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Knowledge modeling: A survey of processes and techniques

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Abstract

Knowledge modeling is an important step in building knowledge-based applications. Understanding the processes of knowledge modeling and the techniques involved can help developers to grasp the knowledge modeling task as a whole and improve the efficiency of execution and management of modeling tasks. However, previous reviews on knowledge modeling mainly focus on ontology-based knowledge modeling. At present, there is no research work to summarize nonontology knowledge modeling methods, nor to systematically summarize the processes and techniques of knowledge modeling. In this paper, the processes, techniques, and characteristics of knowledge modeling methods based on ontology and nonontology are surveyed. Three research questions related to knowledge modeling are proposed. (1) What methods can be used for knowledge modeling? (2) What processes are involved in knowledge modeling? (3) What techniques are used in the processes of knowledge modeling? By answering these questions, the results of the survey help developers choose appropriate knowledge modeling methods in their work and complete modeling tasks effectively. Meanwhile, it is also conducive to the research work of improving knowledge modeling methods in the future.

KEYWORDS

knowledge modeling, modeling process, modeling techniques, ontology

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1 | INTRODUCTION

In recent years, with the continuous development of information technology, people are producing information stored in various forms every day. Many of these information are useful and contain human knowledge. If we can use the knowledge scattered in mass data, it will produce great value. Knowledge modeling is an effective way to organize and utilize this dispersed knowledge, and it is also an important step in constructing knowledge-based applications. Since it uses an interdisciplinary approach to capture knowledge and model data in a reusable format, knowledge and/or specifications about something can be transformed into computer-interpretable models by the processes of knowledge modeling. Knowledge modeling of the knowledge system usually includes knowledge acquisition, knowledge representation, knowledge fusion, knowledge inference, and knowledge evaluation. In the computer world, it is used to simulate intelligence and shifts from local proprietary solutions to produce and disseminate embedded knowledge models into larger computational solutions in an effort to generate applied knowledge. The ultimate goal of knowledge modeling is to organize the scattered knowledge from different data sources to form a unified knowledge model which computer can process for knowledge management or other applications.

The research of knowledge modeling started as early as the 1980s and has been an expanding research field ever since. Although there have been some published reviews on knowledge modeling, they only summarized the literature before 2014. Meanwhile, knowledge modeling using nonontology methods has not been analyzed. Moreover, previous reviews did not systematically analyze and summarize the processes and techniques of knowledge modeling. Clarifying the processes of knowledge modeling and the techniques involved are conducive to the efficient execution and management of modeling tasks. Therefore, this survey focuses on the development of ontology-based methods and other common knowledge modeling methods in recent years. The processes, techniques, and characteristics of different knowledge modeling methods from the perspective of knowledge representation are analyzed. The survey results help developers to choose appropriate knowledge modeling methods and manage modeling tasks efficiently. To better guide developers to understand and choose knowledge modeling methods, the following research questions are proposed:

RQ1. What methods can be used for knowledge modeling?

RQ2. What processes are involved in knowledge modeling?

RQ3. What techniques are used in the processes of knowledge modeling?

The rest of this paper is organized as follows: Section 2 compares our work with the other literature reviews. To answer RQ1, Section 3 surveys and summarizes various ontology modeling methods. The other nonontology knowledge modeling methods are surveyed and summarized in Section 4. Then, Section 5 summarizes the main points of the survey and answers RQ2 and RQ3 about the processes and techniques of knowledge modeling. Finally, the work of this survey is concluded in Section 6.

2 | RELATED REVIEWS

In this section, several review articles related to knowledge modeling will be briefly introduced and compared with our work.

In 1999, Devedzic[1] introduced the technology, systems, applications, and projects of knowledge modeling. But he only involved part of the knowledge representation methods. In 2001, he introduced the basic concepts, theories, approaches, and techniques in knowledge modeling. Then, he introduced projects, systems, and applications that adopted these methodologies.[2] However, his research was published too early to include the latest research results.

Villa et al[3] introduced knowledge modeling using ontology in the domain of ecology and environmental science, but only introduced the processes of ontology-based knowledge modeling. Simperl and Luczak-Roesch[4] introduced the methods, processes, and tools of collaborative ontology engineering. Liu and Zaraté[5] briefly introduced the knowledge modeling methods with clustering and ontology knowledge representation, then the relationships between domain application and used technologies were introduced. Füssl et al[6] studied the differences and connections between knowledge modeling, knowledge engineering or ontology engineering, and the knowledge modeling tools, activities, technologies, and application domains of knowledge models used in an automated decision-making system. But there is no knowledge modeling processes and techniques involved in these reviews. Coffey[7] introduced knowledge modeling based on the concept map, which is only one of the methods to be introduced. When Bimba et al[8] introduced the modeling and processing of the knowledge model. They only introduced the modeling techniques and did not discuss the modeling processes. Gayathri and Uma[9] only introduced knowledge modeling and reasoning based on ontology representation, which is only part of this paper. It can be seen that the existing literature review of knowledge modeling only involves part of the content of knowledge modeling and fails to comprehensively introduce the processes and techniques of knowledge modeling, which is the purpose of this paper.

In the existing knowledge modeling methods, knowledge modeling by constructing ontology is undoubtedly one of the most studied and effective methods. In 1998, Jones et al[10] discussed the processes and principles of different ontology development methods. Then, in 2002, Fernández-López and Gomez-Perez[11] discussed the ontology construction methods, such as KACTUS,[12] METHONTOLOGY,[13] SENSUS,[14] Skeletal methodology,[15] and TOVE,[16] from the aspect of maturity and mentioned re-engineering ontologies. In 2013, Rizwan et al[17] compared the existing ontology development methods based on the established criteria. In 2014, Al-Baltah et al[18] compared and analyzed TOVE, METHONTOLOGY, and Skeletal methodology from the perspective of the ontology development life cycle. These related reviews only discussed the method of manually building models with the full participation of domain experts. With the development of machine learning, natural language processing (NLP), and other technologies, more and more researchers begin to pay attention to automatic or semi-automatic ontology building methods, which are also called ontology learning. Shamsfard and Barforoush[19] introduced common ontology learning systems and proposed a classification and comparison framework to summarize and compare these ontology learning systems from different dimensions, such as input, learning methods, and evaluation methods, to help developers choose the appropriate construction tools. Drumond and Girardi[20] first defined steps of ontology development. Then they mainly summarized the work of ontology learning from structured data, semistructured data, and unstructured data, and then they summarized and compared several common ontology learning tools and evaluation methods. Asim et al[21] summarized previous surveys of ontology learning and specified different levels of ontology learning layers. Various ontology learning techniques were categorized into three classes, namely, linguistic, statistical, and logical. Ontology learning techniques were evaluated. Popular ontology learning data sets were introduced. Somodevilla García et al[22] introduced four fundamental types of ontology

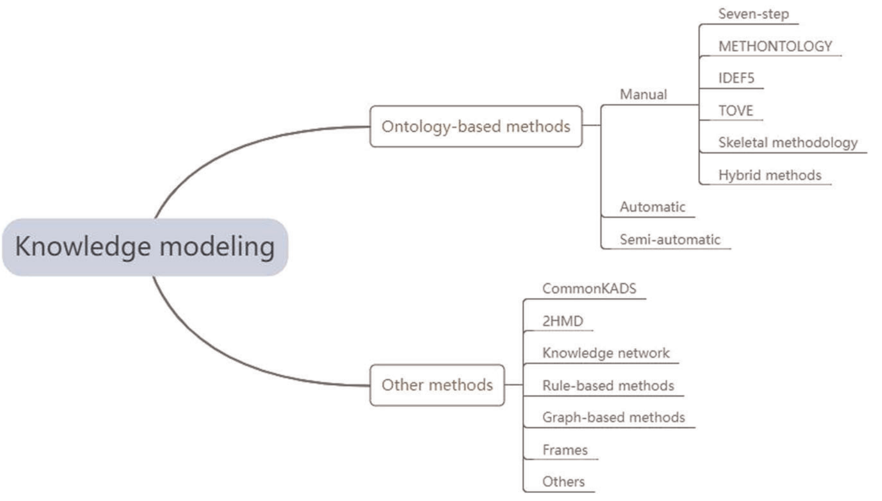

FIGURE 1 The structure of knowledge modeling method in this paper. 2HMD, two-hemisphere model driven; CommonKADS, Common Knowledge Acquisition and Documentation Structuring; IDEF, Integrated Computer Aided Manufacturing Definition method; TOVE, Toronto Virtual Enterprise [Color figure can be viewed at wileyonlinelibrary.com]

learning. The ontology learning process was divided into three tasks: ontology schema extraction, ontology creation, and extraction of ontology instances. Relative works of each task were summarized. Five types of evaluations and six types of ontologies learning systems were introduced.

The existing literature only reviews the part of the work of knowledge modeling, such as Villa et al,[3] Simperl and Luczak Roesch,[4] Liu and Zaraté,[5] Gayathri and Uma,[9] Devedzic,[1] and Füssl et al,[6] which only introduces knowledge modeling from the perspective of a few knowledge representation methods. Coffey[7] only mentioned the knowledge modeling method based on the concept map, Bimba et al[8] only introduced the knowledge modeling techniques without modeling processes. Shamsfard and Barforoush,[19] Drumond and Girardi,[20] Asim et al,[21] and Somodevilla García et al[22] only introduced ontology learning, that is, automatic or semi-automatic ontology construction method, and did not introduce other methods.

Figure 1 shows the knowledge modeling methods introduced in this survey and its organizational structure, and Table 1 shows the detail information about these methods. It can be seen from the figure that the survey introduces the manual, automatic, and semi-automatic ontology construction, and other popular knowledge modeling methods. At the same time, it summarizes the processes and techniques of these methods, which is more complete than the previous reviews.

3 | ONTOLOGY-BASED METHODS

In the process of development of knowledge modeling, there are indeed many researchers who focus on ontology. Figure 2 shows the number of ontology-related papers in the field of science and technology on the Web of Science in recent years.

Since the concept of ontology was introduced into the field of computer science, many researchers have done a lot of research and exploration work on ontology construction and its application. Over the years, many methods, tools, languages, or systems for developing

TABLE 1 The detail information about various methods

Method		Year	Publisher	Citations
Ontology	Seven-step[23]	2001	Knowledge Systems Laboratory	4667
	METHONTOLOGY[13]	1997	AAAI Technical Report	1836
	IDEF5[24]	/	Knowledge Based Systems Inc.	http://www.idef.com.idef5.html
	TOVE[16]	1992	International Conference on Industrial, Engineering and Other Applications of Applied Intelligent Systems	382
	Skeletal methodology[15]	1995	Workshop on Basic Ontological Issues in Knowledge Sharing	1234
Other	CommonKADS[25]	1994	IEEE Expert	215
	2HMD[26]	2004	Lecture Notes in Computer Science	44
	Knowledge network[27]	1995	Springer, Berlin, Heidelberg	301
	Rule based[28]	1984	Addison-Wesley Longman Publishing Co. Inc.	3352
	Graph based[29]	1976	IBM Journal of Research and Development	287
	Frames[30]	1988	Readings in Cognitive Science	6741

Abbreviations: 2HMD, two-hemisphere model driven; CommonKADS, Common Knowledge Acquisition and Documentation Structuring; IDEF, Integrated Computer Aided Manufacturing Definition method; TOVE, Toronto Virtual Enterprise.

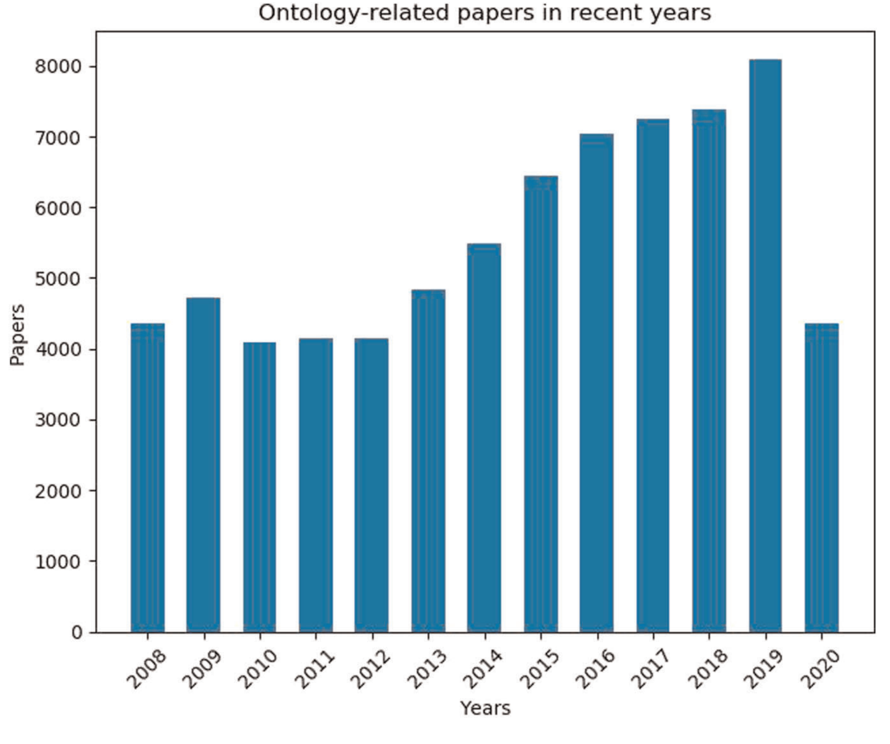

FIGURE 2 Ontology-related literature in Web of Science in recent years [Color figure can be viewed at wileyonlinelibrary.com]

ontology have been proposed and demonstrated their effectiveness. For example, the commonly used ontology construction methods, including seven-step method (aka 101 method),[23] METHONTOLOGY, Skeletal methodology, TOVE, IDEF5,[31] SENSUS, KACTUS, YAMO,[32] and so forth. Ontology editing tools include OntoEdit,[33] WebODE,[34] Ontolingua server,[35] and so forth, and Protégé (developed by Stanford University) is the most commonly used tool. Common ontology languages are Ontolingua,[36] KADS,[37] Web Ontology Language (OWL; https://www.w3.org/OWL/), and so forth. In Reference [38], by comparing the ontology construction method with the IEEE 1074-1997 standard,[39] the maturity level of those methods is obtained. These methods are usually used by domain experts to construct ontology manually. For manual methods, this paper only discusses the top five maturity methods. With the progress of machine learning, NLP, and other technologies, many researchers have shifted their research focus to automatic or semi-automatic ontology development. Besides, some researchers have proposed a hybrid method to develop ontology to overcome the shortcomings caused by the use of a single method. In the following, some representative ontology construction methods are discussed.

3.1 | Manual methods

The semi-automatic construction of ontology can combine the advantages of manual and automatic construction of ontology, which is a more commonly used method at present. The semi-automatic method of constructing ontology requires expert intervention. Therefore, the method of manually constructing ontology still has research value. According to IEEE 1074-1997 standard, Luo et al[38] sorted maturity levels for different ontology construction methods like this: Seven-step > METHONTOLOGY > IDEF5 > TOVE > Skeletal methodology > SENSUS > KACTUS. For manual methods, only five methods with the highest level of maturity are discussed in this section.

The seven-step method, also called 101 method, is a high-maturity method to build domain ontology. It was proposed by the Department of Medicine at Stanford University. Seven essential steps are presented to develop an ontology using this method. The seven-step method is an iterative method to develop an ontology. When using this method to build an ontology, it should start from the first step to build ontology along with these steps. Then, go back and check whether the current ontology meets the requirements. Finally, modify, refine, add details, and make its continuous improvement. For these years, many literatures using this method to construct ontology have been published. As shown in Table 3, the literatures,[38,40–43] and so forth, all have used this method to build ontology to solve the problem. The seven-step method is a flexible and high-maturity ontology construction method because of its versatility and portability. As the most mature method, it has been used in many areas of ontology construction.

Fernández et al[13] proposed METHONTOLOGY in 1997. It is a well-structured methodology to build ontology from scratch. The ontology development process in METHONTOLOGY is regarded as a set of activities. As an appropriate methodology for systematic ontology development, METHONTOLOGY is widely used. Guinebert et al,[44] Bitencourt et al,[45] Kalthoum et al,[46] and Borges et al[47] developed ontologies using METHONTOLOGY in different domains. Besides, the improvement methods for METHONTOLOGY[48,49] are also constantly proposed. Unified modeling language (UML) is also used to assist in the development of ontology using METHONTOLOGY.[50–52] To ensure the quality of ontology, Ghahremanloo et al,[53] Andre et al,[54] and Abanda et al[55] all applied ontology evaluation in the process of building ontology by METHONTOLOGY. In general, METHONTOLOGY is a flexible ontology development method, which makes it easy for developers to modify and expand ontology. The development steps of this method are transparent and logically complete, which can well reflect the ontology development process.[48] However, this method also has some issues, which Park et al[56] found when building the Graduation Screen Ontology: First, METHONTOLOGY did not provide specific guidelines, tools, methods, and explanations for developers to perform certain steps. Second, because METHONTOLOGY allows continuous knowledge acquisition during development, it may cause problems. Third, this method requires developers to write some unnecessary documents. Although METHONTOLOGY has these problems, it is still considered to be one of the best methods of ontology development.

Integrated Computer Aided Manufacturing Definition method (IDEF) means 'integrated definition,' it was a method developed by Knowledge Based Systems Inc. (KBSI).[24] IDEF5 was derived from many practical industrial applications. It is a method of ontology description capture. Menzel et al[31] described five steps for developing an ontology using the IDEF5 method. In the development process, each result produced at each step is reviewed. There are two kinds of IDEF5 language introduced: the IDEF5 schematic language and the IDEF5 elaboration language. The former language is commonly used by domain experts to express the information they want to input into the ontology and support visual knowledge modeling and visualization.[57–60] The latter language is a refinement language that can describe the elements in the ontology in detail. Concepts, attributes, and relationships can be captured and described by the IDEF5 language for formalizing them as ontology. Using IDEF5 to build ontology is very intuitive, efficient, and helpful in revealing the intrinsic relationship of objects. Also, IDEF5 has its own description language. However, there are no tools to edit it directly.[58] To use IDEF5, it needs extra works to transform into Resource Description Framework (RDF)/OWL ontology.

The TOVE method is derived from the TOVE project. It is an acronym for the TOronto Virtual Enterprise project and was proposed by Fox.[16] The main goal of TOVE is to develop an ontology that can be understood and shared by the different agents in a distributed enterprise. Fox[16] achieved this goal by dividing the definition of the representation into three levels: application, generic, and conceptual. Each level has a well-defined terminology and axiomatic definition. It is often used to construct resources or organization ontology.[61,62] In References [63–66], the problem of quality ontology construction based on TOVE was discussed. Especially, Kim and Fox[66] put forward a mature and complete TOVE ontology development method to build TOVE measurement ontology for quality measurement and management. There are several benefits to using this approach. It is a rigorous ontology engineering method with simple and clear construction steps, clear terminology definition, and axioms in the ontology. However, there are several problems in the process of creating an enterprise model. One of them is that the same thing is often described in different ways in real world. Another problem is that different relationships can be defined from different perspectives, which increase the complexity of the model.

Skeletal methodology, also called Uschold and King's methodology, is a general ontology construction method that was first proposed by Uschold and King.[15] This method roughly divides ontology construction into four stages. Uschold and King[15] confirmed this methodology as an effective methodology to handle ambiguous terms, removing an immense barrier to achieve a shared understanding. Subsequently, three approaches for identifying the principal concepts in an ontology were also proposed by Uschold and Gruninger[67]: a bottom-up approach, a top-down approach, and a middle-out approach. As a consequence of starting with the most significant concepts to generalize and specialize in the process of ontology developing, the middle-out

TABLE 2 Literature of hybrid methods

Methods	Literature
Seven-step + cyclic acquisition process	Yu and Cai[71] and Gao and Liang[72]
Seven-step + skeletal methodology	Li et al[73]
METHONTOLOGY + seven-step	AlSanad et al[74]
TOVE + METHONTOLOGY + seven-step + Enterprise Ontology[75]	Afandi et al[76]
METHONTOLOGY + TOVE + Bravo's method[77]	Reyes et al[78]
METHONTOLOGY + TOVE + YAMO[32]	Rahayu et al[79] and Syamili and Rekha[80]
TOVE + IDEON[81] + Enterprise Ontology[75]	Bjeladinović and Marjanović[82]

Abbreviations: IDEON, Intelligent Systems Technology Incorporation Distributed Enterprise Ontology; TOVE, Toronto Virtual Enterprise; YAMO, Yet Another Methodology for Ontology.

approach balances the level of detail, which brings about fewer efforts, therefore, this method is used in many application scenarios.[50,68–70] The skeletal methodology provides a methodological framework for constructing ontology, and compared with other methods, it has steps for documenting operations and ontology evaluation, but this method only provides guidelines for constructing ontology and does not provide specific methods and techniques.

As can be seen from the previous introduction, ontology construction is relatively flexible and there is no absolute correct and standard methodology for ontology development. Although many mainstream ontology construction methods have been proved to be effective through a large number of practical applications, each method still has its limitations. That is, it is not sufficient to use only a single method due to the limitations of the method. Therefore, it is a good practice to adopt a combination of multiple methods in ontology construction. Table 2 shows the literature that combines different manual methods to build ontology.

There are also some researchers combining automatic/semi-ontology development methods with manual methods. Wang et al[83] introduced a method of automatically acquiring knowledge through multiple dictionaries and then constructed domain ontology by METHONTOLOGY methodology. They also implemented a tool based on this method and illustrate the practicability of the method and tool through a case study.

To build a knowledge model in a certain domain, the first step is usually to choose a technique of knowledge representation. This is the premise and foundation of knowledge modeling. In other words, knowledge modeling relies on knowledge representation. In fact, up to now, there is still no perfect knowledge representation method. However, from the introduction of the previous sections, we can see that ontology is an excellent knowledge representation method. Although there are so many ontology building methods at present, all of them have roughly the same steps:

(a) Determine the domain scope of the ontology and the problem to be solved.
(b) Define terms in the ontology.
(c) Define the relationship between terms.
(d) Ontology construction and evaluation.

Most methods of building ontology include these steps, but the details are different. The general processes of their ontology construction activities are shown in Table 3, and the characteristics of these methods and literature using these methods to build ontology to solve problems are shown in Table 4.

3.2 | Automatic methods

The manual methods of ontology construction have the problems of relying on expert knowledge, high cost, and difficult to expand. Also, with the increasing amount of data and the development of techniques, automatic and semi-automatic ontology construction methods have been proposed. Machine learning and NLP methods were usually used for ontology construction. In general, the automatic methods have the following four phases:

(a) data collection and preprocessing;
(b) extracting terms, relationships, and their hierarchy;
(c) generating ontology from terms, relationships, and their hierarchy;
(d) evaluation ontology.

Most of the existing automatic methods are based on NLP technology. Liu et al[88] used NLP technology to implement the automatic construction of Chinese medicine ontology description architecture. Furthermore, they constructed an automatic construction and acquisition system for clinical medical domain of modern medicine.[89] They also proposed a method of automatically retrieving attribute values on the Internet to make up for the limitations of the ontology automatic construction method.

Jung et al[90] proposed a method of automatically constructing large-scale situation ontology through mining large-scale web resources, like, eHow and wikiHow by NLP technology, like, syntactic pattern-based approach and probabilistic conditional random field (CRF)-based approach, and compared it with manually constructing ontology-like resources for validation.

Ochoa et al[91] proposed a new fully automatic ontology learning method based on Spanish data documents. They extracted the structure of the sentence through NLP technology, and then used the linguistic pattern to identify candidate words and used C/NC-value,[92] term frequency–inverse document frequency (TF-IDF), and other methods to filter, extract concepts, and relationships. When enough information was obtained, the OWL application programming interface (http://owlapi.sourceforge.net) was used to build the ontology.

To overcome the shortcomings of manual review of academic literature, Chen and Luo[93] proposed an ontology and NLP-based framework for automatic document knowledge graph and reasoning network model, in which they used NLP technology to automatically extract four predefined ontology elements to construct ontology.

Azevedo et al[94] proposed a method for automatically constructing an expressive ontology based on ontology learning and NLP. Their method can automatically generate a description of complex axioms and implement the expressive ontology according to the definition description provided by the user.

Faria et al[95] proposed a method for automatically extracting instances from textual sources and filling them into ontology through NLP and supervised learning technology.

TABLE 3 Processes of different manual methods of building ontology

Methods	Activities in process						
	Specification	**Knowledge acquisition**	**Conceptualization**	**Integration**	**Implementation**	**Evaluation**	**Documentation**
TOVE	Y	Y	Y	N	N	Y	N
Seven-step	Y	Y	N	Y	Y	N	N
METHONTOLOGY	Y	Y	Y	Y	Y	Y	Y
Skeletal	Y	Y	N	Y	Y	Y	Y
IDEF5	Y	Y	Y	N	Y	Y	N

Abbreviations: IDEF, Integrated Computer Aided Manufacturing Definition method; N, the method does not define the activity; TOVE, Toronto Virtual Enterprise; Y, the method defines the activity.

TABLE 4 Summary of characteristics and comparison of manual ontology construction methods

Method	Advantages	Limitations	Application domain	Literatures
Seven-step	High-maturity level, versatility, and portability. It also has detailed description of the specific steps and operations	It does not reflect the ontology development lifecycle and lacks ontology evaluation and feedback	Medicine, etc.	[23,38,40–43,84,85]
METHONTOLOGY	It is easy for developers to modify and expand ontology. It is transparent and logically complete	It did not provide specific tools, methods, or other guides. Some unnecessary documents may need to be written	It was proposed in the domain of chemicals, but is now widely used in various domains	[13,44–49,51–56]
IDEF5	Intuitive, efficient, and helpful to reveal the intrinsic relationship of objects	No tools to edit it directly. It needs extra works to transform into RDF or OWL ontology	Enterprise	[31,57–60,86,87]
TOVE	Simple and clear construction steps and definition of terminology. It can be used to test the ontology	For large-scale data, the model is complicated. It needs entity disambiguation and resolution	Enterprise	[16,61–66]
Skeletal methodology	Ontology evaluation and documentation operations are explicitly proposed	In the coding phase, domain experts' familiarity with ontology will create bottlenecks	Enterprise	[15,50,67–70]

Abbreviations: IDEF, Integrated Computer Aided Manufacturing Definition method; OWL, Web Ontology Language; RDF, Resource Description Framework; TOVE, Toronto Virtual Enterprise.

Subramaniyaswamy[96] proposed a corpus-based method to automatically construct topic ontology by identifying concepts and semantic relationships from Wikipedia and WordNet.

In addition to NLP technology, methods based on linguistics and statistics are also commonly used for automated ontology development. Pisarev[97] studied the automatic construction of learning ontology based on computer linguistic algorithms for creating an ontology to support students' learning process in information systems and technology. Pisarev[98] used a method based on the joint application of the rules of morphological analysis and frequency analysis to automatically construct dynamic thesaurus to support the automatic development of ontology. Marchenko[99] developed an algorithm to extract explicit semantic relations from semantic–syntactic valence vectors among concepts of ontology, and a basic algorithm for automatically generating ontology knowledge base was proposed based on a natural language model with the help of linguistic tensor factorization.

In addition to the above methods, there are also researchers who use design patterns, dictionaries, and formalization methods to build ontology automatically. Harjito et al[100] proposed a method to automatically construct bilingual domain ontology by combining ontology learning from text and ontology design patterns (ODPs), by extracting terms and relationships from the bilingual corpus and corresponding with glossary and ODPs, the ontology was built automatically. Ma et al[101] proposed a method for automatically constructing OWL ontology based on the Petri Net Markup Language (PNML) model of Petri nets, that is, directly converting the PNML model and document of Petri nets into OWL ontology at the schema and instance levels. At the same time, they also developed a prototype tool named PN2OWL to automatically transform Petri nets into ontology. An and Park[102] proposed a method to automatically generate ontologies and manage the OWL individual through the interaction between database and ontology. The classes and attributes needed for ontology construction were obtained by analyzing the table information of the database, and then the instance data in the database were mapped to the ontology model through specific rules to implement the automatic construction of ontology.

Automated ontology development is indeed more convenient than building ontology by domain experts manually. With the enhancement of computer processing capabilities, large amounts of data can be processed automatically to build large-scale ontology. It can be seen from the existing literature that the technology of automatically constructing ontology is mainly based on NLP, linguistics, and statistics. However, the machine learning, statistics, NLP, and other technologies that the automated construction method relies on are still under development. The currently proposed methods still have some problems, such as low accuracy, ambiguity of entities and relationships, and big data requirements. But with the development of new technologies and methods, these problems will be solved in the future.

3.3 | Semi-automatic methods

Although a lot of research works on automatic ontology constructions have been proposed, full automation without human participation is still very difficult. Especially, the accuracy of automatically constructing ontology using various unstructured data still needs to be improved. The appropriate addition of manual intervention in the automated method can make up for this shortcoming to a certain extent. The semi-automatic ontology construction method only needs a small amount of manpower, which can save human resources and improve the quality of ontology as much as possible, which makes it easier to follow.

Semi-automatic ontology construction methods typically build ontology architectures with the help of experts and then use machine learning or data mining methods to aid in further automated development. Liu and Zhang[103] first constructed the ontology framework manually through a seven-step method, and then extracted hierarchical and nonhierarchical concepts from unstructured text data by combining statistics with rules to implement automatic extension of ontology. Palombia et al[104] constructed a rule-rich lightweight ontology by domain experts and then populate the ontology using an Ontology-based Data Access[105] mapping method. Wang et al[83] conducted research on automatic knowledge acquisition based on multiple dictionaries in the Chinese environment combined with manual methodology of METHONTOLOGY, and developed modeling tools for building domain ontology. They also found that knowledge fusion among multiple dictionaries can effectively assist knowledge modeling.

There are also some semi-automatic methods, which first use automatic methods to build ontology, and then manually revised and refined by experts to ensure the accuracy of the constructed ontology. Xavier and Lima[106] proposed a semi-automatic method of constructing ontology based on the category information of Wikipedia. The domain ontology was automatically generated by extracting the category structures and names from the information table of the Wikipedia database, which was revised and refined by experts. Under the guidance of domain experts, Yang et al[107] constructed a knowledge graph based on domain ontology of geography discipline by using machine learning technology to extract information and referring to other high-quality knowledge graphs. Then, they improved it through crowdsourcing semi-automatic semantic annotation. Jia et al[108] used a machine learning method and named entity recognizer (developed by Stanford) to obtain the information needed for ontology construction. Then, they deduced new rules by calculating the formula and path-ranking algorithm. The relationships and attributes of entities were deduced by using rules. Conde et al[109] introduced LiTeWi, a new method of creating educational ontology from electronic textbooks by using unsupervised terminology extraction technology. Nguyen and Yang[110] used lexical pattern, frequent sequence pattern, and statistics-based data mining to extract concepts and their relationships from Vietnamese texts under human supervision to extract knowledge for constructing Vietnamese ontology. To determine the statistical relationship between documents and terms so as to construct ontology with minimal human intervention, Rani et al[111] studied the method of using LSI & SVD and Mr.LDA algorithm to construct topic ontology.

In addition to machine learning and data mining methods, semi-automated methods in other specific areas have also been proposed. Cristea and Trofin[112] introduced the semi-automatic method of constructing historical document ontology. They manually annotated the document data set. Then, the instances were automatically extracted from the document and populated into the ontology. Gao and Deng[113] proposed a reasoning system based on two-layer ontology architecture. They automatically map domain knowledge from relational database schemas and knowledge items to OWL domain ontology through a low-time complexity mapping algorithm, and enrich and modify the ontology through concept clustering, so as to realize semi-automatic construction of domain ontology. Wang et al[114] used a method based on ontology structure and annotation instances to semi-automatically construct bridge ontology to express complex relationships between different ontologies. Yu and Shen[115] proposed a semi-automatic domain ontology construction method based on Web crawler. It can obtain domain data and extract semantic knowledge from the network through linguistic and statistical methods, and then implement ontology construction through an extension-based method.

In summary, the semi-automatic methods automate data processing through machine learning and other methods in information extraction or knowledge acquisition. However, it still needs the supervision of domain experts or manual intervention, such as providing some seed data, semantic annotation or reviewing and modifying the ontology, and so forth. They are more efficient and easier to use than pure manual or automatic methods. The general processes of semi-automatic methods are as follows:

(a) automatic data collection;
(b) automatic term extraction, concept extraction, and relationship extraction. Or experts define the ontology architecture and then automatically extract the information needed by the ontology;
(c) automatic ontology development;
(d) automatic ontology evaluation or reviewed by experts.

The manual ontology construction needs the full participation of experts, like, ontology engineers or knowledge engineers in knowledge modeling, which makes this study costly, inefficient, and subjective. The rapid development of machine learning methods has brought the possibility of automated implementation for ontology development. Most semi-automatic ontology development uses machine learning and data mining methods, such as References [103,106–111,115]. In addition to machine learning methods, other semi-automated methods have also been proposed, such as References [83,104,112–114]. Table 5 shows the process of automatic and semi-automatic ontology construction. Table 6 shows the characteristics and comparison of automatic and semi-automatic ontology construction methods. In general, with the continuous development of artificial intelligence technology represented by machine learning, the automatic or semi-automatic method is the mainstream of research in the future.

4 | OTHER METHODS

Since the ontology method requires the involvement of domain experts, which brings limitations to the knowledge modeling work, other excellent knowledge modeling methods have also been proposed. Table 7 shows the processes of these methods. The summary of characteristics and comparison of these methods is shown in Table 8.

4.1 | CommonKADS

Common Knowledge Acquisition and Documentation Structuring (CommonKADS)[25] is a flexible approach to build knowledge base systems. It is used to support most aspects of a knowledge management project through the construction of a suite of models. Figure 3 shows the model suite.

Generally, three steps of CommonKADS modeling are shown as follows:

(a) *Modeling the organization environment in four models*:
  (a1) The organization model analyzes the primary features of the organization.
  (a2) The task model describes tasks realized by the specific organization.
  (a3) The agent model includes task executors and their capabilities.
  (a4) The communication model defines communications between agents.

TABLE 5 Processes of automatic and semi-automatic methods of building ontology

Methods	Activities in process						
	Specification	Knowledge acquisition	Conceptualization	Integration	Implementation	Evaluation	Documentation
Automatic methods	N	Y	N	N	Y	Y	N
Semi-automatic methods	Y	Y	N	N	Y	Y	N

Abbreviations: N, the method does not define the activity; Y, the method defines the activity.

TABLE 6 Summary of characteristics and comparison of automatic and semi-automatic ontology construction methods

Method	Advantages	Limitations	Literatures
Automatic methods	It can build ontology efficiently and save manpower	The quality cannot be guaranteed	88–97,99–102
Semi-automatic methods	It combines the efficiency of automated methods with the quality of manual methods	It still needs manual work	83,103,104,106–115

(b) *Modeling expert knowledge*: Agents' behavior of problem handing is modeled in the expertise model. The previous four models offer knowledge about how to execute a task. The offered knowledge is used to describe agents' behavior of problems handing.
(c) System design: Knowledge is acquired through the expertise model and the communication model. The design model uses knowledge to describe the structure of the target system.

Since the expertise model offers essential knowledge structure and specification, it is a vital section of this method. The expertise model contains three parts: domain knowledge, inference knowledge, and task knowledge. A schema is constructed to capture domain knowledge. UML (especially class diagram) can be used to express entities and relationships in domain knowledge. Inference knowledge describes the fundamental inference steps by using domain knowledge. Goals and their implementation methods are expressed in the task knowledge. Besides, there is a library of task templates. These templates are concerned with patterns of usual tasks in reality. They are conducive to the formalization of knowledge.

As a reliable method, CommonKADS can be combined with other methods to achieve better modeling performance. Martins et al[116] described an integrated method to support the management of e-government projects. Besides CommonKADS, this method includes a qualitative research approach and semistructured interviews. They assist the CommonKADS to construct a knowledge base system. Guillén and Maceda[117] described an approach that applying ontology and CommonKADS for the prototype development of a veterinary diagnosis system. In this approach, ontology serves as a knowledge database. At the same time, task taxonomy in CommonKADS is used to develop the interference methods. Surakratanasakul and Hamamoto[120] divided the expertise model into two hierarchical views: architectural level and meta-class level. On the basis of CommonKADS, the UML approach is used for knowledge modeling in these two views. Santirojanakul[121] developed a sports science knowledge management system (SSKM) based on CommonKADS and Kanban board. Yang et al[118] combined CommonKADS and software quality engineering to improve the strategic information management (SIM) plan.

CommonKADS is one of the effective methodologies for knowledge modeling. It is used to capture and enlighten the experience of experts. This method also serves as improving communication, standardization, and supporting the availability of reusable components. Although CommonKADS provides an effective way to the construction of knowledge base systems, there are weak points in the aspect of reusability. Saleh et al[119] introduced an enhancement to CommonKADS methodology to improve reusability. It contains an adaptation of the original CommonKADS methodology and utilization of service-oriented architecture (SOA). Moreover, as CommonKADS is a technique in knowledge-intensive methodology, it is complicated for the development of a small-scale knowledge base system. In response to this issue, Surakratanasakul[122] proposed a

TABLE 7 Processes of other knowledge modeling methods

	Activities in process						
Methods	Specification	Knowledge acquisition	Conceptualization	Integration	Implementation	Evaluation	Documentation
CommonKADS	Y	N	Y	N	Y	N	N
2HMD	N	N	Y	N	Y	Y	N
Knowledge network	N	Y	N	N	Y	N	N
Rule based	N	Y	N	N	Y	Y	N
Graph based	N	Y	Y	N	Y	N	N
Frames	Y	Y	Y	N	Y	N	N

Abbreviations: CommonKADS, Common Knowledge Acquisition and Documentation Structuring; IDEF, Integrated Computer Aided Manufacturing Definition method; N, the method does not define the activity; Y, the method defines the activity.

TABLE 8 Summary of characteristics and comparison of other knowledge modeling methods

Method	Advantage	Limitation	Literatures
CommonKADS	It can be used to improve communication, standardization, and support availability of reusable components	It has poor reusability and is not suitable for small-scale KBS development	25,116–122
2HMD	It is able to eliminate the deficiencies of pure object-oriented and process-oriented methods. And its knowledge representation of this approach is manageable, transparent, and easily modifiable	It lacks the support of appropriate development tools	26,123–125
Knowledge network	It can represent the intrinsic associations and structures between knowledge points	Its description of complex knowledge and tacit knowledge is not comprehensive and in-depth	27,126–132
Rule based	It is easy to interpret, not restricted by data types, and is good for inference	It is not good at expressing structural knowledge and is not easy to retrieve when there are a lot of rules	133–144
Graph based	It is good at handling structural knowledge, it can show knowledge more clearly and intuitively, and also helps knowledge reasoning	It is difficult to establish, retrieve, and maintain when the structure is complex	29,145–149
Frames	It is good at expressing structural knowledge and is easy to understand. It can ensure the consistency of knowledge through inheritance between frameworks	It is not good at expressing procedural knowledge. Some domain-independent rules might be introduced, which are difficult to express in the framework	30,150–164

Abbreviations: 2HMD, two-hemisphere model driven; CommonKADS, Common Knowledge Acquisition and Documentation Structuring; KBS, Knowledge Based Systems.

lightweight of CommonKADS which concentrating on context and concept levels. Lightweight CommonKADS was simplified by reducing processes and removing retail redundancy between models to improve the method for easier learning and application.

4.2 | Two-hemisphere model driven

Two-hemisphere model driven (2HMD) approach proposed by Nikiforova and Kirikova[26] was originally used for software development. Then, a modified 2HMD was proposed to apply to knowledge modeling.[123] This approach consists of four models and two diagrams, as shown in Figure 4. They are divided into problem domain and application domain. Correspondingly, knowledge modeling using 2HMD is divided into the following two procedures:

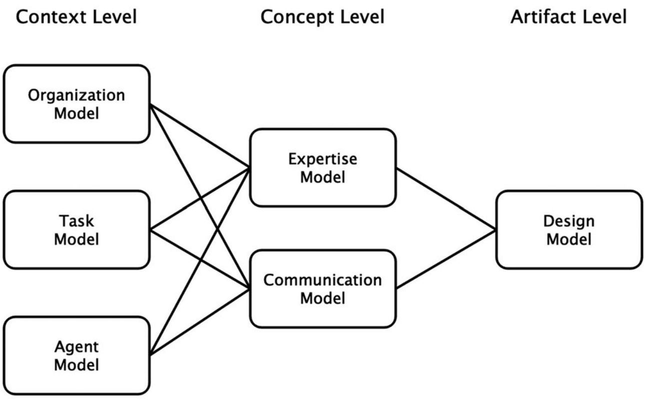

FIGURE 3 CommonKADS model suite. CommonKADS, Common Knowledge Acquisition and Documentation Structuring

(a) Construction of problem domain.
  (a1) The *Model of system functioning* describes processes in the knowledge.
  (a2) The *Conceptual model* depicts the conceptual architecture of the knowledge.

(b) Construction of application domain.
  (b1) The *Subprocess model* and the *Transitional auxiliary model* describe the subprocesses of the *Model of system functioning* and information flow between subprocesses. These two models form a formal base for future design.
  (b2) *Collaboration diagram* serves as a logic transition from the *Model of system functioning* to the emerging interactions of knowledge objects.
  (b3) As the final transition, *Class diagram* synthesizes all previous information to show knowledge classes, as well as their structure, methods, and relationships.

(c) Evaluation of *Class diagram*.

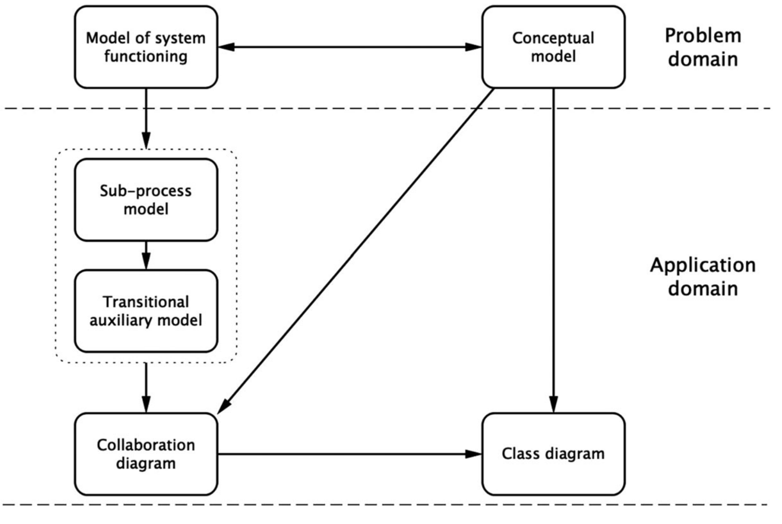

FIGURE 4 Two-hemisphere model driven for knowledge modeling

Two-hemisphere model driven is derived from the domain of software design. Therefore, UML is involved in this approach to represent knowledge. UML diagrams (e.g., collaboration diagram and class diagram) are employed in the process of knowledge modeling to formalize knowledge.

Knowledge of the education domain was modeled by 2HMD.[123] Moreover, Model Driven Architecture (MDA) principles were applied in 2HMD to solve the task of study program evaluation.[124] Furthermore, this approach was used for modeling of the Cyber–Physical System (CPS).[125] Although it is a multidisciplined process of knowledge modeling, the resulting models are suitable for both human understanding and automatic transformation. However, the lack of appropriate development tools is a limitation for this approach in the process of modeling.

4.3 | Knowledge network

As early as 1995, Beckmann[27] put forward the concept of a knowledge network. In knowledge networks, domain knowledge can generally be expressed as Domain_Knowledge $= (K, R)$, where K is a collection of knowledge points and R is a collection of associations between knowledge points.

Xi and Dang[126] used the text mining method to mine knowledge points from text documents and established the relationships between knowledge points with predefined decision rules. Then a knowledge network was constructed to represent and model domain knowledge of experts. Wang et al[128] used the knowledge elements in the patent data of microprocessors and the connections between them to build a knowledge network. They also promoted a method of mining knowledge points from the knowledge network through a social network of researchers. Liao et al[127] proposed a weighted knowledge network. It is a method of adding weights to the edge of knowledge networks to represent the degree of association. Zhao et al[129] built an electronic medical records (EMR)-based medical knowledge network through medical entities extracted from EMR. Their representation and reasoning of medical knowledge were implemented by combining with Markov random fields. Alexandridis et al[130] used latent semantic index analysis in natural language corpus to classify knowledge and calculate its similarity through TF-IDF and associated co-occurrence Jaccard scores to build a semantic knowledge network. Wang et al[131] set up the temporal-weighted co-occurrence relationship between users' innovative knowledge points by assigning different weights in different times to build a knowledge network. Liu and Wen[132] used social network analysis method to study the syllabus. Adjacency matrix was used to build the knowledge network through the syllabus's knowledge structure. Through analyzing the content of the course, knowledge points and knowledge relationships were obtained to establish a knowledge network of course content.

Modeling knowledge using knowledge networks mainly includes two parts of work: knowledge points modeling and knowledge points association modeling. It can represent the intrinsic associations and structures between knowledge points, while also ensuring the objectivity of domain knowledge representation. However, due to the complexity of knowledge, the description of knowledge, especially tacit knowledge is not comprehensive enough.

4.4 | Rule-based methods

One of the most common methods of domain knowledge modeling is to use IF–THEN rules to represent knowledge. These rules are also called production rules. They can be provided by domain experts or automatically generated from domain data. Generally, the method comprises the following steps:

(a) Collection and analysis of the domain data.
(b) Encoding domain knowledge into rule base in IF–THEN form.

Nowak-Brzezińska[133] proposed rule-based knowledge bases and used LEM2[135] algorithm to automatically generate rules from the UCI machine learning repository to represent knowledge. Nowak-Brzezińska and Wakulicz-Deja[134] clustered the rules in the rule-based knowledge base to explore the knowledge base more effectively. Bosl[136] modeled the knowledge of biological systems with human experts writing rules. Kim et al[137] proposed a Ripple Down Rules (RDR)-based knowledge base for fault detection. Their knowledge base used the RDR algorithm to generate knowledge from human experts and was improved and extended by combining machine learning with domain expert participation. Botta et al[143] proposed a context adaptation approach, which uses a set of operators selected by context to adapt the meaning of terms to a specific context to obtain a balance between interpretability and accuracy in the development of a fuzzy rule-based system. Shahbazova[142] established a fuzzy knowledge base in the education domain through two types of fuzzy rules in the educational environment. Solovjev et al[138] used fuzzy rules to model the knowledge and experience of decision-makers to solve the problem of uneven thickness distribution during the plating process. Bäuml et al[139] introduced a prototypical representation for the planning of a kanban loop based on a modeling language and rule-based representation method suitable for the logistics planning process. Chen et al[140] proposed a model based on fuzzy rules to correlate web design features with user evaluation of web aesthetics, thereby describing the ambiguity and nonlinearity of human perception and gaining more specific web design knowledge. Sarabakha and Kayacan[141] proposed an online learning-based control method to improve drone trajectory tracking. They used deep learning methods to train the controller and help understand system dynamics in real-time through expert knowledge represented by rules. Pasini and Baralis[144] proposed a semantic anomaly detection method. By learning semantic information from the training set and storing it in the form of configuration rules in the knowledge base, anomalies in the prediction of any pixel semantic segmentation algorithm can be detected. The semantic information in the configuration rules can also be used to interpret the detected anomaly.

The main advantage of the rule-based methods is that it is easy to interpret and not restricted by data types. Therefore, numerical and categorical data can also be handled well, and it is good for rule inference in the knowledge base. However, it is not good at expressing structural knowledge. When there are a large number of rules in the knowledge base, the search of the knowledge base and the relationship or similarity finding between rules will become difficult. Moreover, the quality of rules needs to be evaluated and continuously improved.

4.5 | Graph-based approach

The graph-based approach is also important in knowledge representation and modeling. It shows knowledge more clearly and intuitively. It also facilitates knowledge reasoning.

A conceptual graph is a common graph-based approach. It is a formal knowledge modeling method that can be used to describe entities and relationships. Sowa[29] used a conceptual graph to represent conceptual schemas of database systems. Chein and Mugnier[145] developed a knowledge representation and reasoning model based on the conceptual graph. With the development of artificial intelligence and semantic web, the conceptual graph has gradually become an important knowledge representation and modeling method. Kamsu-Foguem et al[146] proposed a conceptual graph-based representation method of traditional African medical knowledge. Then the modeling of traditional African medical knowledge was completed through visual reasoning and verification. Molnar et al[147] used a conceptual graph to model the knowledge contained in relational databases, which can accurately express the semantic information contained in the data, and the expression ability of the conceptual graph can also make the query more natural and intuitive.

In addition to the conceptual graph, semantic networks are also an important graph-based knowledge modeling method. Semantic network is used to express human knowledge structure in the form of a network. Like a conceptual graph, semantic networks express knowledge by describing the nodes of things and the relationships between them. Mathematically, they are directed graphs with labels on edges. Agt and Kutsche[148] constructed a large terms-related semantic network from natural languages to model domain modeling knowledge. Long et al[149] used semantic network to model semantic knowledge to illustrate computational experiments and multiple decision-making of a supply chain network. Knowledge graphs, built on a semantic network foundation of standards and practices, have been included in the 2018 hype cycle for emerging technologies by Gartner, as shown in Figure 5.

Conceptual graph and semantic networks are very similar in form, but arcs that connect different entities in the conceptual graph have no labels, while the edges linking different nodes in the semantic network have labels, which can convey more information and enable the semantic network to express the inheritance hierarchy of entities.

4.6 | Frames

Frames or framework is a complex data structure proposed by Minsky[30] to describe a thing or object and its attributes, it is very suitable for representing knowledge. A framework is the most basic unit of knowledge representation. A framework is a network of nodes and slots to represent the attributes of various aspects of a thing. Different frameworks can also connect with each other. Many researchers have studied knowledge modeling based on framework representation.

Jain et al[150] described a knowledge sharing framework that defines scope, requirements, specifications, resources, and other elements to model homeland security knowledge to promote knowledge sharing. Lei et al[151] developed a composable modeling framework (CMF) in weapon systems effectiveness simulation (WESS) domain to model WESS knowledge which simplified the simulation application development. Gudas and Brundzaite[152,153] defined a formal modeling structure based on Porter's value chain model (VCM) and a framework for enterprise knowledge modeling.

In recent years, with the continuous development of the research and application of the Semantic Web and knowledge graph, a semantic representation framework based on the Semantic Web received increasing attention. It is the RDF and RDF Schema (RDFS) released by the World Wide Web Consortium. By representing knowledge as triples (subject, predicate, and object), users can use this general framework to describe entities, relationships, and properties. Song et al[154] used RDF to model enterprise knowledge. Entity linking technology was used to link entities and relationships extracted from text through machine learning and NLP

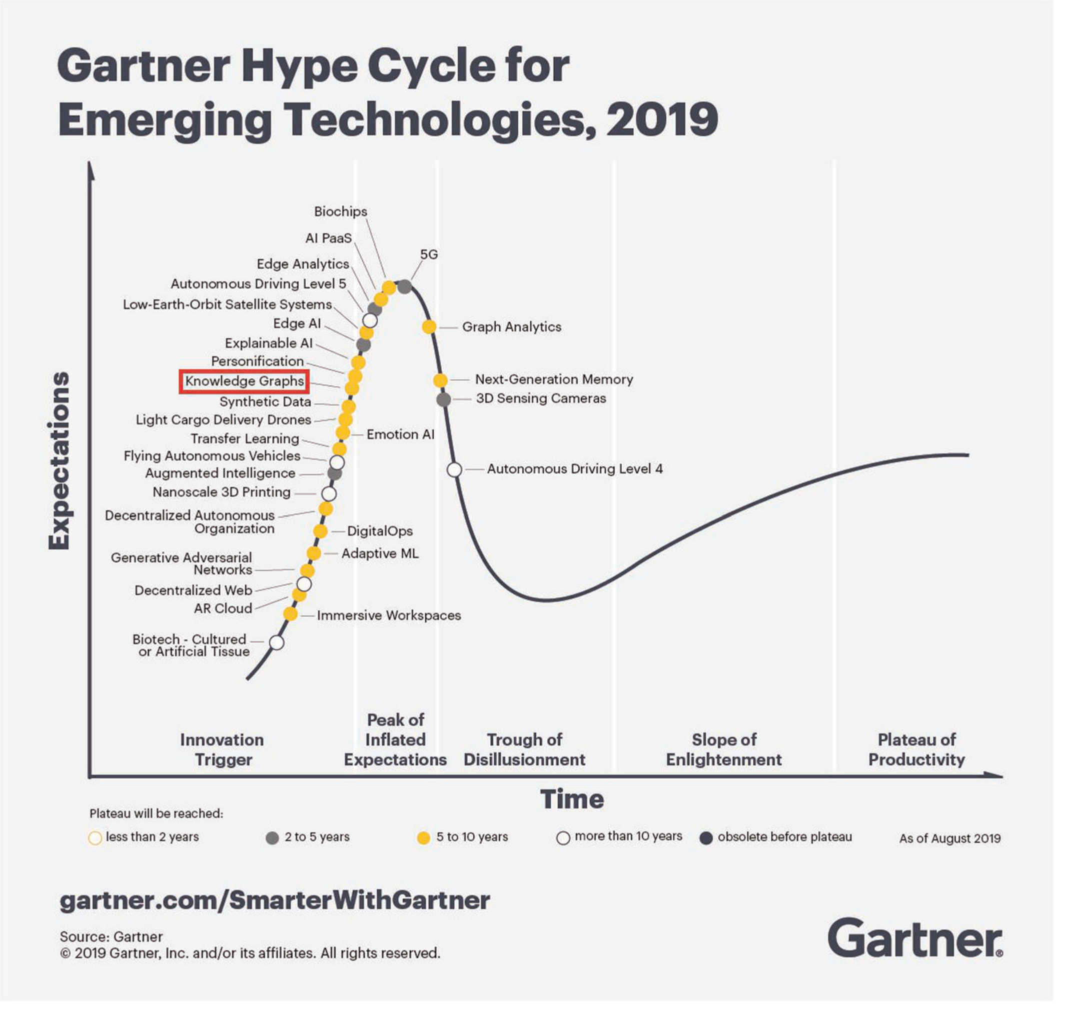

FIGURE 5 2019 Gartner hype cycle for emerging technologies (https://www.gartner.com/smarterwithgartner/5-trends-appear-on-the-gartner-hype-cycle-for-emerging-technologies-2019/) [Color figure can be viewed at wileyonlinelibrary.com]

techniques. Abbas et al[155] used RDFS to establish a domain knowledge model for the preschool education curriculum of an intelligent guidance system (ITS).

RDF(s) are often used to build ontologies. OWL, which describes ontologies, was created to compensate for the lack of expressiveness of RDF(s). Abburu and Golla[156] extracted information from structured and semistructured documents by NLP and used RDF to represent the information. Then these RDF triples are mapped to a domain ontology. Awangga et al[157] used OWL and RDF as tools to build ontology to correlate and describe the resources contained in family planning data. Bakakeu et al[161] implemented a solution to transform the information model into an OWL ontology expressed by RDF. Alshahrani et al[162] proposed a method for generating OWL ontology from SPARQL queries using n-ary relational patterns. In addition to the normal triples, some researchers proposed the supplement and improvement of RDF. Aiming at temporal data, Zhang et al[158] proposed a temporal data representation model RDFt based on RDF and a query language SPARQL[t]. Duroyon et al[159] presented a model that combines temporal and belief dimensions to trace the propagation of knowledge along time. Hoffart et al[160] integrated the spatiotemporal dimension into the original RDF triple in YAGO2. Ma and Yan[163] combined fuzzy logic with the RDF model to overcome the inconsistency of multivariate heterogeneous data in open web environment and expand the application scope of the RDF data model. Li et al[164] provide new semantic properties for predicates in RDF triples, and use a method of semantically extended scheme for linked data sources (SESLDS) to obtain the implicit semantics between linked entities with different attributes, so as to realize semantic extension on the target linked data source.

Semantic Web, Semantic network, and Ontology are a set of concepts that are often confused. The Semantic Web is a set of technologies and standards that make data on computers readable and understandable. Semantic network is a graph model that expresses information through the nodes and the relationships between nodes. An ontology is a specification of types of entities and their properties and relations. Ontology has become one of the building blocks of the semantic web because of its powerful ability to express knowledge. As a tool of knowledge representation, ontology and semantic network are very similar. Semantic network has no special requirement for modeling. Objects or scopes described are broader than ontology, while ontology is bound by elements, such as classes, attributes, and axioms. But ontology is better than semantic network in the depth of knowledge representation.

The framework eliminates some defects of semantic network and can be considered as an extension of the semantic network. It is good at expressing structural knowledge and conforms to the storage structure of the human brain for knowledge, which is easy to understand. The consistency of knowledge can be ensured by the inheritance between frameworks, and the framework network can be formed by establishing the connection between frameworks to enhance its expression ability. However, because the framework lacks the description of how to use the knowledge in the framework, it is not good at expressing procedural knowledge, and it will introduce some rules that are domain-independent and difficult to express in the framework.

4.7 | Other modeling methods

In addition to the most common knowledge modeling methods mentioned above, many other methods have also been proposed.

Yang et al[165] proposed a knowledge representation method that combines framework and object-oriented methods and uses UML to model knowledge. Rhem[166] used UML as standard notation and RHEM-KAF (Knowledge Acquisition Framework) as a standard process to acquire knowledge and model. Wei et al[167] used OWL ontology to manage the consistency and completeness of UML models and presented the transformation of the UML diagram to ontology.

To solve the problem of the logical relationship between a large number of knowledge rules in the modeling of complex knowledge systems, Pan and Sun[168] proposed a general hierarchical fuzzy Petri net, which can be used to describe and analyze knowledge systems at different abstract levels.

On the basis of the extended SBF (Structure, Behavior, and Function)[169] model, Chen et al[170] proposed a problem–solution-based knowledge modeling method to model detailed design knowledge. Their method allows designers to model detailed design knowledge about structures, behaviors, and functions through the issues they considered and the corresponding solutions.

Wang et al[171] established a mixed corpus and parsed the documents into a single content word using the Chinese phrase rule of CRF. Then, statistical methods were used to analyze the semantic connections between the content words and the knowledge of earth sciences that exist in documents was clearly expressed.

Liu et al[172] presented a method for automatically extracts domain knowledge in application descriptions from the mobile application market. They built a Data-based Raw Domain Model (DRDM) and organized domain knowledge in a tree form.

Knowledge modeling methods are not limited to the methods we introduced above. In addition to those commonly used methods, more knowledge modeling methods can be proposed for specific domain knowledge or business requirements to achieve the purpose of transforming knowledge into a computer-interpretable model.[173] With the continuous development of technology and application fields, more and more new methods will appear.

5 | SUMMARY AND DISCUSSION

To select a suitable knowledge modeling method, it is necessary to have a sufficient understanding of it. Through the previous review of Sections 3 and 4, it is not difficult to summarize the existing methods and the features, processes, and techniques involved in these methods. To answer RQ1, this paper organizes the knowledge modeling methods into the structure as shown in Figure 1. The knowledge modeling methods are divided into two categories: ontology-based methods and nonontological methods (other methods). The knowledge modeling methods included in these two categories are introduced, respectively. Among them, the ontology-based methods are divided into manual methods, automatic methods, and semi-automatic methods. Tables 4, 6, and 8, respectively, summarize the characteristics of these knowledge modeling methods.

To answer RQ2 and RQ3, Tables 3, 5, 7, and 9 list the processes and techniques, respectively. Tables 3, 5, and 7 summarize the processes of different knowledge modeling methods involved in this paper. These processes are divided into seven activities: Specification, Knowledge acquisition, Conceptualization, Integration, Implementation, Evaluation, and Documentation. Although domain experts rarely build ontology manually at present, for some fields or methods, especially for semi-automatic methods that require expert intervention, these manual ontology construction methods still have reference significance. Also, as can be seen from these tables, most methods do not consider integrating existing resources into the current task, and lack of documentation, which is not conducive to resource reuse and maintenance.

Table 9 summarizes the techniques involved in the processes of knowledge modeling that can be used to answer RQ3. The techniques in Table 9 do not include all knowledge modeling technologies. However, it can be seen from the table that modern knowledge modeling usually uses techniques, such as machine learning and NLP, when facing large-scale data. In recent years, knowledge graph has been widely used and knowledge modeling is indispensable for constructing knowledge graph, especially in the knowledge acquisition stage. When facing large-scale data, it is unrealistic to rely on manual knowledge modeling. Therefore, there are different knowledge modeling methods that have the trend of developing towards automation.

TABLE 9 Techniques of knowledge modeling

Methods		Techniques
Manual methods	TOVE	Quality assurance by ISO 9000 standard, build ontology by the domain expert
	Seven-step	Build ontology by the domain expert
	METHONTOLOGY	UML for modeling, ROMEO (requirements-oriented methodology for evaluating ontologies) method for evaluation
	Skeletal	Build ontology by the domain expert
	IDEF5	Build ontology by the domain expert
Automatic methods		Use machine learning or data mining methods in knowledge acquisition and ontology generation
Semi-automatic methods		Build ontology architectures with the help of experts. Use machine learning or data mining methods in knowledge acquisition
Others	CommonKADS	Conceptual Modeling Language (CML)/UML, ontology, and structure-preserving design approach for modeling. Propose-and-revise method for task decomposition
	2HMD	UML for modeling
	Knowledge network	Text mining, Markov random fields, latent semantic index analysis, TF-IDF, and associated co-occurrence Jaccard scores
	Rule based	LEM2 (Learning from Examples Module, version 2) algorithm, human experts writing rules, Ripple Down Rules (RDR) algorithm, and fuzzy rules
	Graph based	Conceptual graph and semantic networks
	Framework	Resource Description Framework (RDF) and Semantic Web
	Others	UML for modeling, fuzzy Petri net, and statistical methods

Abbreviations: 2HMD, two-hemisphere model driven; IDEF, Integrated Computer Aided Manufacturing Definition method; TF-IDF, term frequency–inverse document frequency; TOVE, Toronto Virtual Enterprise; UML, Unified Modeling Language.

6 | CONCLUSION

In this paper, the processes, techniques, and characteristics of different knowledge modeling methods are summarized. We first introduce the knowledge modeling methods using ontology, including manual, automatic, and semi-automatic modeling methods, of which the latter two are the focus of research in recent years and the future trend. Then, the knowledge modeling methods based on other knowledge representations are summarized. Finally, the advantages and limitations of these knowledge modeling methods are discussed and modeling processes and techniques are summarized from the survey. It can be seen from the survey that semi-automatic knowledge modeling method which requires a small amount of manual work is widely used, but knowledge modeling is developing towards full automation. However, techniques, such as machine learning and NLP, are mainly applied in the knowledge acquisition stage. It does not cover the whole process of modeling at present. Fully automatic knowledge modeling needs further study. At the same time, due to the rise of technologies, such as the semantic web and knowledge graph, ontology, an excellent knowledge representation and modeling method, has once again become a research hotspot. Additionally, it is also a good practice to mix different methods based on the existing techniques. This can be easily achieved through the summary of the knowledge modeling processes and techniques in this paper. The results of this survey do not only help developers to choose appropriate knowledge modeling methods but also help improve the research work of knowledge modeling methods in the future.

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