Ontological Approach in Smart Service Systems: A Literature Review

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4 authors, including:

Thi My Hang Vu
Ho Chi Minh City University of Science

Thang Le Dinh
Université du Québec à Trois-Rivières

Md Saidur Rahman
Polytechnique Montréal

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Thi My Hang Vu
University of Science, vtmhang@fit.hcmus.edu.vn

Thang Le Dinh
Université du Québec à Trois-Rivières, thang.ledinh@uqtr.ca

Md Saidur Rahman
Desjardins, saidur.rahman@desjardins.com

Annie Brasseur
Desjardins, annie.brasseur@desjardins.com

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Thi My Hang Vu
University of Science, Ho Chi Minh City, Viet Nam
Vietnam National University, Ho Chi Minh City, Viet Nam
vtmhang@fit.hcmus.edu.vn

Thang Le Dinh
Université du Québec à Trois-Rivières,
Trois-Rivières, Canada
Thang.ledinh@uqtr.ca

Md Saidur Rahman
Desjardins, Montréal, Canada
saidur.rahman@desjardins.com

Annie Brasseur
Desjardins, Montréal, Canada
annie.brasseur@desjardins.com

Abstract

A smart service system is defined as one that can understand a customer's situation and then recommend the best solutions to the customer, thereby increasing customer value creation. Exploring knowledge related to customers, context, and services/products is essential to offer services intelligently. Ontological approaches are promising methods for organizing and exploring knowledge due to their strong capacity of expression and reasoning. Smart service systems leveraging ontologies have been investigated for decades, but the conception and design of those systems remain difficult tasks due to the lack of an overall framework served as a guideline. This paper aims at conducting a literature review of ontology-based smart service systems to address this challenge. The findings include a classification and an analysis to determine essential elements of those systems, identified research gaps, and suggestions for future research.

Keywords

Ontology, smart service, literature review.

Introduction

The term "smart service" refers to a service that can understand a customer's situation (customer profiles, interests) and then recommend the best services to the customer, thereby increasing the customer value creation (Romero et al. 2020). For example, a smart conversational service, can drive a conversation more naturally by recognizing customer's situation and then automatically or semi-automatically generating appropriate responses for this situation. This type of services is rapidly gaining popularity and has a big impact in many domains (Le Dinh et al., 2022; Spohrer and Demirkan 2015). For example, offering customers with appropriate services or solutions to fulfil customer needs is a key factor for any organization to succeed. In this light, smart service systems, which offer smart services, are capable of learning, dynamic adaptation, and decision-making based upon data received, transmitted, and/or processed to improve its response to a future situation (Medina-Borja 2015).

In these service systems, knowledge about customers, context, or services is essential. The knowledge should be well-structured to facilitate knowledge exploration and exploitation. An ontology, which is defined as a "formal specification of a shared conceptualization" (Gruber 1993), is a promising method for organizing and exploring knowledge due to its strong capacity of expression and reasoning. There are numerous studies that look into how ontologies are used to organize knowledge in smart service systems (dos Santos Pacheco et al. 2013; Sengupta et al. 2018). However, there is still a lack of a general framework to offer suggestions for the conception and development of ontology-based smart service systems.

Nowadays, smart service systems and artificial intelligence (AI) based systems are about to create a complete transformation in how companies create and deliver value to customers. However, those systems work only when they understand and operate based on ontologies, which are the soul of the business (Earley and Davenport, 2020). For this reason, the paper focuses on conducting a literature review to explore the key elements of an ontology-based smart service system, which could address the two following research questions: *"**RQ#1**: What elements should an ontology-based smart service system include?"; and "**RQ#2:** What functions do ontologies play in those systems?".*

The findings of this study can provide a summary of ontology-based smart service systems, highlight current challenges, and then suggest potential future research directions to address those challenges. The rest of this paper is organized as follows. The *methodology* section clarifies the process carried out to complete this literature review. A table of analysis then shows a *classification* of selected papers, followed by *analysis* results. Following that, research gaps are identified and then future research directions to fill these gaps are also presented in the *discussion* section. Finally, the *conclusion* section summarizes the findings of the paper.

Methodology

A search process based on Webster and Watson's (2002) approach, which is appropriate for conducting a concept-centric review to identify key elements of ontology-based smart service systems, is used for analysis in this study. The process includes the four following phases.

In the *Identification* phase, searches on titles, abstracts, and keywords are performed from six academic databases ScienceDirect, AIS Library, IEEE Xplore, ACM Digital Library, ProQuest, and JSTOR by using two keywords "smart" (or its synonym: "context-aware", "intelligence") and "ontology" to retrieve the first list of papers. The selected papers must be published in English (language constraint) within 2017-2022 (time constraint) since smart service systems have been emerging in recent years.

In the *Abstract screening* phase, irrelevant papers are eliminated using five exclusion criteria to the abstracts of papers selected in the previous step. ***EC#1***: Papers are not published in a peer-reviewed conference/journal. ***EC#2***: Papers are not provided in the full text. ***EC#3***: Papers are surveys or literature reviews. ***EC#4***: Papers do not mention ontologies or knowledge bases in the abstract. ***EC#5***: Papers do not clarify the major elements of a smart service system.

The *Full-text screening* phase is concerned with full-text reading to determine which papers will be chosen for analysis. A selected paper must satisfy all three inclusion criteria as follows. ***IC#1***: Papers clarify smart system components. ***IC#2***: Papers mention ontologies as an important part in the solutions. ***IC#3***: Papers are related to smart service-oriented applications that consider human as service consumers.

The *Backward and forward searches* phase is to find more relevant studies by performing further searches on the references and citations of the selected papers in the previous phase (Webster and Watson 2002).

Table 1 presents the distribution of selected papers. The "first retrieval" denotes the initial number of papers obtained. The next three columns express the results after eliminating irrelevant papers. The following column presents the number of additional papers found through backward and forward searches. The "final list" indicates the number of selected papers. As shown in Table 1, a significant proportion of relevant articles comes from technically focused databases like IEEE and ScienceDirect (61%). This implies that the research topic is more concerned with engineering aspects than with how the system can truly generate business values.

Database	Identification		Abstract screening	Full-text screening	Backward and forward searches	Final list	%
	First retrieval	*Time & language constraint*					
ScienceDirect	31	29	17	6	3	9	23%
AIS Library	487	57	7	3	0	3	8%
IEEE Xplore	81	78	24	15	0	15	38%
ACM Library	115	87	87	4	0	4	10%

Database	Identification		Abstract screening	Full-text screening	Backward and forward searches	Final list	%
	First retrieval	*Time & language constraint*					
ProQuest	28	14	12	6	0	6	15%
JSTOR	12	5	2	2	0	2	5%
Other	0	0	0	0	1	1	3%
Total	**754**	**270**	**74**	**36**	**4**	**40**	**100%**

Table 1. Distribution of selected papers

Classification of selected papers

This section introduces the structure of the table of analysis for the classification of final selected papers, which includes units of analysis (UA), i.e., aspects to be examined (Webster and Watson 2002), classified into four groups: data, information, knowledge management modules (Rowley, 2007), and ontology function. Since the central focus of ontology-based systems is to create, organize, and discover knowledge to generate insights, the classification relies on the DIKW model (Rowley, 2007) has been used for investigating all essential stages, from the initial phase where raw data is collected, to the last phase where the data is transformed into information and knowledge, and then used to create business values.

The first three groups *(Data, Information, and Knowledge management)* address the first research question (RQ#1) about ontology-based smart service systems' elements. *Data management* is concerned with raw databases and/or traditional databases, which are typically based on a tabular structure (relational databases) or non-schema structure (NoSQL databases). This group consists of three units of analysis as follows. Data sources (UA1.1) determine where data comes from. Data processing (UA1.2) involves algorithms or methodologies for acquiring and processing data from data sources. A data repository (UA1.3) is a type of storage unit in an information system. *Information management* is concerned with more meaningful data organized in a well-structured format for knowledge generation. This group includes Ontology modeling (UA2.1), which defines the structure of ontologies; and Ontology elaboration (UA2.2), which deals with populating data into ontology structures. *Knowledge management* is concerned with how to explore ontologies to generate insights (UA3.1. Knowledge reasoning) and how to communicate the reasoning results to users/other systems (UA3.2 Knowledge delivery). Papers are noted by three levels of interests as follows: **(*)** the unit of analysis is mentioned without specification; **(**)** the unit of analysis is mentioned and described in small paragraphs; **(***)** the unit of analysis is clarified in detail.

The last group (*Ontology function*) addresses the second research question (RQ#2) about the functions of ontology in those systems. Full-text reading's results identifies five major types of information modeled by ontologies as follows. *General (G), Domain (D), and Merged* (M) ontologies represent concepts/terminologies that can be independent and reusable across domains (G); dedicated to a specific domain such as agriculture, biology, and smart building (D); or combine concepts from various domains (M). *User ontologies* (U) specifies user data such as user profiles, interests, and needs. *Context ontologies* (C) represent context information such as time, location, user interaction, that can be used to retrieve the most relevant knowledge based on the recognized context.

Table 2 depicts paper classification based on the four groups of analysis units.

Selected papers	Data			Information		Knowledge		Ontology function
	UA1.1	*UA1.2*	*UA1.3*	*UA2.1*	*UA2.2*	*UA3.1*	*UA3.2*	
Ali et al. (2017a)	**	***		***		***		G
Ali et al. (2017b)	***	***	*	***	***	***	**	M
Alian et al. (2018)			*	***	**	***	**	D, U
Andrade et al. (2019)			*	*		***	**	D
Benfares et al. (2017)			***	***		***	*	D, U
Bensassi et al. (2019)	*		*	***		**	**	D, U

Selected papers	Data			Information		Knowledge		Ontology function
	UA1.1	*UA1.2*	*UA1.3*	*UA2.1*	*UA2.2*	*UA3.1*	*UA3.2*	
Cano-Benito et al. (2021)	*			***	**			D
Chang et al. (2020)	***			***	***			U
Chukkapalli et al. (2020)	**	***		***			***	D
Demaidi et al. (2018)				***		***	***	D, U
Fang et al. (2019)	***	***	**	***		***	***	G
Ghazal et al. (2020)	***	***	**	***	***	***	***	G, U
Ginige et al. (2020)			**	**			***	D
Hamim et al. (2021)	*		**	***	**	***		U
Hamrouni et al. (2018)				***		***		G
Huang et al. (2017)	**			**				U
Jiang et al. (2022)			***	***		***	***	D
Ke et al. (2017)				***		***		U
Ouissem et al. (2021)		*	*	***		***	*	G, U, C
Romero et al. (2019)				***		***		G, U
Sayah et al. (2021)	*	***	***	***		***	**	D, U, C
Stefanidi et al. (2022)	**			***		***	***	D, U, C
Teixeira et al. (2020)	*		*	***			**	G
Unhelkar and Arntzen (2020)	*	*	*	*		*		D
Wei and Shao (2022)	*	**		**	***	***		D
Wen et al. (2022)	*	***	***	***		***		D, U
Zehra et al. (2021)	**	**		***	***	***		D
Albatayneh et al. (2018)	*	**	**	**		***	***	U
Ali et al. (2021)	*	***		***	***	***		D, C
Chen et al. (2017)	*		*	*		***	**	G
Elshenawy et al. (2018)	*	*		***	**	***		D, C
Gomolka et al. (2022)			*	***		***		D
Lacasta et al. (2018)	*	**		***	***	*		D
LeClair et al. (2022)				***		***	**	G, D
Sermet (2018)	***	***	**	**	***			D
Verdú et al. (2017)				***	*	***	*	G, D
Aguilar et al. (2018)	*	*	*	***		***		G, U, C
Gayathri et al. (2017)	*	*		**	***	**		D
Soui et al. (2017)				***		**		D, U, C
Gu et al. (2020)	**		**	***		***	*	C, D
Total (papers)	26	18	21	40	14	33	20	G:11, D:25, U:17, C:8, M: 1
Total (weighted) *Weighted = sum of (*)*	42	40	36	108	36	92	44	

Table 2. Classification of selected papers

Analysis of selected papers

Using the aforementioned classification, this section analyzes the chosen papers to further investigate how each unit of analysis has been examined in current literature. The detailed analysis is shown below, according to three groups of analysis units: Data, Information, and Knowledge management (Figure 1). Indeed, the analysis is based on the DIKW hierarchy (Rowley, 2007), which is one of the fundamental and widely recognized models in the information and knowledge management literatures. Furthermore, since ontology structures are highly coupled with their functionality, the analysis of the last group related to ontology functions will be combined with the ontology modeling.

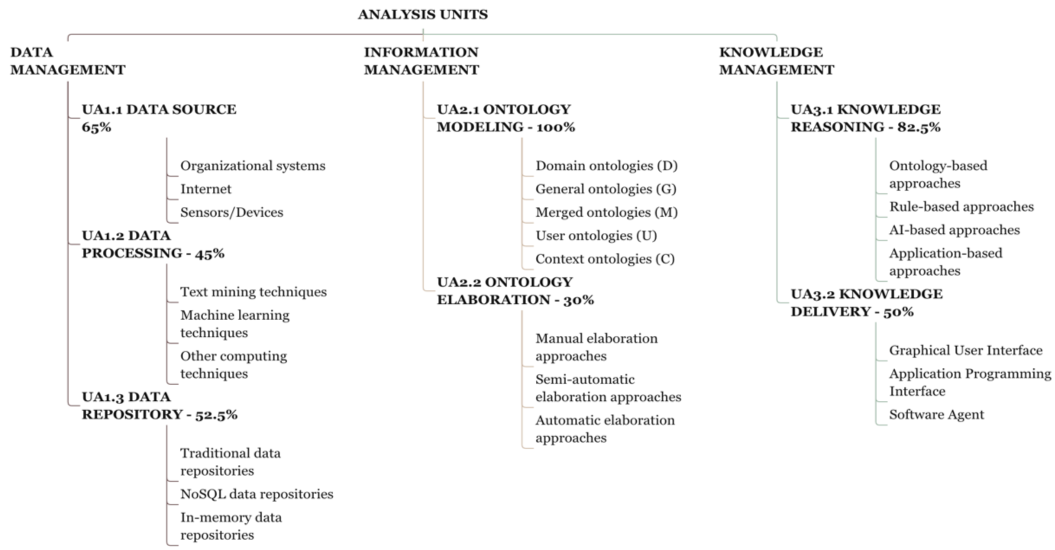

Figure 1. Summary of literature analysis

Data management

The data management received less attention in the field of smart systems, but it remains an important element.

Data source (UA1.1) is discussed in 26 papers (65%). Data can come from *enterprise systems* (documents, datasets), *Internet* (websites, social networks), and *sensors/devices*. For instance, Zehra et al. (2021) concentrate on annual reports as a data source to build a financial ontology. Chang et al. (2020) deal with tutoring system datasets derived from observations of human tutors. Social networks are exploited to obtain user data (Ali et al. 2021; Fang et al. 2019). Sensors or devices can provide raw context data such as time, location (Elshenawy et al. 2018; Gayathri et al. 2017), or event occurrence (Ali et al. 2021).

Data processing (UA1.2) is discussed in only 18 papers (45%). *Text mining* techniques process textual data retrieved from websites, organizational documents, social networks, and other sources. For example, natural language processing (NLP) based solutions (sentence splitter, tokenizer, and name-entity recognition) are used to extract key concepts from enterprise reports (Zehra et al. 2021) or from social network (user tweets, ratings, preferences) for recommendations (Lacasta et al. 2018). *Machine learning techniques* deal with sensor data, image/video data, and text data. For example, deep neuron network is used for extracting enterprise information (roles, tasks, resources) from enterprise documents (Ghazal et al. 2020). *Other computing techniques* such as edge computing (Cao et al. 2020) can also be used to process sensor data (Chukkapalli et al. 2020).

Data repositories (UA1.3) are mentioned in only 21 papers (52.5%). *Traditional data repositories* generally use a tabular structure to store organizational data such as product, supplier, and customer data (Ginige et al. 2020; Hamim et al. 2021). *NoSQL data repositories*, sometimes associated with big data technologies (Sayah et al. 2021; Unhelkar and Arntzen 2020), contain data retrieved from big data sources such as sensors, internet. *In-memory repositories* are auxiliary or intermediate storage that holds data temporarily for later processing (Ghazal et al. 2020).

Information management

The information management is concerned with organizing data in an appropriate manner to facilitate knowledge exploration. To accomplish this goal, the data structure must support discovering relationships between data to gain insights. An ontology-based approach is still the most prominent solution due to its expressiveness and capacity of reasoning (Hertel et al. 2009).

Ontology modelling (UA2.1) receives the most attention in this group, with 40 papers (100%) studying this topic. *Domain ontology* (D) is mentioned in 25 articles to model concepts within a specific field such as smart building (Sayah et al. 2021), agriculture (Chukkapalli et al. 2020; Ginige et al. 2020), finance (Zehra et al. 2021), graphical user interface elements (Stefanidi et al. 2022), and healthcare (Alian et al. 2018). *General ontology* (G), studied in 11 papers, models concepts dedicated to a specific task rather than a specific domain (Fang et al. 2019; Hamrouni et al. 2018; Ouissem et al. 2021; Teixeira et al. 2020). For example, the ontology proposed in Hamrouni et al. (2018) represents abstract concepts related to business models (resource, value proposition, service) across different business sectors. *Merged ontology* (M) combines concepts from various domains (Ali et al. 2017a). *User ontology* (U) has been investigated in 17 papers (Albatayneh et al. 2018; Chang et al. 2020; Hamim et al. 2021). Learner profiles, for example, can help deliver appropriate learning material or services based on learners' learning styles or knowledge level (Ouissem et al. 2021; Romero et al. 2019). *Context ontology* (C) has been investigated in 8 papers (Aguilar et al. 2018; Ali et al. 2021; Soui et al. 2017; Stefanidi et al. 2022). For example, Aguilar et al. (2018) apply the 5W1H abstract model to create a hierarchical context ontology that can be reused across domains.

Ontology elaboration (UA2.2) appears to be less focused, with only 14 papers (30%) considering this topic. Ontology elaboration processes can be done manually, semi-automatically, and automatically. *Manual approaches* are based on the ontology data as the result of expert analysis on a particular domain. For example, in Verdú et al. (2017), teachers annotate data and import it into an ontology structure to ensure that the course objective and syllabus are met. *Automatic approaches* use natural language processing, data mining, or machine learning algorithms to extract information from unstructured data, such as textual data, and then import this data into ontology structure without the need for human intervention. For example, the process of Ali et al. (2017b) uses SVM (Support Vector Machine) to extract textual content from websites for the detection of adult content features. *Semi-automatic approaches* involve both domain experts and algorithms (Cano-Benito et al. 2021; Chang et al. 2020; Ghazal et al. 2020). Several parts of the process are performed or supervised by experts while others are carried out by algorithms (Vu and Tchounikine 2021). In the approach proposed by Chang et al. (2020), association rule mining, a category of data mining techniques, are applied to extract and classify ontology data from a structural data set derived from observations of human tutors.

Knowledge management

The knowledge management module works with reasoning ontologies built in the information module to gain insights (such as knowledge reasoning techniques) and then deliver those insights to users and/or other applications via knowledge delivery mechanisms (i.e., knowledge delivery).

Knowledge reasoning (UA3.1) receives the most attention in this group, with 33 papers (82.5%) on the topic. In *ontology-based approaches*, knowledge reasoning can be performed through query systems based on an ontology query language such as SPARQL (Fang et al. 2019; Lacasta et al. 2022), ontology editors' reasoners such as HermiT, Pellet (Andrade et al. 2019; LeClair et al. 2022), or software modules developed by using third-party providers' built-in libraries such as JenaAPI (Wen et al. 2022). In *rule-based approaches,* reasoning rules, which are used to discover knowledge from ontologies, are defined by humans using a rule language such as SWRL (Semantic Web Rule Language) (Bensassi et al. 2019; Ghazal et al. 2020; Romero et al. 2019; Sayah et al. 2021). *AI-based approaches* deduce new knowledge from ontologies by using data mining or machine learning algorithms such as decision tree for task predicting (Hamim et al. 2021), matrix factorization for knowledge exploitation (Jiang et al. 2022), content-based filtering for post message recommendations in e-learning forums (Albatayneh et al. 2018). *Application-based approaches* propose solutions/algorithms defined by authors to solve their specific application and purpose (Demaidi et al. 2018; Ke et al. 2017). A personalized feedback algorithm, for example, developed by Demaidi et al. (2018) is used to generate questions and feedback based on student profiles and pedagogical content.

Knowledge delivery (UA3.2), which addresses the question of how to deliver knowledge reasoning results to end-users or to integrate with other systems (i.e., communication/interaction module between context-aware system and external actors), has been investigated in 20 papers (50%). *GUI* (Graphical User Interface) is mainly used to interact with end-users (Ouissem et al. 2021; Stefanidi et al. 2022; Teixeira et al. 2020). For example, Stefanidi et al. (2022) use knowledge reasoning results to generate the most appropriate GUI elements for user profiles. *Other solutions such as API* (Application Programming Interface) or *software agent* can also handle communication tasks (Fang et al. 2019).

Discussion

This section presents the research gaps (RG) identified in the previous analysis and propose future research directions to address these gaps. Filling these gaps can provide insights to answer the research questions (RQ) outlined in this paper, which are summarized in Table 3.

RG	Unit of Analysis (UA)	Future work	RQ
RG#1	UA1.1, 1.2, and 1.3	Investigate and then refine data pipelines	RQ#1
RG#2	UA2.1	Clarify context types and context ontology structures	RQ#1, 2
RG#3	UA2.3	Clarify ontology elaboration process	RQ#1
RG#4	UA1.1, 1.2, 1.3, 2.1, 2.2, 3.1, and 3.2	Propose a general framework for ontology-based smart service system conception	RQ#1

Table 3. Summary of research gaps

Research gaps #1. *The importance of data management appears to have been underestimated from the perspective of ontology-based smart service systems.* Data is an essential source of knowledge creation. With the proliferation of data, data management tasks today face many challenges and require further investigation. A potential **future work** is to conduct more in-depth research of processes and major elements of the data management from the perspective of knowledge-based systems. This kind of work allows addressing the research questions such as "What types of processing and data storage techniques should be considered for a typical data format in smart services?", or "How to store and organize various forms of data, enabling a more efficient transformation of data into knowledge bases?".

Research gaps #2. *Context information is critical in smart service systems, but context ontologies have received insufficient attention.* The term "context" originated from ubiquitous computing and mostly refers to low-level context sensed by sensors/devices (Abowd et al. 1999; Gellersen 1999). Sensor context is typically stored temporarily in a simple structure or processed directly without the use of a context model. In the field of information systems, the term "context", also termed as high-level context, refers to any information that can help identify an entity and take actions appropriate to the recognized entity (Perera et al. 2014). Such a context may provide more insightful information, so it should be further investigated. There are several possible **future directions** to fill this research gap, including clarifying context types to cover essential context information in smart services (see, as an example; Aguilar et al. 2018), determining context ontology structures for organizing high-level context information, and studying context mapping to link context to another information for deriving relevant information based on context. This kind of work allows addressing the research question of how to propose suitable services (context-what) to a particular customer profile (context-who) in a specified location (context-where) and time (context-when) ".

Research gaps #3. *There has been less emphasis on the ontology elaboration process (manual, semi-automatic, and automatic process).* Manual approaches can be costly, time-consuming, and potentially error prone. Automatic approaches can be limited if the domain is complex and still requires the intervention of domain specialists to ensure the data rationale. Semi-automatic approaches guarantee the accessibility of both humans and algorithms/software components. One possible **future work** is to study an appropriate solution for constructing ontologies in smart service systems, and then determine main phases and activities of the solution. More specifically, degrees of automation, levels of human involvement, applicable methods, tools for putting the solutions into practice, input sources (like text data from enterprise documents), and outputs of each step in the elaboration process should be clarified.

Research gap #4. *As observed in the literature, few studies clarify the process of designing an intelligent system while considering all essential aspects of data, information, and knowledge management.* Data is only valuable if it is processed in a way that promotes knowledge discovery and generates business value. The transition between these three aspects is critical, as it could potentially enhance communication between engineering and business teams (see, for example; Ghazal et al. 2020). One **future goal** is to propose a framework that clarifies both the structural aspect, which determines essential elements (e.g., software components, algorithms) of ontology-based smart service systems, and the behavioral aspect, which is concerned with how to implement those systems while considering the transfer of data, information, and knowledge to produce business insights.

Conclusion

The major contribution of the paper is the collection, classification, and analysis of pertinent articles on the development and application of smart service systems that use ontologies as their knowledge bases. In terms of engineering implication, such an analysis offers a comprehensive perspective to define the key elements of ontology-based smart service systems, which can serve as a guideline for their future development. In terms of scientific implication, the analysis identifies current challenges, and then recommends potential future research directions for researchers in the domain.

Our upcoming work focuses on developing a comprehensive framework for ontology-based smart service systems, covering all three aspects of data, information, and knowledge management modules. The framework will identify the necessary components and processes and suggest appropriate technologies for implementation. To ensure its usefulness, we will validate the framework in a specific domain such as the banking or education sectors.

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