, 42–48. [CrossRef]
12. Bolat, F.; Alpaslan, S. Cumulative Analysis of Port State Control Based on Paris MoU Inspections. *Trans. Marit. Sci.* **2021**, *10*, 224–246. [CrossRef]
13. Tsou, M.C. Big data analysis of port state control ship detention database. *J. Mar. Eng. Technol.* **2019**, *18*, 113–121. [CrossRef]
14. Fu, J.J.; Chen, X.Q.; Wu, S.B.; Shi, C.J.; Zhao, J.S.; Xian, J.F. Ship Detention Situation Prediction via Optimized Analytic Hierarchy Process and Naive Bayes Model. *Math. Probl. Eng.* **2020**, *2020*, 8147310. [CrossRef]
15. Wu, S.B.; Chen, X.Q.; Shi, C.J.; Fu, J.J.; Yan, Y.; Wang, S.Z. Ship detention prediction via feature selection scheme and support vector machine (SVM). *Marit. Policy Manag.* **2022**, *49*, 140–153. [CrossRef]
16. Liu, J.T.; Schmid, F.; Li, K.P.; Zheng, W. A knowledge graph-based approach for exploring railway operational accidents. *Reliab. Eng. Syst. Saf.* **2021**, *207*, 107352. [CrossRef]
17. Tan, J.Y.; Qiu, Q.Q.; Guo, W.W.; Li, T.S. Research on the Construction of a Knowledge Graph and Knowledge Reasoning Model in the Field of Urban Traffic. *Sustainability* **2021**, *13*, 3191. [CrossRef]
18. Chen, T.; Zhang, Y.; Qian, X.; Li, J. A knowledge graph-based method for epidemic contact tracing in public transportation. *Transp. Res. Part C Emerg. Technol.* **2022**, *137*, 103587. [CrossRef]

19. Zhang, Q.; Wen, Y.Q.; Zhou, C.H.; Long, H.; Han, D.; Zhang, F.; Xiao, C.S. Construction of Knowledge Graphs for Maritime Dangerous Goods. *Sustainability* **2019**, *11*, 2849. [CrossRef]
20. Liu, S.K.; Wang, F.X. Knowledge Graph of Maritime Collision Avoidance Rules in Chinese. In Proceedings of the 11th International Conference on Intelligent Human-Machine Systems and Cybernetics (IHMSC), Hangzhou, China, 24–25 August 2019; pp. 169–172.
21. Dong, J.; Jing, X.; Lu, X.; Liu, J.; Li, H.; Cao, X.; Du, C.; Li, J.; Li, L. Process knowledge graph modeling techniques and application methods for ship heterogeneous models. *Sci. Rep.* **2022**, *12*, 2911. [CrossRef]
22. Zhou, X.G.; Gong, R.B.; Shi, F.G.; Wang, Z.F. PetroKG: Construction and Application of Knowledge Graph in Upstream Area of PetroChina. *J. Comput. Sci. Technol.* **2020**, *35*, 368–378. [CrossRef]
23. Ji, S.X.; Pan, S.R.; Cambria, E.; Marttinen, P.; Yu, P.S. A Survey on Knowledge Graphs: Representation, Acquisition, and Applications. *IEEE Trans. Neural Netw. Learn. Syst.* **2022**, *33*, 494–514. [CrossRef] [PubMed]
24. Liu, P.C.; Huang, Y.L.; Wang, P.; Zhao, Q.F.; Nie, J.; Tang, Y.Y.; Sun, L.; Wang, H.L.; Wu, X.L.; Li, W.B. Construction of typhoon disaster knowledge graph based on graph database Neo4j. In Proceedings of the 32nd Chinese Control And Decision Conference (CCDC), Hefei, China, 22–24 August 2020; pp. 3612–3616.
25. Rubin, D.L.; Noy, N.F.; Musen, M.A. Protege: A tool for managing and using terminology in radiology applications. *J. Digit. Imaging* **2007**, *20*, 34–46. [CrossRef] [PubMed]
26. Kamel, M.N.; Lee, A.Y.; Powers, E.C. A methodology for developing ontologies using the Ontology Web Language (OWL). In Proceedings of the 9th International Conference on Enterprise Information Systems (ICEIS 2007), Funchal, Portugal, 12–16 June 2007; pp. 261–268.
27. Tenney, I.; Das, D.; Pavlick, E. BERT Rediscovers the Classical NLP Pipeline. In Proceedings of the 57th Annual Meeting of the Association-for-Computational-Linguistics (ACL), Florence, Italy, 28 July–2 August 2019; pp. 4593–4601.
28. Cho, K.; Merrienboer, B.V.; Gulcehre, C.; Ba Hdanau, D.; Bougares, F.; Schwenk, H.; Bengio, Y. Learning Phrase Representations using RNN Encoder-Decoder for Statistical Machine Translation. *arXiv* **2014**. [CrossRef]
29. Qin, Q.L.; Zhao, S.; Liu, C.M. A BERT-BiGRU-CRF Model for Entity Recognition of Chinese Electronic Medical Records. *Complexity* **2021**, *2021*, 6631837. [CrossRef]
30. Sutton, C.; McCallum, A.; Rohanimanesh, K. Dynamic conditional random fields: Factorized probabilistic models for labeling and segmenting sequence data. *J. Mach. Learn. Res.* **2007**, *8*, 693–723.
31. Sherstinsky, A. Fundamentals of Recurrent Neural Network (RNN) and Long Short-Term Memory (LSTM) network. *Phys. D Nonlinear Phenom.* **2020**, *404*, 132306. [CrossRef]
32. Li, F.G.; Zhang, B.K.; Gao, D. Chinese Named Entity Recognition for Hazard And Operability Analysis Text. In Proceedings of the 32nd Chinese Control And Decision Conference (CCDC), Hefei, China, 22–24 August 2020; pp. 374–378.
33. Nadeau, D.; Sekine, S. A survey of named entity recognition and classification. *Lingvisticae Investig.* **2007**, *30*, 3–26. [CrossRef]
34. Ganguly, D.; Roy, D.; Mitra, M.; Jones, G.J.F. A Word Embedding based Generalized Language Model for Information Retrieval. In Proceedings of the 38th Annual International ACM SIGIR Conference on Research and Development in Information Retrieval (SIGIR), Santiago, Chile, 9–13 August 2015; pp. 795–798.
35. Cho, M.; Ha, J.; Park, C.; Park, S. Combinatorial feature embedding based on CNN and LSTM for biomedical named entity recognition. *J. Biomed. Inform.* **2020**, *103*, 103381. [CrossRef]
36. Liu, K.Z.; Yu, Q.; Yuan, Z.T.; Yang, Z.S.; Shu, Y.Q. A systematic analysis for maritime accidents causation in Chinese coastal waters using machine learning approaches. *Ocean Coast. Manag.* **2021**, *213*, 105859. [CrossRef]
37. Bye, R.J.; Holmen, I.M.; Størkersen, K.V. Safety in marine and maritime operations: Uniting systems and practice. *Saf. Sci.* **2021**, *139*, 105249. [CrossRef]
38. Hamad, H.B. The Roles of Flag States in Maritime Security Governance: A Case Study of the East African Community. *Soc. Sci. Electron. Publ.* **2017**, *6*, 95–102.
39. Zhang, S.; Chen, J.; Wan, Z.; Yu, M.; Shu, Y.; Tan, Z.; Liu, J. Challenges and countermeasures for international ship waste management: IMO, China, United States, and EU. *Ocean Coast. Manag.* **2021**, *213*, 105836. [CrossRef]
40. Xu, S.Y.; Hu, H. Development of a maritime safety management database using relational database approach. *Int. J. Shipp. Transp. Logist.* **2019**, *11*, 334–353. [CrossRef]
41. Wang, Y.H.; Zhang, F.; Yang, Z.S.; Yang, Z.L. Incorporation of deficiency data into the analysis of the dependency and interdependency among the risk factors influencing port state control inspection. *Reliab. Eng. Syst. Saf.* **2021**, *206*, 107277. [CrossRef]
42. Yan, R.; Wang, S.; Cao, J.; Sun, D. Shipping Domain Knowledge Informed Prediction and Optimization in Port State Control. *Transp. Res. Part B Methodol.* **2021**, *149*, 52–78. [CrossRef]
43. Osman, M.T.; Yuli, C.; Li, T.; Senin, S.F. Association rule mining for identification of port state control patterns in Malaysian ports. *Marit. Policy Manag.* **2021**, *48*, 1082–1095. [CrossRef]
44. Kara, E.G.E.; Oksas, O.; Kara, G. The similarity analysis of Port State Control regimes based on the performance of flag states. *Proc. Inst. Mech. Eng. Part M J. Eng. Marit. Environ.* **2020**, *234*, 558–572. [CrossRef]
45. Fan, L.X.; Luo, M.F.; Yin, J.B. Flag choice and Port State Control inspections—Empirical evidence using a simultaneous model. *Transp. Policy* **2014**, *35*, 350–357. [CrossRef]
46. Demirci, S.M.E.; Cicek, K.; Ozturk, U. A Fuzzy Rule-Based Ship Risk Profile Prediction Model for Port State Control Inspections. In Proceedings of the INFUS 2021 Conference, Istanbul, Turkey, 24–26 August 2021; pp. 498–505.

47. Hänninen, M.; Kujala, P. Bayesian network modeling of Port State Control inspection findings and ship accident involvement. *Expert Syst. Appl.* **2014**, *41*, 1632–1646. [CrossRef]
48. Zhang, L.F.; Gang, L.H.; Liu, Z.J. Analyzing Inspection Results of Port State Control by Using PCA. *Appl. Mech. Mater.* **2014**, *686*, 730–735. [CrossRef]
49. Chen, J.H.; Zhang, S.H.; Xu, L.; Wan, Z.; Fei, Y.J.; Zheng, T.X. Identification of key factors of ship detention under Port State Control. *Mar. Policy* **2019**, *102*, 21–27. [CrossRef]
50. Yoon, B.-H.; Kim, S.-K.; Kim, S.-Y. Use of Graph Database for the Integration of Heterogeneous Biological Data. *Genom. Inform.* **2017**, *15*, 19–27. [CrossRef] [PubMed]