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Knowledge Element Model and Visual Representation of Government Website Information Resources: Postprint

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Abstract

[Purpose/Significance] This research employs knowledge element model theory to explore optimization paths for improving knowledge service effectiveness on government websites, complemented by visualization representation techniques, to reduce the operational load of information acquisition and cognitive load of knowledge processing for e-government users within big data environments. [Method/Process] Drawing upon related knowledge element model research, this study deduces a six-tuple knowledge element representation method and a four-tuple knowledge element ontology structure that align with the attribute characteristics of government website information resources. TextRank and HDP algorithms are utilized to extract keywords and subject terms from government website information resources, respectively, and domain experts identify knowledge elements based on these extraction results. This study constructs a knowledge element visualization representation model for the domain of government website information resources, encompassing knowledge element ontology library generation and visual knowledge services. [Result/Conclusion] Using a bike-sharing case study published on government websites, the effectiveness and feasibility of the knowledge element visualization representation model are validated. This opens new research perspectives for the transition of government websites from coarse-grained information services to a fine-grained knowledge service paradigm centered on knowledge elements. The visual knowledge service model enhances the structural organization of government information navigation and improves the effectiveness of users' interpretation of domain text semantics.

Full Text

Preamble

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Abstract

[Purpose/Significance] This study employs knowledge element model theory to investigate optimization pathways for knowledge service effectiveness on government websites, supplemented by visualization representation techniques to reduce operational load for information retrieval and cognitive load for knowledge processing among government users in big data environments.

[Method/Process] Based on relevant knowledge element model research, we deduced a six-tuple knowledge element representation method and a four-tuple knowledge element ontology structure that conform to the attribute characteristics of government website information resources. We utilized TextRank and HDP algorithms to extract keywords and subject terms from government website information resources, respectively, and domain experts determined knowledge elements according to the extraction results. Subsequently, we constructed a visual representation model for domain knowledge elements of government website information resources, encompassing knowledge element ontology database generation and visual knowledge services.

[Result/Conclusion] Through a case study of bike-sharing information published on government websites, we validated the effectiveness and feasibility of the knowledge element visual representation model. This approach opens new research avenues for transitioning government website information services from document-level coarse-grained classification to fine-grained knowledge services using knowledge elements as the basic unit. The visual knowledge service model enhances the structured navigation of government information and improves users' ability to interpret domain text semantics.

Keywords: government website information resources; knowledge element; ontology; visual representation

2 Research Status

2.1 Government Website Information Resource Organization

With the rapid development of information technology in China, e-government plays a crucial role in improving administrative efficiency, service delivery, and

management capabilities. In big data environments, government website information resources exhibit characteristics of large volume, rapid updates, broad content coverage, and distributed storage. Effectively organizing and managing these resources to enhance knowledge service capabilities has become a critical research issue in this field. Current theoretical and practical research has achieved certain results, focusing primarily on domain ontologies, cloud computing, topic maps, and linked data. Bouguettaya et al. [3] developed a prototype system for organizing and dynamically managing government data and electronic services based on distributed ontology models. Prokopiadou et al. [4] proposed a knowledge ontology-oriented approach for managing and disseminating government public information resources. Chinese scholars Gao Jie and Li Jiawei [5] and Geng Ruili [6] utilized government thesauri to construct domain ontologies for organizing government information resources. Deng Feng et al. [7] built a cloud computing-based framework for integrating government information resources, elaborating on three processes: resource pool construction, cloud platform development, and service implementation, while proposing solutions to existing platform problems. Lü Yuanzhi [8] constructed a theoretical model for e-government information resource sharing using cloud computing, comprising a resource layer, management middleware layer, and service layer, thereby promoting the application of cloud computing in government information resource management. Zhang Yutao and Xia Lixin [9] developed a topic map-based integration model for e-government information resources and demonstrated the integration process in a Metamorphosis topic map environment. Additionally, applying linked data [10] to achieve semantic-level organization of government information resources provides a new research direction for this field.

2.2 Knowledge Element Research

Changes in information technology, social environments, and cognitive demands have triggered transformations in knowledge organization methods, representing an inevitable outcome of the big data era. This has expanded research and applications of knowledge element-based organization and mining across multiple disciplines, including library science, information and archive management, computer science, education, and medicine. Wen Youkui [11] proposed a navigation transformation theory between knowledge elements and guide information, clarifying the attribute characteristics of knowledge elements in knowledge structures, their navigation linking functions, and the value-added transformation patterns of knowledge element-guide information combinations, laying a theoretical foundation for knowledge organization, retrieval, and integration using knowledge elements as units. Jiang Yongchang et al. [12] constructed knowledge networks and semantic webs using knowledge elements as basic units and knowledge links, elaborating on the service functions of knowledge elements in knowledge discovery, innovation, mining, and evaluation. Wang Yu and Li Xiuxiu [13] used knowledge elements as the smallest units for organizing literature knowledge, achieving journal literature organization and retrieval through knowledge element representation, extraction, classification, linking, and knowl-

edge base construction. Bi Chongwu et al. [14] analyzed user needs for multi-granularity knowledge services in digital libraries and constructed a knowledge element-based service model, demonstrating that this method effectively provides hierarchical, multi-granularity knowledge resources to meet diverse user needs. Additionally, knowledge element organization plays important roles in tacit knowledge discovery [15] and risk prediction and assessment [16].

In summary, current research on government website information resource organization has made progress, but knowledge retrieval, organization, and utilization still follow a coarse-grained information service model using documents as control units. Drawing on successful experiences from other domains and combining them with the characteristics of government website knowledge structures, this study constructs a knowledge element model for government website information resources and employs visual representation to present structured content to users, reducing cognitive barriers in knowledge acquisition and promoting efficient circulation of government website information resources.

3 Government Website Information Resource Knowledge Element Model Construction

Government website information resources are described and stored in data formats, but computers cannot directly recognize knowledge in natural language. Symbolic representation through domain knowledge models is necessary. Using knowledge elements to represent domain knowledge of government website information resources and describing domain knowledge structures through relationships between knowledge elements facilitates a shift from document-level to knowledge element-level organization, achieving efficient knowledge management.

3.1 Government Website Information Resource Domain Knowledge Element Representation

Government website information resources exhibit characteristics of shareability, replicability, regenerability, and carrier inseparability [18]. Knowledge elements constitute the smallest units of domain knowledge, and unified representation standards can effectively integrate resources and promote effective knowledge acquisition, storage, and utilization. With deepening research in knowledge management and services, scholars have proposed various knowledge element models based on domain attributes, including binary, ternary, quintuple, and septuple structures, as shown in Table 1 .

Table 1 Knowledge Element Representation Methods

Knowledge Element Model	Knowledge Element Attributes
Zhou Ning et al. [19]	Object name, attribute set, state set
Wen Youkui et al. [20]	Concept, relationship, problem
Gao Guowei et al. [21]	Link, source, name, function, content
Bi Jingyuan et al. [22]	Knowledge element ID, knowledge name, keyword set, brief description, knowledge category, knowledge level, knowledge address
Yu Yang [23]	(Similar attributes as above)

This study synthesizes the above knowledge element models and combines them with the core metadata standards from China's "Government Information Disclosure Catalog System Implementation Guidelines (Trial)" [24] to propose a six-tuple knowledge element representation:

$$KE = \langle I, T, K, D, C, O \rangle$$

where KE represents a knowledge element, and I, T, K, D, C, O represent identifier, title, keywords, description, category, and online location, respectively:

- **Identifier (I):** A unique identifier for disclosed information, primarily used in cross-regional and cross-departmental government information disclosure and sharing systems to ensure each piece of information has a unique ID.
- **Title (T):** The name of government disclosed information, providing a high-level summary of published content.
- **Keywords (K):** Terms reflecting the content characteristics of government disclosed information, including subject keywords and location keywords.
- **Description (D):** A summary of government disclosed information content, including policies, regulations, government announcements, and work updates. This attribute is crucial for users to obtain precise knowledge content and improve knowledge retrieval and utilization efficiency.
- **Category (C):** Labels indicating the category of government disclosed information, including category names and classification codes. Government information resource classification methods include subject classification, organizational classification, genre classification, and service object classification.
- **Online (O):** The uniform resource identifier for government disclosed information online, marking the information source location. Users can access complete information content through the website address.

3.2 Government Website Information Resource Knowledge Element Ontology Structure

Y. Yao et al. [25] noted that semantic knowledge retrieval systems organize data not through indexing but through knowledge element connections. Establishing a knowledge element ontology for government website information resources reveals complex semantic relationships between knowledge elements and clarifies their attributes and structures, forming the foundation for semantic knowledge retrieval. The knowledge element ontology database comprises a relational feature database, a metadata information database, and a knowledge element semantic graph. The relational feature database stores various relationships between knowledge element ontologies, including parallel, associative, and containment relationships, forming the basis for knowledge element communication and reasoning. The metadata information database stores data types of knowledge element ontologies. The knowledge element semantic graph consists of internal knowledge element entities and external inter-element relationships. The knowledge element structure can be described as a four-tuple [4]:

$$k = \langle c, p, m, r \rangle$$

where k represents a knowledge element ontology element, c represents a domain concept, p and m are sets of attributes and methods on concept c , respectively, and r is a set of relationships established between c and other concepts. Based on this description, if a knowledge element ontology consists of n elements, then the concept set $C = \{c_1, c_2, c_3, \dots, c_n\}$, attribute set $P = \{p_1, p_2, p_3, \dots, p_n\}$, method set $M = \{m_1, m_2, m_3, \dots, m_n\}$, and relationship set $R = \{r_1, r_2, r_3, \dots, r_n\}$ together form a directed graph $G = \{X; E\}$, where X is the vertex set and E is the edge set. The value domain of X is the concept set C , and the value domain of E is the relationship set R , as shown in Figure 1 [Figure 1: see original paper].

Given the dynamic updates and growth of government website information resources, knowledge element ontology structures and relationships evolve accordingly. Due to limitations in automated ontology updating technology, domain expert intervention is required during the evolution process to ensure efficiency and accuracy. The introduction of knowledge element ontologies clarifies the position of knowledge elements within domain ontologies and enables combinatorial linking between knowledge elements, which is critical for achieving knowledge element visualization of government website information resources.

4 Government Website Information Resource Knowledge Element Extraction and Visualization

4.1 Government Website Information Resource Knowledge Element Extraction

Knowledge element extraction is a prerequisite for knowledge storage, management, and visualization of government website information resources. Based on keywords from government information resources, knowledge elements are identified by determining whether they contain knowledge elements. Since government website information resources involve relatively single-domain knowledge corpora, extraction results may suffer from high keyword redundancy and difficulty in topic clustering. This study combines keyword and topic model approaches, comparing and analyzing extracted keywords to obtain more comprehensive domain knowledge elements.

4.1.1 TextRank Keyword Extraction The primary goal of keyword extraction is to automatically identify words that express the main topics of a document. The most typical keyword extraction algorithm is the TextRank algorithm [26] based on lexical co-occurrence graphs. TextRank evaluates the weight of each lexical node in the co-occurrence graph based on the assumption that the more important a lexical node is, the more important its connected nodes are. Words with higher weights are more likely to express the document's main idea, so keywords are determined based on weight ranking. The basic extraction process is shown in Figure 2 [Figure 2: see original paper].

The algorithm proceeds as follows: 1. Segment text T into sentences: $T(S_1, S_2, \dots, S_m)$. 2. Perform word segmentation and stop-word filtering for each sentence $S_i \in T$ to obtain sentence and word sets. 3. Construct a candidate keyword co-occurrence graph $G = (V, E)$, where V is the node set consisting of candidate keywords, and E is the edge set consisting of connections between co-occurring words. With window size K , if a sentence consists of words $w_1, w_2, w_3, \dots, w_n$, then $[w_1, w_2, \dots, w_k]$, $[w_2, w_3, \dots, w_{k+1}]$, ..., $[w_{n-k+1}, w_{n-k+2}, \dots, w_n]$ each form a window. Any two lexical nodes within a window are connected, forming an undirected, unweighted graph. 4. Calculate weight $S(V_i)$ for each word using formula (1) to iteratively compute the weight of any word V_i in the text, where d is a damping coefficient (typically 0.85), and the initial value of $S(V_i)$ is set to 1. Iteration stops when the weight difference for any node is less than 0.0001.

$$S(v_i) = (1 - d) + d \times \sum_{j \in In(v_i)} \frac{S(v_j)}{|Out(v_j)|}$$

5. Rank nodes by weight $S(V_i)$ and select the top T words as the document's keywords.

4.1.2 HDP Model Topic Division Y. W. Teh proposed the HDP (Hierarchical Dirichlet Process) model [27] in 2005 based on DP (Dirichlet Process). Compared to the mainstream LDA topic model, HDP offers advantages in handling highly sparse data, automatically generating topics, and enabling dynamic topic evolution. Single documents in government website information resources typically reflect multiple thematic contents. Relying solely on sentence importance or keyword extraction may result in incomplete information that fails to fully reflect all themes in a document. To extract comprehensive domain knowledge elements, topic division is necessary. When processing large text data, the HDP model can mine deep semantic meanings and automatically determine the number of topics, improving extraction accuracy. The extraction process is shown in Figure 3 [Figure 3: see original paper].

The procedure includes: 1. Preprocess the target document set through word segmentation, stop-word filtering, and constructing word frequency features. 2. Perform HDP topic analysis on the document collection to determine the weights of N topics in the documents. Select specific topic words based on the weights of candidate topic words within each topic. Topic T can be represented as:

$$T = (w_0, v_0; w_1, v_1; w_2, v_2; \dots; w_n, v_n)$$

where $T(topic)$ represents a topic containing n topic words, $w_n(word_n)$ represents a topic word, and $v_n(value_n)$ represents the word's weight in the topic. 3. Rank topics by contribution degree. Extract keywords using both TextRank and HDP algorithms, perform manual comparative analysis to establish a keyword set, and have domain experts determine knowledge element attributes according to the six-tuple representation method for government website information resources. Store complete knowledge elements in the knowledge element ontology database.

4.2 Government Website Information Resource Domain Knowledge Element Visualization Representation Model

Cognitive psychology suggests that information organization and external representation directly affect human cognition, understanding, and internalization [28]. Visualization representation can structurally organize information resources bearing knowledge, facilitating holistic and intuitive understanding and promoting knowledge acquisition, construction, application, and dissemination. Knowledge visualization uses visual means to construct and convey knowledge and complex semantic relationships between knowledge units, which helps enhance government website knowledge service capabilities and application value. Based on knowledge element model theory and visualization concepts, we constructed a domain knowledge element visualization representation model for government website information resources, consisting of a knowledge element ontology database generation module and a visual knowledge service module, as shown in Figure 4 [Figure 4: see original paper].

4.2.1 Knowledge Element Ontology Database Generation Module Constructing a knowledge element ontology for government website information resources is fundamental to semantic retrieval. The knowledge element ontology describes resources themselves and rich semantic relationships between resources, enabling computer-understandable semantics. Using the aforementioned keyword and topic clustering methods, we extract metadata from government website information resources. After manual comparison and screening, a keyword set is formed, and domain experts select domain ontology templates for knowledge element annotation. Due to limitations in automated annotation technology, we currently employ semi-automatic annotation methods. Based on annotation results, knowledge elements are obtained and a temporary knowledge element database is established. Reasoning algorithms perform dynamic inference on the temporary database, and after manual identification and correction of imperfect or unreasonable knowledge elements, they are stored in the knowledge element database. The ontology editor interface provides users with semantic annotation context information, allowing and encouraging user participation in information exchange and sharing to acquire and generate new knowledge elements, continuously updating the knowledge element database [1].

4.2.2 Visual Knowledge Service Module Government website knowledge visualization services are built upon deep information understanding, analysis, and mining. To improve knowledge retrieval accuracy, this study visualizes domain knowledge elements of government website information resources based on knowledge element model theory, knowledge graph concepts, and visualization technologies. Preparatory work includes algorithm selection, threshold setting, time segmentation, and network layout. Algorithm selection may employ clustering algorithms (e.g., K-means, spectral clustering), association strength measures (e.g., BTM, HD, Jaccard), and feature weighting methods (e.g., TF-IDF, MI). Time segmentation can be based on analysis year nodes, and network layout can use algorithms such as visio, 2D/3D Fruchterman-Reingold, MDS, and Kamada-Kawai to calculate distances between semantically similar knowledge elements in co-occurrence networks, helping users understand knowledge content in the knowledge element database. The aforementioned algorithms and functions are used for automatic tagging to generate various types of visual knowledge graphs.

Users can issue queries using subject terms or keywords. The government website information system decomposes the request into a query command sent to the knowledge element database, matches corresponding knowledge elements based on the search task, and generates visual knowledge graphs [29] demonstrating keyword co-occurrence, information source organizations, government information themes, and domain categories using the aforementioned algorithms and visualization tools. Users then provide feedback on service satisfaction based on query results.

5 Case Study

Bike-sharing, as a typical representative of the sharing economy innovation model in the mobile Internet environment, plays a positive role in solving traffic congestion and short-distance public transportation connections. According to the 2017 Bike-Sharing White Paper, bike-sharing has spread to over 50 cities in more than 20 provinces and autonomous regions. Aurora Big Data also shows that by December 2017, user numbers for the two major bike-sharing giants, Ofo and Mobike, reached 26.93 million and 23.782 million, respectively [30]. However, bike-sharing has also brought numerous issues including safety hazards, accident liability determination, fund management, bicycle parking, market operation order, and technical problems. In Shanghai alone, consumer complaints related to bike-sharing reached 7,978 cases in 2017 [31]. Regulating orderly bike-sharing operations and development has become a hot issue of widespread concern to the government and the public. Therefore, this study collected relevant content from government websites on “bike-sharing” and “Internet shared bicycles” as experimental data.

5.1 Data Selection and Preprocessing

To ensure data comprehensiveness and accuracy, we selected only URLs with the “gov.cn” domain. Using “bike-sharing site:gov.cn” and “Internet shared bicycle site:gov.cn” as search keywords, we retrieved relevant documents through Baidu up to March 20, 2018, obtaining 1,131 entries. We used Python to crawl the corresponding URLs and filtered them: webpages whose URLs did not contain “htm,” “asp,” or “php” were generally dynamic pages without useful content and were therefore excluded. The webpage structure includes navigation bars, main content sections, and comment sections. For analysis, we employed the Harbin Institute of Technology’s general webpage content extraction algorithm based on line block distribution functions [32] to extract only the main content. Additionally, some websites could not be crawled due to firewalls or page failures, and these were excluded from the analysis. After filtering, 797 webpages were obtained. During text preprocessing, we used the jieba segmentation tool and employed the Harbin Institute of Technology’s Information Retrieval Laboratory’s general stopword list to filter stopwords.

5.2 Experimental Process

5.2.1 Keyword and Topic Extraction We used the TextRank algorithm to extract keywords from 797 bike-sharing documents, calculating each word’s importance in the co-occurrence graph. The top 30 words were selected as domain keywords. Since computer extraction results contained redundant and useless terms, manual correction was performed (removing regional words, quantifiers, etc.). Keyword statistics were based on document frequency—if a keyword

appeared in a document (regardless of frequency), it was counted once. The statistical results are shown in Figure 5 [Figure 5: see original paper] and Figure 6 [Figure 6: see original paper].

To obtain more comprehensive and accurate domain knowledge, in addition to TextRank, we used the HDP topic model algorithm for topic modeling on the bike-sharing text corpus. Since HDP does not require specifying the number of topics and automatically learns topics from the corpus, it significantly improves the accuracy of topic extraction from large-scale government documents. We used the open-source topic analysis toolkit gensim to analyze the bike-sharing corpus, extracting the top 20 topics and topic words by intensity and contribution. After manual identification, 30 topic words under 3 topics were determined, as shown in Table 2 .

Comparing bike-sharing keyword and topic extraction results shows that keyword extraction basically covers topic words representing the domain's themes. We ultimately identified three themes: bike-sharing public services, operation and maintenance supervision, and governance measures, along with 30 domain keywords: sharing, management, enterprise, problem, parking, travel, regulation, Internet, deployment, service, operation, user, government, behavior, traffic, safety, information, responsibility, deposit, credit, standard, measure, fund, economy, policy, intelligence, theft, damage, charging, and real-name.

5.2.2 Knowledge Element “Description” Attribute Extraction

Through preprocessing, keyword extraction, and topic identification, we obtained domain-related themes and keywords. Since computer-based domain knowledge classification and identification have certain biases, manual intervention is required during extraction. The extraction of knowledge element attribute D (description) forms the basis for acquiring other attributes. Therefore, this case study focuses on D extraction and introduces the extraction approach for other attributes. Using “fund” in bike-sharing documents as an example, we constructed knowledge element attributes:

- **I (Identifier):** Information identification code.
- **T (Title):** The knowledge element name—fund.
- **K (Keywords):** Based on domain corpus keyword extraction and manual screening, high-frequency words are selected as the keyword set. For the fund knowledge element: deposit, dedicated use, joint custody, credit system.
- **D (Description):** Encourage deposit-free services and establish credit systems; deposit and refund immediately; establish dedicated accounts for dedicated use with joint financial institution supervision.
- **C (Category):** Knowledge category extraction is relatively complex and requires combining domain ontology division. Bike-sharing belongs to the transportation category, while fund is a sub-category, and fund management can also be considered a financial domain category—this represents a key focus for subsequent research.

- **O (Online):** The knowledge address attribute is the hyperlink to the knowledge element source. Due to the thematic distribution characteristics of government documents, which involve multiple themes, extracting this attribute requires redundancy removal and clustering based on knowledge element content attributes.

5.3 Bike-Sharing Domain Knowledge Element Visualization

Based on the extraction principles of bike-sharing knowledge element content attributes and the government website information resource domain knowledge element visualization representation model, we constructed a bike-sharing domain knowledge element visualization navigation map, as shown in Figure 7 [Figure 7: see original paper].

The bike-sharing knowledge element visualization navigation map uses nodes of different colors and sizes and connecting lines expressing semantic relationships to clearly display domain knowledge content and structure. This hierarchical structured representation using knowledge elements as nodes and semantic relationships as connections facilitates users' intuitive and accurate retrieval and browsing decisions. Users can simply click on target knowledge nodes to browse matching knowledge content in a one-click or one-stop manner. Knowledge element visualization of government website information resources enables knowledge discovery, integration, and dissemination services that maximize user cognitive needs. Domain knowledge element structured navigation conforms to the principle of least effort for user operations, improves retrieval precision, and effectively promotes information interaction efficiency.

6 Conclusion

The multi-source, heterogeneous, and dynamic growth characteristics of government website information resources, combined with the coarse-grained information service model of government webpages, hinder efficient and accurate information acquisition and interpretation by government users. This study investigated a fine-grained knowledge service paradigm for government website information resources from the perspective of knowledge elements—the smallest knowledge units. By integrating knowledge element model theory and knowledge visualization concepts, we constructed a knowledge element visualization representation model for government website information resources. The bike-sharing case study validated the model's feasibility, demonstrating its effectiveness in improving knowledge circulation efficiency, discovery probability, and service accuracy for government website information resources. This provides a new research path for knowledge organization and services on government websites. Future work will focus on designing and developing a prototype system for knowledge element visualization based on this model.

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Wang Meiyue: Responsible for research design, data collection and analysis, and paper writing.

Wang Yicheng: Responsible for literature collection and paper revision.

Huang Xinping: Responsible for paper revision and framework adjustment.

Note: Figure translations are in progress. See original paper for figures.

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