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A systematic knowledge graph-based smart management method for operations: A case study of standardized management

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A R T I C L E I N F O

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A B S T R A C T

Standardized routine operation management (SROM) has been widely accepted and applied by kinds of enterprises and played a key supporting role. With full use of the emerging knowledge-based smart management technology, SROM will further increase comprehensive efficiency and save human resources greatly at the same time, especially for small and medium enterprises (SMEs). Hence, we propose a systematic knowledge-based smart management method to transfer SROM activities from human operations to automatic response by means of knowledge explicitation, organization, sharing and reusing, which can be further achieved by employing knowledge graph. We took a typical SROM instance, ISO 9000 implementation management, as an example to validate the transformation from human activities to knowledge graph-based automatic operation. We firstly analyzed characteristics of domain knowledge and constructed an ontology model according to the knowledge stability. Secondly, a hybrid knowledge graph construction and dynamic updating framework together with related algorithms were designed by deliberately integrating semantic similarity calculation and natural language processing. Thirdly, we developed a question-answering mechanism and reasoning system based on the ISO 9000 implementation knowledge graph to support automatic decision and feedback for ISO 9000 routine operation management including knowledge learning and processes auditing. Finally, the practicability and effectiveness of SROM knowledge graph has been validated in a SME in China, realizing the application of question-answering, job responsibility recommendation, conflict detection, semantic detection, multidimensional statistical analysis. The proposed method can also be generalized to support auxiliary optimization decision, vertical risk control, operation mode analysis, optimization model improvement experience and so on.

1. Introduction

With the advent of intelligent manufacturing, small and medium enterprises (SMEs) are facing unprecedented opportunities and challenges [1]. On the one hand, the introduction of advanced technology and equipment can greatly improve production efficiency, reduce costs, and expand business scale [2]. On the other hand, with the increase of knowledge involved in enterprise operations, standardized routine operation management (SROM) becomes more complex and challenging [3].

As a part of enterprise operations management, SROM is a management approach that emphasizes the standardization of routine tasks and operations within an organization [4]. Almost all SMEs want to improve SROM proficiency, however, most have been

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constrained with quite finite and valuable human resources, as well as the lacking of accumulation of related knowledge [5]. The above circumstances motivate us to study knowledge organization and management, and then propose the knowledge-based smart management for SROM of SMEs.

The integration of knowledge management (KM) and SROM has become increasingly important due to the rapid pace of technological advancements and globalization [6]. KM refers to the processes and strategies that are used by organizations to identify, capture, store, share, and utilize knowledge and information. One of the key benefits of knowledge management is its ability to provide necessary information to support decision-making, problem-solving, and business process improvement activities in SROM. However, the importance of KM is often weak or lacking, which is not conducive to the development of enterprises in intelligent manufacturing, especially for SMEs [7]. If enterprises do not accumulate knowledge and form a unique competitive advantage, it is easy to be eliminated by the market [8]. SMEs' KM is still limited [9]. Hence, we take KM as the starting point and summarize three characteristics of SROM related knowledge as follows.

(1) **Knowledge identification.** In general, knowledge can be categorized as explicit knowledge and tacit knowledge [10]. Explicit knowledge can be articulated clearly, communicated openly, and set down in documents transmitted from one person to another via formal languages or codes. By contrast, tacit knowledge is a kind of knowledge that is difficult to transfer to another person through writing it down or verbalizing it [11]. Current knowledge management systems tend to focus on information organization, and make it difficult to analyze information behavior [12]. During SROM, most management decisions rely on managers' experiences that are difficult to be explained in plain language. Most explicit knowledge in SROM knowledge sources (books, online documents) exists in the form of unstructured knowledge. Whereas tacit knowledge exists in every aspect of enterprise's daily activities and is difficult to be captured [13]. Expressing tacit knowledge in the form of a knowledge graph (KG) has become a research focus [14,15].
(2) **Knowledge retention.** SROM is continuously evolving and updating, as knowledge continues to expand [16]. SMEs often operate with limited budgets and manpower, which hinders their ability to invest on comprehensive training programs or allocate dedicated resources for knowledge acquisition and dissemination. Consequently, there may be a reliance on informal methods of knowledge transfer, such as on-the-job training or ad hoc information sharing among colleagues [17]. Although the above methods can be valuable, there is not a systematic approach to capture, organize, and disseminate knowledge throughout the organization.
(3) **Knowledge utilization.** SMEs may refer to or even copy the existing experience of large companies in the implementation of knowledge management system, which will lead to poor KM effect and low knowledge utilization [7]. Moreover, SME-related KM tools do not address KM in a holistic managerial way [18]. The aforementioned challenges can be attributed to the inadequacy of a robust knowledge management system within SMEs [19].

The above characteristics call for effective knowledge organization and management tools, which motivates us to introduce KG [20], a semantic network with a directed graph [21] composed of concepts, entities and relationships. Entities can be real-world objects and abstractions. Relationships containing types and attributes with well-defined meanings represent relationships between

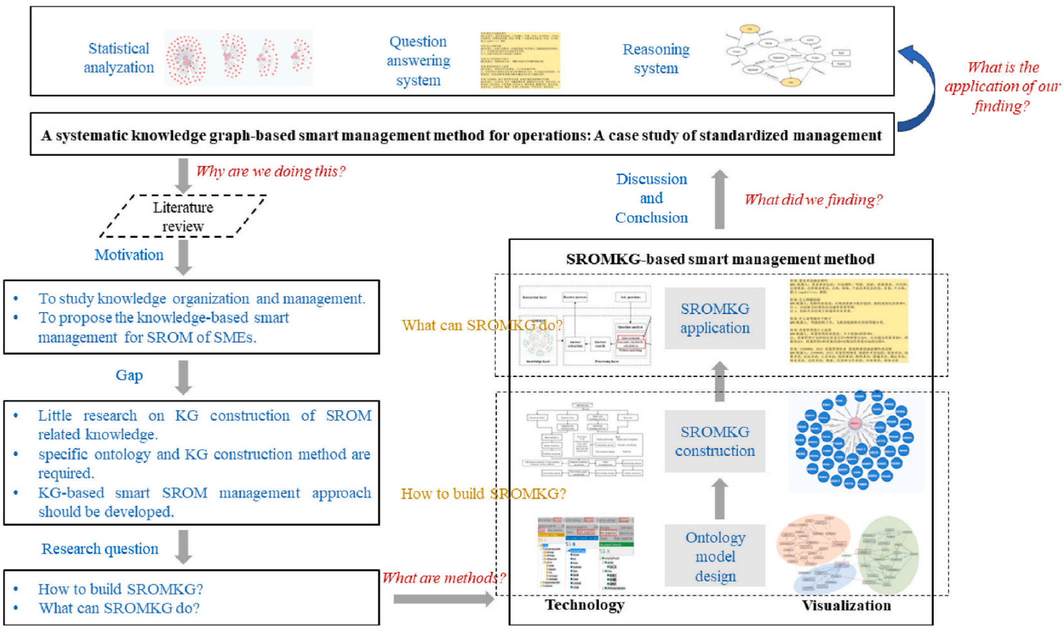

Fig. 1. Schema of KG-based smart management of SROM.

entities and semantic descriptions of entities [13].

KGs are widely used in question-answering, personalized recommendation, decision-making [22] and other fields. In question-answering, KGs have been applied to software design rules management [23], building energy management [24] and chemical management [25]. Personalized recommendation functions of KGs can be used to recommend drugs for patients [26], design surgical plans for doctors [27]. Wang uses a KG-based inference system to analyze interactive information between users and commodities [28]. In prediction, KGs are mainly used for student performance [29].

The wide application and good performance of KGs inspire us to design a SROM related KG (SROMKG) for enterprises to implement SROM better by means of the following four advantages. Firstly, people are subjective and may make subjective emotional judgments, whereas KGs can be used to assist people's decision-making with objective answers and/or recommendations. Secondly, employees who complete SROM often have other jobs in the company. They are professional in their positions, but often have little knowledge in the field of SROM. KGs can reduce learning costs and save manpower. Finally, KGs can act as an intelligent and structural enterprise information pool during the management process.

Currently, there is little research on KG construction of SROM related knowledge. Hence, specific ontology and KG construction method are required to be developed because of the three characteristics of SROM related knowledge, together with KG-based smart SROM management approach.

All the above motivates us to study the following questions: (1) From what dimension should the knowledge in the field of SROM be organized? (2) What method should be used to extract the knowledge? (3) How to build SROMKG? (4) What kind of management decisions can SROMKG help enterprises to make? (5) What application effects can be achieved?

The overall schema to support us explore KG-based smart management of SROM is as shown in Fig. 1, and our main contributions are four-folded.

(1) We design an ontology of SROM related knowledge, propose a new framework to capture and reuse SROM related knowledge by means of ontology-based KG construction.
(2) We propose a semi-automatic SROMKG construction method combining rule extraction, dependency syntax analysis and manual sorting, as well a knowledge updating method is designed by combining edit distance similarity and position weight in order to solve problems of low structure, many long and difficult sentences, complex relationships and difficult understanding in SROM domain.
(3) We integrate Aho-Corasick algorithm, similarity calculation and pattern matching to build SROMKG-based Question Answering (SROMKG-QA) prototype system by combining characteristics of multiple and heterogeneous data sources in SROM domain. Entity matching based on attribute and distance is integrated to realize knowledge reasoning.
(4) We validate audit result portrait and multi-dimensional analysis functions by means of visualizing SROMKG with real data of a Chinese SME.

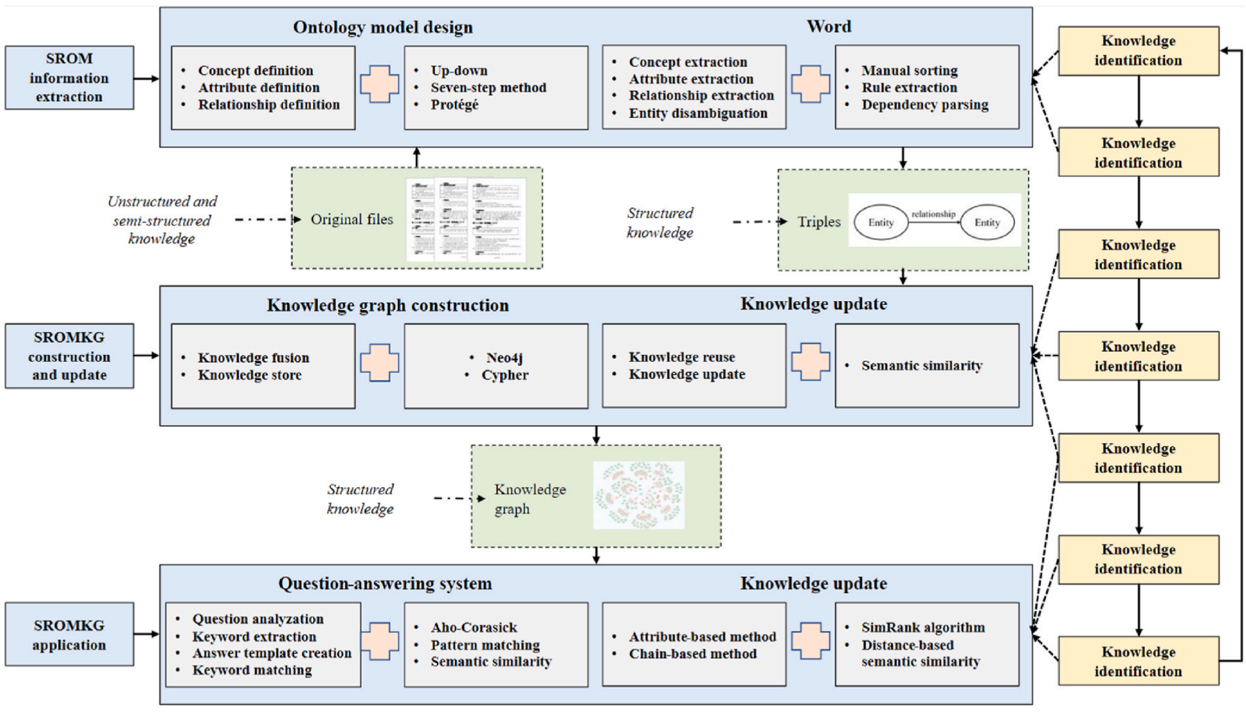

Fig. 2. Three-stage framework of SROMKG.

The remainder of the paper is organized as follows. In Section 2, we present the construction schema of SROMKG in detail. Section 3 shows three application scenarios via a practical case. In Section 4, we discuss about results, implications, limitations and future research. Finally, Section 5 concludes this paper.

2. Model

A novel model for a smart SROM knowledge management system is proposed. Fig. 2 illustrates the overall structure of the method. It encompasses and integrates a multitude of techniques in a coherent framework including three stages of SROM information extraction, SROMKG construction and SROMKG application. At stage 1, SROM knowledge is organized through a newly designed domain ontology. At Stage 2, knowledge is employed to store and maintain knowledge. At Stage 3, knowledge can be reused and generated new knowledge, finally returning to stage 1. The interaction of these three stages enables the efficient generation of SROMKG.

SROM-related documents, which contain unstructured and semi-structured data, are collected as data sources and input to SROM information extraction, finally, structured knowledge triples are extracted and input to SROMKG construction and maintenance.

Thus, stage 1 (SROM information extraction) is to provide underpinning data structure to unify heterogeneous information from different source. The collected SROM knowledge can be finally converted to triples though ontology model design and knowledge extraction. After converting unstructured knowledge into structured knowledge, the purpose of stage 2 is to store the extracted knowledge and update it. With the constructed SROMKG, stage 3 aims to reuse the SROM knowledge, ensuring the sustainable development of enterprise operational management. Normally, SROMKG application is a comprehensive process including knowledge retrieve, reuse, question-answering, and reasoning. Finally, generating new knowledge returns to stage 1.

2.1. SROM information extraction

Quality management system (QMS), as a set of standards to regulate the daily activities of enterprises, is one of the basic management systems of SROM. We take the QMS domain as an example to study. For example, ISO 9000 implementation heavily depends on humans' skills and experience since it is often a recursive optimization process. QMS is often in charge of the middle managers [30]. Managers play a pivotal role in their respective departments but have little time and energy for QMS. Particularly, due to the misalignment of information among professional staff, there may be obstacles to their cooperation. In addition, to successfully internalize the ISO 9000 standards within an organization, all employees should have a clear understanding of the standards [31] Firms thus need to educate various internal stakeholders about the standards in a more appropriate way. Essentially, ISO 9000 implementation is very knowledge-intensive, including acquisition knowledge of practical operation and mapping theory and practice [32]. To better implement ISO 9000 standards for improving SROM, some scholars propose that knowledge management and quality management can be combined [33,34].

In order to ensure the normal operation of standardized process management of enterprises, first of all, the specific content of the international standard system documents should be analyzed, taking ISO 9000 as an example, and then the enterprise combined with its situation to prepare four-level documents, and finally after a review, the formation of nonconforming item report [35]. Therefore, according to the source and stability, knowledge is classified into three categories as follows, and sources of knowledge are shown in Fig. 3.

(1) Enterprise External Knowledge (EEK) is a standard policy document issued by the relevant government, which helps enterprises to implement operation management, such as ISO 9001: 2015 Internal Auditor Practical General Course. EEK is very stable and does not change easily.
(2) Enterprise Internal Knowledge (EIK) is derived from the enterprise internal documents for standardized management. Most companies follow the four-level pyramid document structure required by EEK to ensure clear logic and smooth connection between all levels of documents and develop internal operational management documents. Enterprise system knowledge

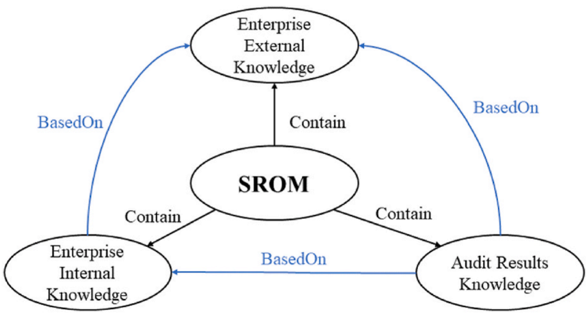

Fig. 3. SROM knowledge source.

generally includes four-level system documents, job descriptions and department responsibilities. ESK is relatively stable and will only be changed after internal audit.

(3) Audit Result Knowledge (ARK) is summarized nonconformance reports generated after each audit, recording the actual daily operation activities of the enterprise that do not comply with the rules and regulations. ARK is highly dynamic.

2.1.1. *Ontology model design*

Most of current KGs are domain-specific, with certain underlying ontologies [36]. The most important task of constructing a KG is to design ontology. Based on the characteristics of multiple SROM data types and complex data sources, a new ontology is required to represent the basic structure of SROM knowledge.

There are two ways to construct ontologies: top-down and bottom-up [37]. The bottom-up ontology construction method is typically used for the general KG to automatically extract concepts, types of concepts and relationships between concepts from the KG. Based on the characteristics of SROM domain, we improve the domain adaptability of domain ontology construction, and finally store ontology in protégé, as shown in Fig. 4.

In practice, to distinguish the semantic of the concept of SROM more finely, a more fine-grained as far as possible. For example, in the definition of ESK, system, organization, process, risk opportunity and form are defined, which is shown in Fig. 5.

In the presented concept model, we employ directed edges that link two nodes to represent the relationship of them. After that, we create properties and instances of each concept and set property thresholds. Finally, it is visualized on protégé which is a common ontology editing tool, as shown in Fig. 6.

2.1.2. *Knowledge extraction*

Knowledge extraction plays a crucial role in building the SROMKG. Typically, automatic or semi-automatic machine learning technology is used to extract entities, relationships, properties, and other information about the KG from open multisource data. Manual knowledge modeling is suitable for corpus with small capacity and high quality, but it cannot meet the requirements of large-scale knowledge construction. In addition, manual modeling is a time-consuming, expensive and highly specialized task. The data set in this paper has a certain scale and is limited. As for the data source format, the number of different types of knowledge, and the structural characteristics of the data source, we have adopted a semi-automatic KG construction approach that combines manual sorting, rule extraction, and dependency parsing [38] to extract knowledge.

(1) Manual sorting

We classify the knowledge in Word or PDF documents, including requirements, terminology, quality management overview and principal knowledge, ISO 9001 clause audit points, audit case analysis and program documents.

(2) Rule extraction

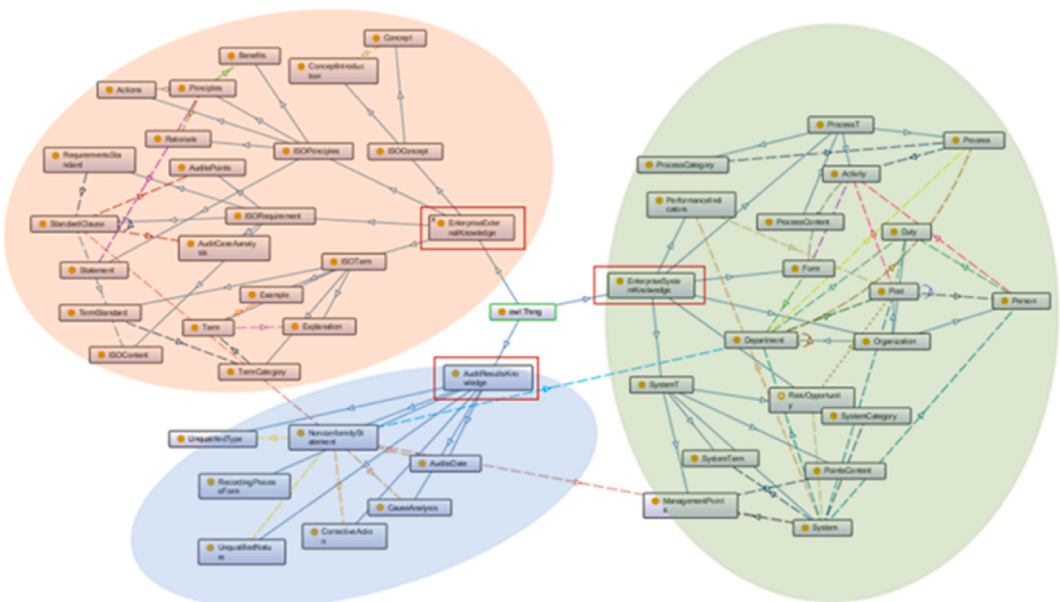

Fig. 4. Ontology model.

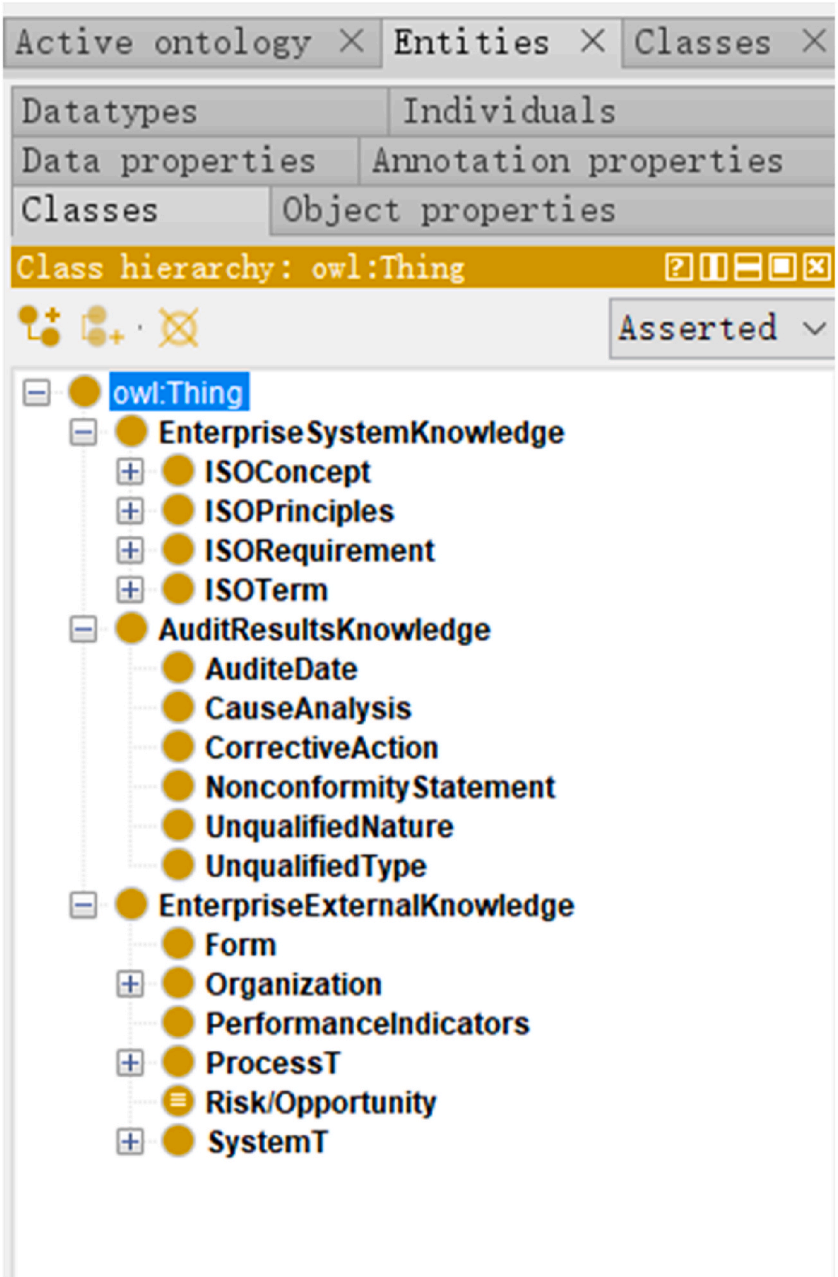

Fig. 5. ESK concepts.

For a large number of texts with a certain regularity in the text format, the method of rule extraction can be used to extract information. Rule extraction is writing code after understanding the format rules of the text and using programs to assist in the extraction. For example, in the unqualified report completed by the company after the review, the entities, relationships and properties are relatively clear. According to the aforementioned defined relationship types, 1755 triples of unqualified report is obtained.

(3) Dependency parsing

Enterprises place a high emphasis on the security and confidentiality of quality management system documents that involve internal business operations, leading to limitations in obtaining authentic and effective data. In addition, the text of the quality management system is special. In general, most of the texts extracted by triples are texts that state facts. The quality management system text is more about describing the requirements for related positions, roles, and departments, not simply relationship extraction for relationship classification, therefore, it is difficult to label. Moreover, to avoid errors in restoring the original meaning of sentences,

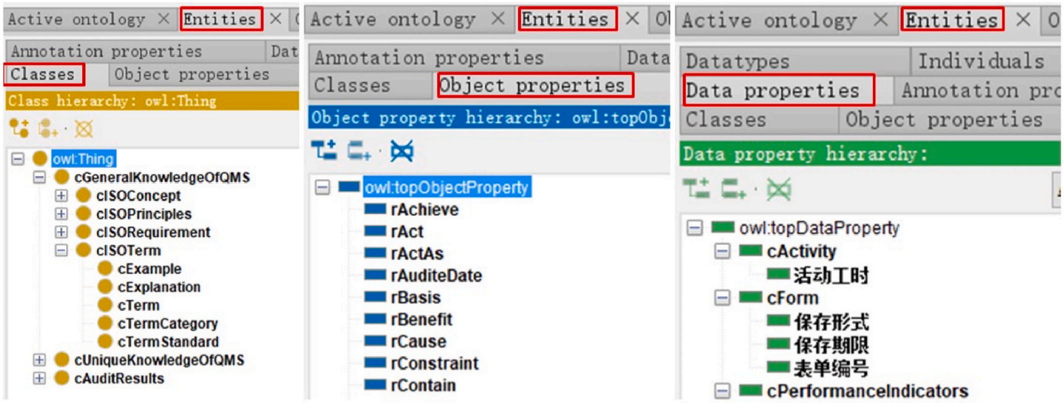

Fig. 6. Construction of ontology class (left), object properties (middle), and data properties (right).

much information in the quality management system text cannot be directly discarded. Therefore, to achieve the ultimate goal of serving enterprises and providing real-time guidance for employees, dependency parsing is added to improve the accuracy of building SROMKG.

Fig. 7 shows the knowledge extraction construction workflow. Dependency parsing reveals the semantic modification relationship between components in a sentence by analyzing the dependencies between components in a language unit. It points out the syntactic collocation between words in a sentence, and analyzes the subject, predicate, object, definite, adjective, and complement structure of a sentence. Through dependency parsing, the intricate interdependencies between words within a sentence are described, enabling its application in Natural Language Processing (NLP) tasks such as text analysis and semantic comprehension with enhanced precision.

2.2. SROMKG construction and updating

In the field of SROM, knowledge update often exists in the change of work instructions, or the increase of enterprise work business. These updates often do not add new relationships and new nodes, but only extend and expand from existing entities and relationships. Therefore, entity alignment is critical, which can also improve the speed and accuracy of KG updating.

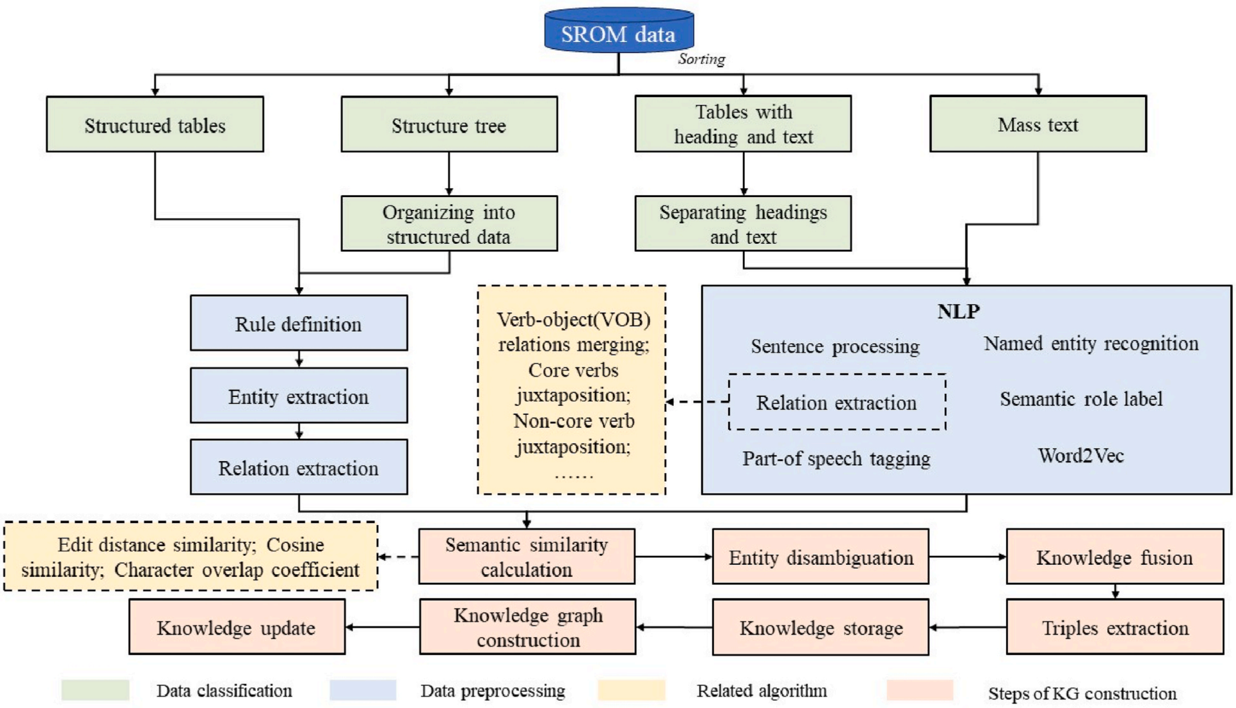

Fig. 7. Knowledge extraction construction workflow.

Thus, aiming at the high dynamic knowledge update problem of forms involved in the actual activities of enterprises, we propose a knowledge update framework based on the similarity matching of entity semantic blocks from the perspective of comprehensively, utilizing the semantics of the ontology concept itself and the hierarchical structure between entities. The framework is presented in Fig. 8.

We assumed that the semantic information of an entity could be expressed as self and neighbor features. First, denote the target entity as e_i , and the entity e_j to be matched is extracted from SROMKG as the matching calculation object. Second, regular expressions are used for initial matching and the matching entity pair and the entity pair to be matched are determined. Next, establish the semantic block of the entity: use the semantics of the entity itself and the hierarchical structure between the ontology concepts to establish the entity semantic block. We define the neighbor nodes with a distance of at most three as the semantic block of the entity. Then, the similarity matching of semantic blocks is performed: for the entity pair to be matched, the similarity of conceptual semantic blocks is calculated. $W_i = (w_e, s_i, \omega_i)$ is used to describe the entity semantic block word sequence, among them, w_e means the name of entity, s_i means the weight of word features similarity, and ω_i means positional weights of neighbor words. Denote the word sequence of e_i and e_j as $(1), \cdots, c(i), \cdots, c(m_1)$, $c^{'}(1), \cdots, c^{'}(i), \cdots, c^{'}(m_2)$ respectively, m_1, m_2 are expressed as the number of words. Calculate similarity s_i of the corresponding words in the word sequence of the entity semantic block using the edit distance method: S, $e(c(i), c^{'}(i))$ is the edit distance of two strings, $m(|c(i)|, |c^{'}(i)|)$ is the longest string length. The semantic distance of neighbors is, the weaker the semantic connection with the concept, and the smaller the weight ω_i is. Here, we define $\omega_i = \frac{1}{2}\omega_{i+1} = \frac{1}{2}\omega_{i-1} = \frac{1}{4}\omega_{i+2} = \frac{1}{4}\omega_{i+2} = \cdots = \frac{1}{2^n}\omega_{i\pm 2^{n-1}}$, and $\sum_{i=1}^{m}\omega_i = 1$. Therefore, the semantic similarity of entity pair e_i and e_j is $s(e_i, e_j) = \sum s_i \times \omega_i$. Finally, the matching relationship is determined, and knowledge is updated.

2.3. SROMKG application

The SROMKG-based Question Answering (SROMKG-QA) holds significance as an application within the field of SROM. Fig. 9 shows

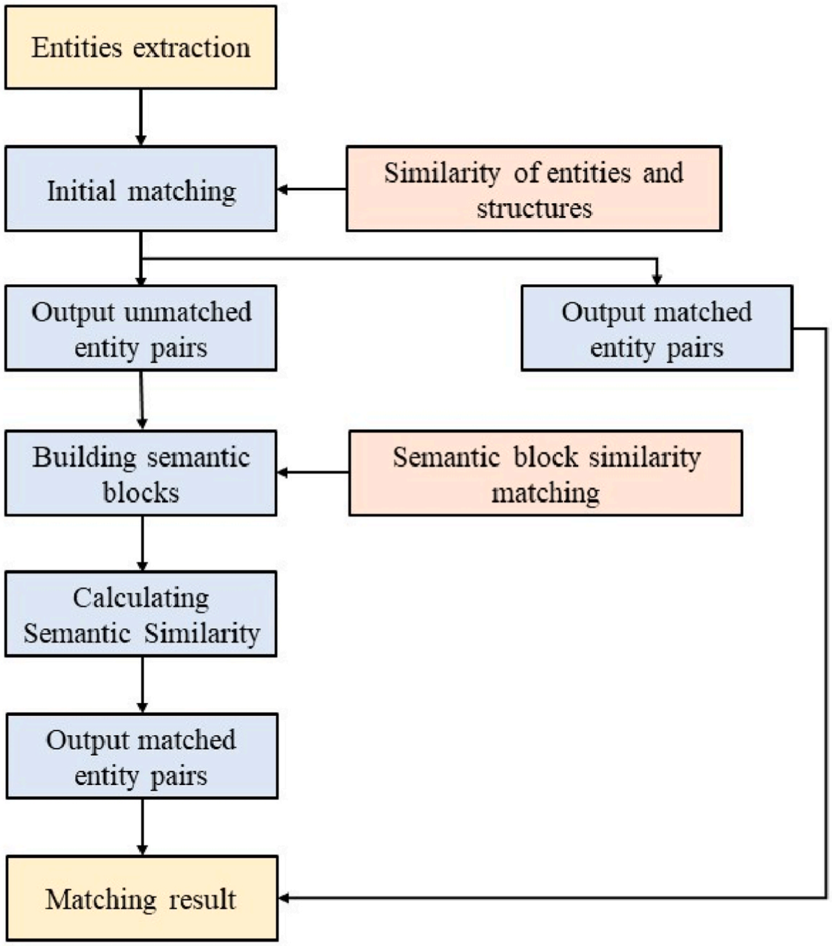

Fig. 8. SROMKG update framework.

the workflow of SROMKG-QA. Question-Answering (QA) can also be viewed as a single-turn dialogue system by generating the correct answer as a response. QA system needs to convert the questions in natural language into query sentences on SROMKG. First, we clarify the real intention of users, and then associate the intention with the properties or complex relationships in KG to construct a structured query statement. Finally, the answer is obtained by executing the structured query on SROMKG and returned to users. So, there are three parts in SROMKG-QA as follows:

Interaction layer: Directly to the user, provide users with an interface for inputting questions in natural language and return the results to users.

Processing layer: Consists of three main components, question analysis, answer search, and answer extraction. These components collectively serve as the fundamental and crucial function of QA.

Question analysis: A joint algorithm is designed, including Aho-Corasick [39], semantic similarity calculation [40] and pattern matching, aiming to accurate analysis of questions related to the quality management system.

Answer search: Transform question sentences into Cypher sentences supported by Neo4j.

Answer extraction: The result is the node of SROMKG or the properties of the node. In order to improve the friendliness of the system, in this step, the answer information is nested on the pre-designed answer template, and then returned to users.

Knowledge layer: SROMKG.

2.3.1. A joint algorithm for keywords extraction

The specific steps of the joint algorithm for problem analysis are as follows.

(1) Aho-Corasick algorithm

Firstly, identify the keywords in the question by multi-pattern string matching algorithm for Aho-Corasick automata.

The basic idea of the Aho-Corasick algorithm is to convert the matching process of the text string into the state transition process on Trie. The process is shown in Fig. 9. The algorithm consists of several steps. Firstly, the Trie data structure is constructed based on the pattern string. Then, the Trie is expanded into an automaton by assigning appropriate behavior functions to the nodes in the tree, enabling efficient pattern matching. By employing the Aho-Corasick algorithm, the text is scanned only once, allowing for the identification of keywords present in the question. This process facilitates the retrieval of relevant information from the text using keyword matching. The construction process of the tree is the process of continuously inserting keywords into a tree with only one root node in the initial state: Assume that the current keywords to be inserted are P_i, ($i \epsilon N$, N is the total number of physical nodes in the SROMKG), $P_i = \{P_{i1}, P_{i2}, \cdots, P_{i(j-1)}, P_{ij}, P_{i(j+1)}, \cdots, P_{iL}\}$, $j \epsilon [1, L]$, j, L stands for the length of the keyword P_i. Starting from the root node of the tree, search down the edge of the tree whose value is the current character P_{ij} in P_i (j starts from 1). If the characters in P_i have not yet ended and the path has ended, then a new node and new path must be created for the remaining characters in P_i. When the last character P_{iL} of the keyword P_i is inserted, it indicates that the current keyword is terminated. Deduce the rest from this and insert all entity keywords to get a complete quality management system Trie.

Then, three behavior functions are added: goto, fail, and output. The goto function is the state that the algorithm can reach directly according to the input; the fail function is the algorithm jump to other paths when no state can be directly reached according to the input; the output function is the corresponding pattern string associated with the state of the output node.

After constructing the Trie, the next step involves using the breadth-first search algorithm to systematically traverse each node in the quality management system terminology Trie tree. During this traversal, the appropriate behavior function is assigned to each node, facilitating the expansion of the quality management system Trie into an automaton.

Specifically, we need to construct a keyword dictionary. According to the classification of the entity types in the txt file storing the general knowledge entities of the quality management system above, the entity type dictionary corresponding to the keywords is constructed from the pattern string in the Aho-Corasick tree path, and the keywords entered by the user are clearly defined and marked corresponding tags such as "Term Standard", "Term Category", "Term", etc., for example, the keyword "personnel term" appears in the

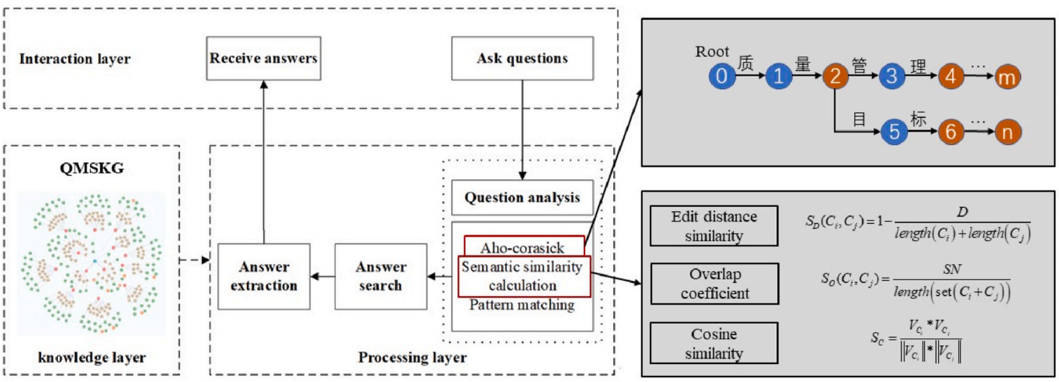

Fig. 9. SROMKG-QA workflow.

"TermCategory.txt" file, so tag it with "Term Category".

(2) Semantic similarity calculation

In case the identification process fails, we proceed with similarity calculation to determine the most suitable entity keyword. To achieve this, we employ various calculation methods such as edit distance similarity, character overlap coefficient similarity, and cosine similarity. These methods contribute to accurately measuring the similarity between keywords and entities, aiding in the identification process.

Eq. (1) suggests that the formula for calculating the editing distance. The edit distance refers to the minimum number of insertions, replacement, and deletion operations performed when the string C_i is converted to the string C_j and is defined as follows, where D stands for the edit distance.

$$S_D(C_i, C_j) = 1 - \frac{D}{length(C_i) + length(C_j)} \tag{1}$$

The definition of semantic similarity based on the character overlap coefficient used to determine how many similar characters C_i and C_j, as shown in Eq. (2), $set(C_i + C_j)$ represents the set of characters that are not repeated in the two characters C_i and C_j , and O represents the overlap coefficient, SN represents the number of identical characters.

$$S_O(C_i, C_j) = \frac{SN}{length(\mathrm{set}(C_i + C_j))} \tag{2}$$

Cosine similarity measures the difference between two characters by the cosine value of the angle between two vectors in the vector space. The more similar the two characters are, the closer the cosine value is to 1. The definition is as shown in Eq. (3), V_{c_i} and V_{c_j} are the vectorized representations of the strings C_i and C_j , respectively; $\|V_{c_i}\|$ and $\|V_{c_j}\|$ represent the vector length of the string C_i and C_j.

$$S_C = \frac{V_{C_i} * V_{C_j}}{\|V_{C_i}\| * \|V_{C_j}\|} \tag{3}$$

The final semantic similarity is defined as Eq. (4).

$$S = \frac{S_D + S_O + S_C}{3} \tag{4}$$

(3) Pattern matching

Finally, determine the entity corresponding to the keyword in the KG, and use the method based on pattern matching to determine the relationship or attribute to realize the entity link.

Question relationship or attribute matching is to determine the main purpose of the natural language question input by the user and match it to the corresponding relationship or attribute type of the KG. The method based on pattern matching uses linguistic knowledge to analyze and match from the character level fast speed, the key is to be able to accurately identify the relationship or attribute described in the question, which is more suitable for the question and answer of SROMKG in the professional field. The steps of this method are as follows and shown in Fig. 10.

Step 1. Construct a large set of problem words for all the problems involved.

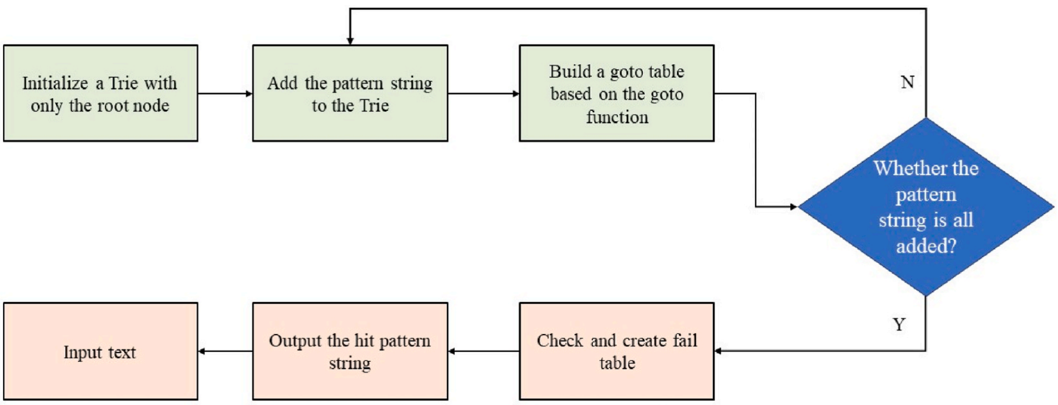

Fig. 10. Aho-Corasick algorithm flow.

Step 2. The question text is matched with different types of vocabulary in the question word set, and the entity and type obtained by keyword extraction are combined to determine the specific relationship of the specific entity or the specific property of the entity in SROMKG pointed to by the user's question intention.

Step 3. Match different types of question templates for specific relationships or specific properties of entities, convert natural language questions entered by users into Cypher sentences supported by Neo4j, and search for answers in the KG.

2.3.2. SROMKG-QA building

By performing question analysis, we can extract the entity objects and intentions embedded within the question. The system's answer is mainly to use the above information to perform entity linking, Cypher transformation, query and return to the user's answer in the KG. In SROMKG-QA, the entity link refers to the ability to identify the keywords that reflect the question intention in the sentences of natural language questions and map them to the entity nodes corresponding to the keywords in the KG. We complete the question intent in the natural language question and the entity mapping in Neo4j. Neo4j supports the Cypher statement for data interaction and uses the MATCH command in the Cypher statement to cooperate with other commands. It can accurately find and locate nodes, properties and relationships, to realize the entity link operation between question keywords and SROMKG.

After obtaining the entity type, entity name, relation type or attribute type of the question, convert the question into a Cypher query for Neo4j according to the rules shown Table 1.

2.4. Knowledge graph reasoning

The ultimate purpose of establishing SROMKG is to assist enterprise managers to make decisions and optimize enterprise internal operation activities. In the process of integration of explicit knowledge and tacit knowledge inside the enterprise, new knowledge can be deduced for decision-makers through the connection between the semantics of KG. In the SROM domain, new nodes are not created out of thin air because of existing jobs. Therefore, we need to explore whether there is a new relationship between entities, which is accomplished by using KG node similarity in this paper. At present, there are two kinds of methods to calculate the similarity between nodes: attribute-based method and chain-based method. Attribute-based semantic similarity computing model is more consistent with the cognitive process of similarity recognition of things in the objective world. But if we want to achieve accurate identification, we must describe all the attributes of objective things in detail to ensure the correctness of the results. The distance-based semantic similarity computing model is relatively intuitive and easy to understand, but it should first play its role based on a complete conceptual hierarchy network. The organizational structure of conceptual level can directly affect the semantic computation result. Therefore, we combine the two approaches. Attribute-based similarity calculation is implemented by editing distance similarity aforementioned. In this paper, SimRank algorithm is used to calculate the distance-based similarity.

3. Case study

After the establishment of SROMKG, the method of searching, browsing and visualizing based on the KG was developed. In this section, we use the data of a radiator manufacturer in China to verify our model.

3.1. Data collection

For EEK, we select "ISO 9001: 2015 Internal Auditor Practical General Course". For ESK and ARK, we select 43 D company's program documents and non-conformity reports. Company D is a high-tech enterprise integrating design, development and sales. Its products mainly include various types of radiators, chassis and power supplies. Company D started to run the ISO 9001 quality management system officially in July 2019 after conducting preliminary research, sorting out the post system process, establishing

Table 1
Cypher sentence conversion rules.

Entity type	Relationship type	Cypher sentences
TermStandard	include_qwds	"MATCH(m:TermStandard)[r:Contain]->(n:c TermCategory) where m.name = '{0}' return m.name, r.name, n.name"
TermCategory	include_qwds	"MATCH (m:TermCategory)-[r:Contain]->(n:cTerm) where m.name = '{0}' returm m.name, r.name, n.name"
RequirementsStandard	include_qwds	"MATCH(m:RequirementsStandard)-[r:Contain]->(n:StandardClause) where m.name = '{0}' return m.name, r.name, n.name"
StandardClause	include_qwds	"MATCH(m:StandardClause)-[r:Contain]->(n:StandardClause)where m.name = '{0}' returm m.name, r.name, n.name"
Term	explain_qwds	"MATCH (m:c Term)-[r:Explain]->(n:Explanation) where m.name = '{0}' return m.name, r.name, n.name"
Term	illustrate_qwds	"MATCH (m:Term)-r:llustrate]->(n:Example) where m.name = '{0}' return m.name, r.name, n.name"
StandardClause	content_qwds	"MATCH (m:StandardClause)-[r:Contain]->(n:ISOContent) where m.name = '{0}' return m.name, r.name, n.name"
StandardClause	audit_qwds	"MATCH(m:StandardClause)-[r:Derive]->(n:AuditePoints) where m.name = '{0}' return m.name, r.name, n.name""

system documents, and training from October 2018. The enterprise focuses on internal operation management. In January 2020, D company passed the certification of the quality management system of the ISO9001:2015 standard.

3.2. SROMKG construction and visualization

According to the above methods, taking enterprise organization and process as an example, the following ontology is constructed, as shown in Fig. 11.

SROMKG is a visual environment for browsing KG represented as directed graphs. Graphs are visualized using circles and arcs between them. Nodes are class and instance nodes, with relations represented as the edges linking these nodes.

The KG is derived from multi-source heterogeneous data sources and has rich information, which can describe entity characteristics more comprehensively. A portrait refers to a description of something from different perspectives based on a variety of data. In this paper, the knowledge representing the characteristics of the audit results extracted from the unqualified item report is structured and stored in the nodes of the KG. Based on the KG, portraits can provide a more comprehensive feature of the non-conformance problems in the audit result data of D company. It is centered on the “nonconforming factual statement” and described with the characteristics of the associated nodes, which constitutes the “audit result portrait” of D company. The "Audit Result Portrait” based on the KG, as shown in Fig. 15, describes the non-conformity fact statement, responsible department, non-conformity nature, non-conformity type, audit date, non-compliance with system regulations, non-compliance with ISO 9001 clauses, reason analysis, corrective actions, etc. At the same time, through relationship expansion, more information can be displayed.

The distribution of the audit result is the distribution of the "non-conforming fact statement” according to a certain selected dimension, according to the relationship path between the entities corresponding to different dimensions and the "non-conforming fact statement” entity. Construct Cypher sentences and perform visual display analysis in different dimensions.

(1) Audit date

As shown in Fig. 12, the audit date type (AuditeDate) entity is constructed according to the audit time, the relationship between the non-conforming fact statement and the audit date (AuditeDate) is established, and the Cypher statement "MATCH p=(a: Non-conformityStatement) is constructed)-[r: AuditeDate]-> (b:AuditeDate) RETURN p”, execute the statement and get the result. It can be seen that since the establishment and implementation of the quality management system of D Company, the problems found in the four audits conducted have successively decreased.

(2) Responsible department

In SROMKG audit results, there is a "Responsibility” relationship between the department (Department) and the nonconformity statement (NonconformityStatement), and the Cypher sentence "MATCH p=(a: NonconformityStatement)-[r: Responsibility]-> (b: Department) RETURN p”, execute the statement and get the result as shown in Fig. 13 and Fig. 14. It can be seen that during the 4 audits from 2019 to 2020, the R&D center has the largest number of non-conformance problems, followed by the industry customer department. The internal audit and internal control department have the least problems. And it can be seen from the figure that some

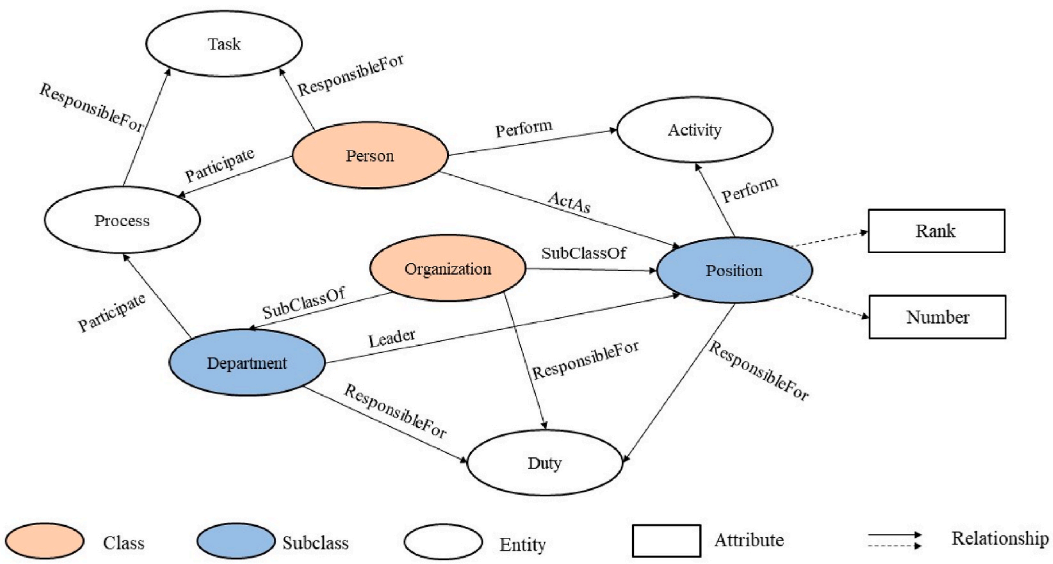

Fig. 11. Organization and process.

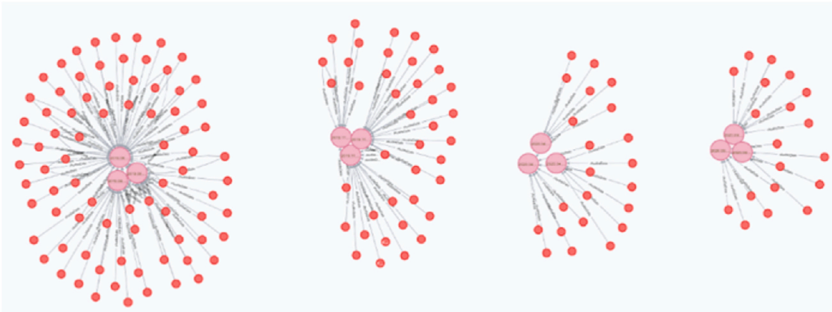

Fig. 12. Audit results are distributed by audit time (Fewer non-conforming items over time).

problems are common in many departments of the company. If there are too many non-conformance items in the quality management system, it can reflect the failure of a certain area or a certain process in the company. It is necessary to further identify common problems and conduct targeted training and learning for all staff.

3.3. SROMKG application

After the establishment of SROMKG, the method of searching, browsing and visualizing based on the KG was developed. This section verifies the intelligent question answering system and intelligent reasoning system.

Position duty detection. Based on Figs. 11, Figs. 15 and 16 show the Attribute similarity model and position similarity model respectively. By comparing the Task and Duty of "chief designer" and comparing their semantic similarity, it is found that in "exhibition publicity management regulations", "confirming the progress of change" should not be held by the chief designer, but by the product manager. In addition, in the process of establishing responsibilities after creating a new position, the same method can be used to determine whether there is a conflict with the existing job responsibilities.

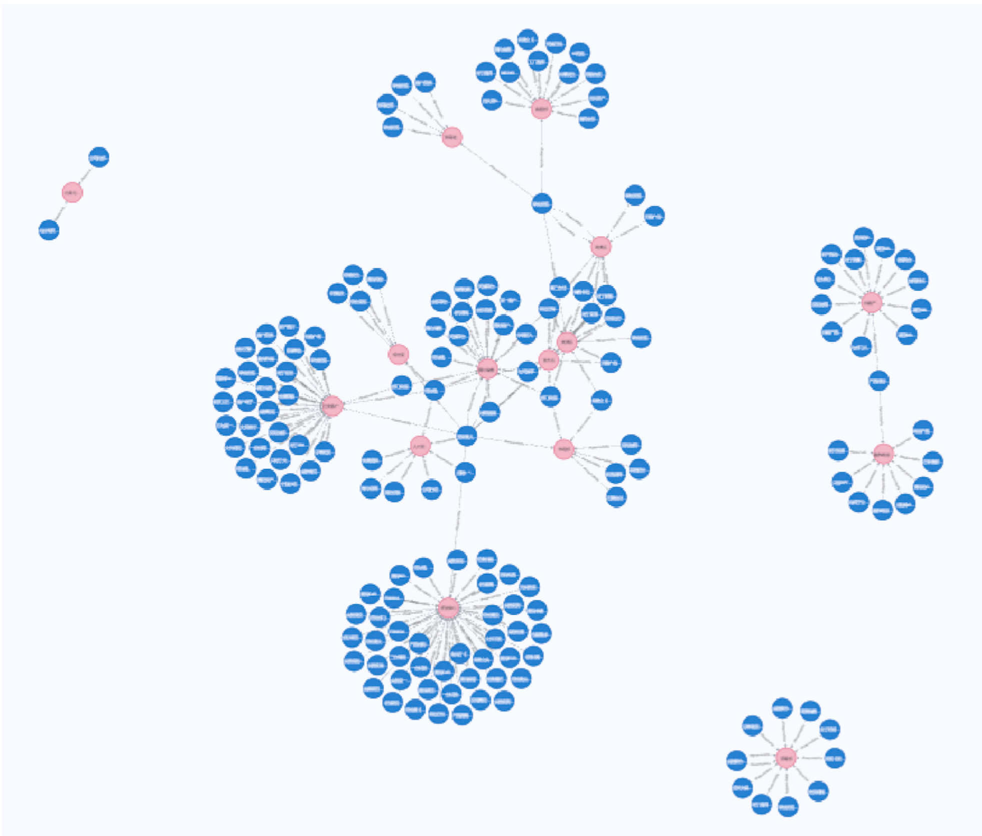

Fig. 13. Audit results are distributed by responsible department (entire).

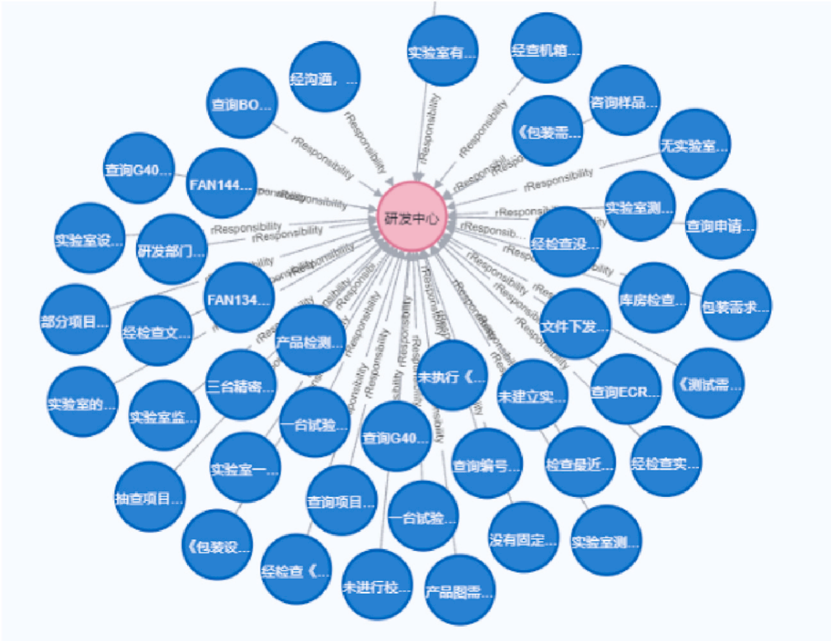

Fig. 14. Audit results are distributed by responsible department (partial).

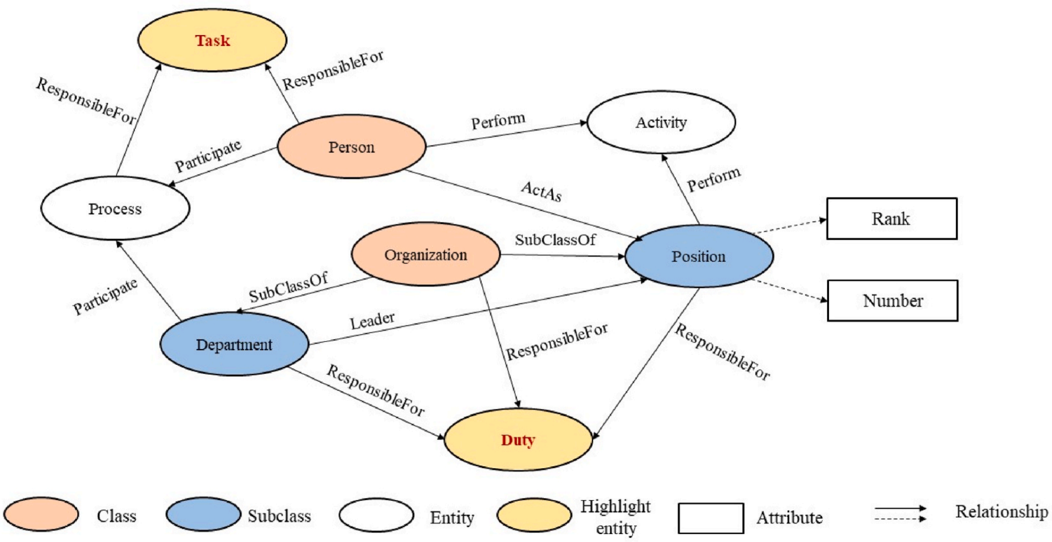

Fig. 15. Attribute similarity model.

SROMKG can also make job referrals. For example, the company has added a new China International Trust and Investment Corporation (CITIC) insurance business, and it needs to add a CITIC insurance specialist. In reality, the company can't set up a single position, and only one person can be selected from the existing position to undertake this business. According to the semantic similarity matching of task and duty, the commercial director of the operation department can be selected as the CITIC insurance specialist.

3.4. SROMKG-QA

3.4.1. SROMKG-QA implementation

We can realize the question and answer including all the entities, relationships and properties in the quality management system proprietary knowledge and general knowledge determined in the previous section.

Since there are many questions of all types, only terminology and system are used as examples as shown in Fig. 17. The left sub-

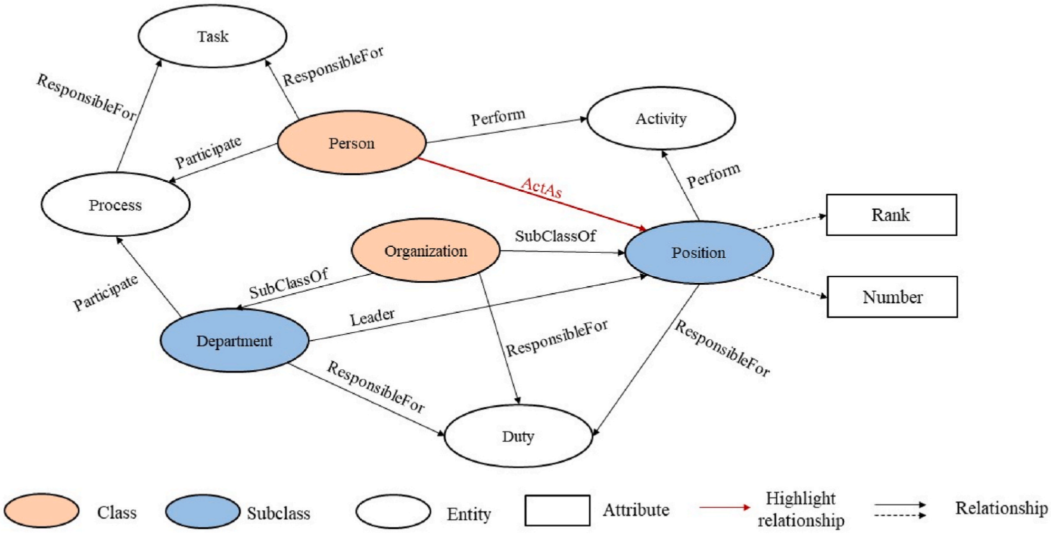

Fig. 16. Position similarity model.

figure shows the effect of terminology question and answer, and the right one shows the effect of system question and answer. The * set in the effect of terminology question and answer means that the nouns in front of the * are also quality management system terms. Users can directly ask questions if they don't understand.

3.4.2. SROMKG-QA test analysis

To test the usability of the quality management system's intelligent question answering system and the accuracy of answering questions, twenty employees of the company are randomly invited to ask 10 questions they want to ask according to the entities, relationships and attributes defined in the previous chapter's quality management system proprietary knowledge and general knowledge. Collected 151 questions related to the proprietary knowledge of the quality management system and 49 questions related to the general knowledge of the quality management system. After removing the duplicated questions, there are 127 questions related to the quality management system's proprietary knowledge and 38 questions related to the general knowledge of the quality management system.

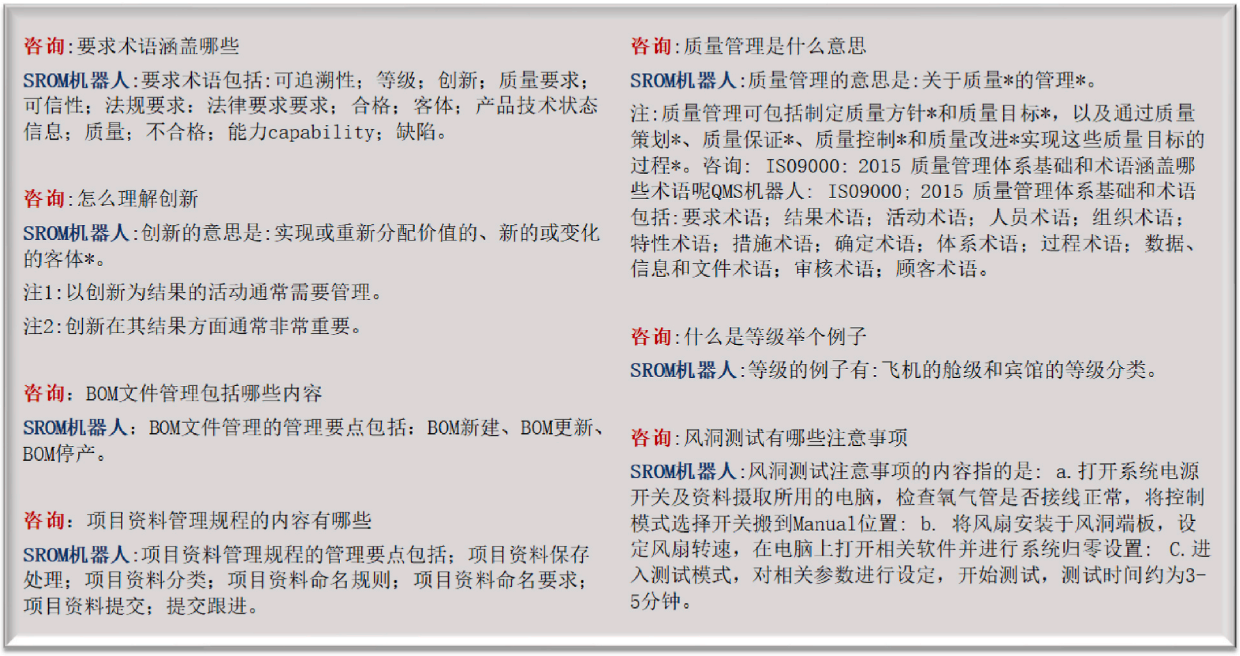

Fig. 17. SROMKG-QA example.

In terms of accuracy, the accuracy of general knowledge is higher than that of proprietary knowledge, because the former has less content and the corresponding entities and relationships are easier to identify and match. Table 2 shows the test results of the question answering system. Overall, the system meets the requirements, but there is still room for improvement.

4. Discussion

We first analyze the results, and then discuss theoretical and practical implications. Furthermore, we put forward the limitations and future directions of research.

4.1. Result analysis

The results will be analyzed from the perspectives of knowledge structure, knowledge use, and wrong answers or no answers.

In terms of *knowledge structure*, the auxiliary functions that KG can provide are as follows.

(1) KG can effectively integrate and continuously accumulate knowledge in the SROM domain. Because the knowledge representation method of KG uses semantic network, it is very flexible and highly expandable, so that knowledge from different data sources can be quickly integrated, and it is possible to continuously accumulate knowledge in SROM domain.
(2) KGs can integrate knowledge elements of different dimensions. The current unstructured data described in natural language inevitably has the characteristics of random expression and various formats, which has caused great obstacles to the extraction and reuse of knowledge. Knowledge can provide a more complete and comprehensive description of knowledge objects.
(3) KGs can manage SROM knowledge of different granularities. The KG can integrate knowledge of different granularities through its generic relationship and obtain different knowledge flexibly according to the different needs of knowledge in different situations and situations.

In terms of *knowledge use*, the auxiliary functions that KGs can provide are as follows.

(1) KGs can provide convenient retrieval. Since KGs represent knowledge in a fine-grained and structured manner, using the language rules that come with the database can quickly and conveniently retrieve the required fine-grained knowledge, which provides great convenience for the further use of subsequent knowledge.
(2) Compared with traditional keyword-based retrieval, KGs make it possible for machines to understand user needs from a semantic level. The KG stores knowledge in the form of triples and can be searched along the specified path, so that the question and answer based on the KG can provide users with faster and more accurate information.
(3) KGs can provide visual search results of various complex networks between entities and relationships. The related entities and relationships in the KG form a network graph, which provides great convenience for the association mining and analysis of related entities and relationships.
(4) The KG integrates various kinds of knowledge extracted from multi-source heterogeneous data sources, and supplements entity information from a multi-dimensional perspective, which is of great help in building a comprehensive cognitive structure.
(5) The storage method of the graph structure in the KG is beneficial to the statistical analysis of the data. The linked data contained in the KG provides the basis for multi-dimensional and multi-level in-depth analysis, and the computing functions that come with some databases provide great convenience.

The reasons for *wrong answers or no answers* are as follows.

(1) The questions raised by employees are not in the systematic KG, such as the question "Is there any change in the format of the order review form?". In the KG, there are no attributes related to the storage format defined for the form SROMKG.
(2) In the process of entity recognition, keywords were not successfully matched, such as the question "What are the responsibilities of PLM", the system did not successfully identify the position referred to by PLM (production line management).
(3) Relationships or properties matching fails, such as the question "Which process should be the most concerned for the general room", the system did not successfully identify the relationship that you want to ask is the dominant relationship between the department and the process.

4.2. Implications

Theoretical implication. SROMKG can be used to improve the efficiency and accuracy of enterprise internal KM. Specifically, this study has made an original contribution to SROMKG construction and application in SMEs. SROM is characterized by the systematic and strategic approach of identifying, organizing, storing, sharing, and utilizing both explicit and tacit knowledge to enhance overall organizational performance [13]. In terms of knowledge acquisition, we have proposed a comprehensive three-stage model, including an ontology-based KG construction. The model effectively addresses the challenges of identifying knowledge in the field of SROM and enables the induction of explicit knowledge while summarizing implicit knowledge [12].

Practical implication. By utilizing Neo4j to store a KG, it is possible to effectively address the challenges raised regarding the continuous updating of knowledge [16] and the difficulties in information sharing [17]. By constructing a KG and extracting structured

Table 2
SROMKG-QA test results.

	Proprietary knowledge	General knowledge	Total
Number of questions tested after deduplication/item	127	38	165
Number of correctly answered questions/item	111	35	146
Answer accuracy rate	87.4%	92.1%	88.5%

information from knowledge, it is possible to alleviate to some extent the challenges of knowledge heterogeneity and multimodality in SROM domain. In reality, SMEs hope to utilize KG to achieve standardized processes, ensuring consistency and reliability in their operations. Fortunately, KG has been extensively applied in various domains [41], demonstrating its maturity and effectiveness through practical implementations. In SROMKG process, employees could use a semantic search using the Cypher query language of Neo4j to effectively obtain the relevant knowledge required for SROM domain. For example, when enterprise internal auditors have doubts about the relevant content of regulations, the obtained information can provide a timely institutional guarantee for their field inspection to improve inspection efficiency and accuracy [42]. Moreover, by implementing functions such as job recommendation and conflict detection, SROMKG can assist managers in decision-making.

4.3. Limitations and future directions of research

The limitations and future research for constructing a KG of daily standardization management in enterprises involve several aspects.

Firstly, the principle of expanding sources of knowledge remains to be studied. One aspect of data collection is the identification and selection of authoritative sources. It is important to gather information from trusted and reputable sources, such as industry standards organizations, regulatory bodies, academic research papers, and industry reports. These sources provide valuable insights and established practices that can contribute to SROMKG. Another aspect is the consideration of knowledge variety. In addition to including text documents, digital data, the sources of knowledge will also consider images and even multimedia content in the future to capture the multidimensional nature of the SROM domain.

Secondly, the development of advanced knowledge extraction techniques is crucial. Natural language processing and machine learning algorithms can be further explored to automatically extract relevant information from various sources, such as documents, reports, and online resources, to enrich the KG. Fortunately, some substantial models or pre-training models rooted in deep learning have been created and put into practice across certain knowledge domains [43]. In addition, several natural language process training models for the Chinese corpus have been published and applied to some knowledge domains, including classical poetry [44] and bio-medicine [45]. These cases indicate the feasibility of automatic entity extraction and KG construction. In the future, it is possible to integrate advanced techniques and mature case studies to facilitate the application of KG in more companies within the manufacturing industry. Simultaneously, this collaborative effort will contribute to the development of a comprehensive corpus specific to this field.

Thirdly, enhancing the interoperability and integration of the KG with other enterprise systems is essential. This can facilitate seamless data exchange and collaboration across different functional areas, enabling a more holistic and comprehensive understanding of the standardization management process. On multi-system interactions Issues such as data privacy, data integrity, and data consistency need to be carefully addressed. Proper anonymization and aggregation techniques should be employed to protect sensitive information, and data validation procedures should be implemented to ensure the reliability and consistency of the collected data. Moreover, A limitation is not only in SROM, Nicholson [46] concluded that utilization of automated systems was scarce during KG construction and application. Despite employing automated methods, we have resorted to manual approaches out of consideration for the accuracy of the SROMKG. Thus, the method of KG construction was typically inefficient and required large numbers of human intervention.

In the future, the scalability and sustainability of the SROMKG need to be considered. As the amount of available knowledge increases over time, ensuring efficient storage, retrieval, and maintenance of the SROMKG becomes a challenge that requires continuous optimization and resource allocation.

5. Conclusion

Theoretically speaking, we proposed a method for constructing KGs in the field of SROM. Firstly, we build an ontology model in SROM domain. The formal expressions of related concepts, properties and relationships were defined from the three dimensions of EEK, EIK and ARK. Ontology editing is implemented, as well concepts, object properties and data properties are created. In addition, we propose a semi-automatic KG construction method combining rule extraction, dependency syntax analysis and manual sorting, and design entity content completion together with parallel structure processing rules to optimize fine-grained knowledge extraction, storing with a SROMKG after knowledge fusion so as to realize the interconnection of complex knowledge and the visual display of knowledge levels. As a specific application, we built an intelligent question and answer system (SROMKG-QA) that integrates the Aho-Corasick algorithm, similarity calculation and pattern matching, covering the proprietary and general knowledge of SROM to provide users in specific situations with timely and accurate fine-grained knowledge, and promote the efficient and convenient acquisition, sharing and dissemination.

Practically speaking, the construction and application of SROMKG can help SMEs achieve standardized processes, ensuring consistency and reliability in their operations. By capturing and representing the best practices and standards within the organization, it becomes easier to disseminate and implement these standards across different departments and teams, which leads to enhanced coordination and cooperation, reducing errors and inefficiencies. Users can visualize knowledge through SROMKG to quickly analyze relationships between knowledge. Meanwhile, SROMKG has functions such as detecting file system conflicts, detecting compliance with daily activities, intelligent retrieval, and job responsibility recommendations.

There are two kinds of limitations that should be paid attention to while applying SROMKG. One is the expansion of knowledge sources. It is important to identify and select authoritative sources, such as industry standards organizations, regulatory bodies, research papers, and industry reports, to gather valuable insights and established practices. And the other is the development of advanced knowledge extraction techniques.

In the future, the scalability and sustainability of SROMKG should be concentrated. We will integrate more data sources and continue to enrich SROMKG to improve application functions and efficiency. In particular, we plan to conduct research on multiple rounds of knowledge question answering to improve the flexibility, improve the accuracy of question understanding with deep learning methods, expand types of questions, and enrich properties of entities.

Author contribution statement

Peihan Wen: Conceived and designed the experiments; Analyzed and interpreted the data; Contributed reagents, materials, analysis tools or data; Wrote the paper.

Yiming Zhao: Performed the experiments; Analyzed and interpreted the data; Contributed reagents, materials, analysis tools or data; Wrote the paper.

Jin Liu: Performed the experiments; Contributed reagents, materials, analysis tools or data.

Data availability statement

Data will be made available on request.

Additional information

No additional information is available for this paper.

Declaration of competing interest

The authors declare the following financial interests/personal relationships which may be considered as potential competing interests:Wen Peihan reports financial support was provided by Chongqing Natural Science Foundation, China (grant No. CSTB2022NSCQ-MSX1118).

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