Constructing a Concept Flow Model for Knowledge Evolution: A Case Study of "Data Management and Data Science"

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Abstract

[Purpose/Significance] Addressing the current need for constructing an autonomous knowledge system for the first-level discipline of Information Resource Management, this study constructs a concept flow model oriented toward knowledge evolution. [Method/Process] Based on a collection of academic papers that represent concepts, it employs paper frequency statistics and bibliometric methods to describe important characteristics such as flow velocity and density of concepts, introduces the Reynolds number from fluid mechanics to construct a domain concept flow model, and distinguishes three distinct flow patterns: laminar flow, transitional flow, and turbulent flow. Finally, taking "Data Management and Data Science" as an example, it demonstrates the fundamental processes and characteristics of domain concept flow. [Results/Conclusions] Empirical research demonstrates that the domain concept flow model proposed in this paper can reveal the characteristics and phenomena of concept flow within a domain: concepts within a domain typically exist in an orderly laminar flow state during the emergence stage, exhibit alternating transitions between laminar and turbulent flow during the development stage, conforming to the law of spiral ascent in the development process of phenomena, until reaching a stage of suspension or demise. [Limitations] This study only selects some core concepts from the second-level discipline of "Data Management and Data Science" for empirical analysis, and has not yet extended to various second-level disciplines within the first-level discipline of Information Resource Management.

Full Text

Research on the Construction of a Conceptual Flow Model for Knowledge Evolution: A Case Study of "Data Management and Data Science"

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Abstract

[**Purpose/Significance**] In response to the demand for constructing an autonomous knowledge system within the primary discipline of information resource management, this study develops a conceptual flow model oriented toward knowledge evolution. [**Method/Process**] Based on a collection of academic papers representing concepts, we employ paper frequency statistics and bibliometric methods to characterize important features such as flow velocity and density of concepts. We introduce the Reynolds number from fluid mechanics to construct a domain conceptual flow model that distinguishes three distinct flow patterns: laminar flow, transitional flow, and turbulent flow. Finally, using "Data Management and Data Science" as an empirical case, we demonstrate the fundamental processes and characteristics of conceptual flow within a domain. [**Results/Conclusion**] Empirical research shows that the proposed domain conceptual flow model can effectively reveal the features and phenomena of conceptual flow within a domain: concepts typically exist in an orderly laminar state during their emergence phase, exhibit alternating patterns of laminar and turbulent flow during their development phase—consistent with the spiral ascent pattern of developmental processes—and eventually reach a pause or extinction phase. [**Limitation**] This study only selects a subset of core concepts from the secondary discipline of "Data Management and Data Science" for empirical analysis and has not yet extended to various secondary disciplines within the primary discipline of information resource management.

Keywords: Knowledge Evolution; Conceptual Flow; Measurement Model; Data Management; Data Science

In the era of the knowledge economy, knowledge creation and dissemination have become core drivers of social progress and technological innovation. However, knowledge is not a static entity but rather exists in a state of continuous evolution and flow. This evolution manifests not only in the dissemination and interaction of knowledge across different domains and among different actors but also in the self-renewal of knowledge itself. Therefore, in-depth research on the laws of knowledge evolution is of great significance for understanding the essence of knowledge development, optimizing knowledge management, and promoting knowledge innovation.

As an important branch of information science, traditional bibliometrics has gradually evolved into sub-disciplines such as scientometrics, informetrics, and webometrics during its development [?, ?]. The unit of measurement has shifted from document units to information units—encompassing both external and surface-level features of documents—and subsequently to more fine-grained document content units and deeper knowledge units [?]. Knowledge units consist of concepts and relationships between concepts, representing one of the primary research objects in modern information science and informatics. From a philosophical perspective, concepts are considered thought units composed of extension and intension [?]. In this study, concepts serve as the basic semantic units of knowledge and fundamental elements of knowledge units. The development of domain concepts reflects the process of knowledge accumulation and deepening, representing a crucial factor influencing knowledge evolution.

In recent years, the development of interdisciplinary fields such as complex networks, information science, and computer science has provided new perspectives and methods for studying knowledge evolution. Among these, the conceptual flow model has emerged as a novel research tool that reveals the micro-structures and dynamic laws of knowledge evolution by capturing fine-grained dynamic interactions between concepts. However, research on conceptual flow models remains in its infancy, particularly regarding model construction, which still requires further exploration.

This paper addresses two research questions concerning the development processes of different concepts within a domain: (1) How do concepts flow within a domain? We aim to describe the main characteristics of concepts as they change over time, thereby revealing dynamic evolutionary trends of knowledge at the conceptual level. (2) What contributions does this conceptual flow theory make to the construction of domain knowledge systems? To answer these questions, we introduce indicators from fluid mechanics—including fluid flow velocity, density, and dynamic viscosity—combined with the Reynolds number formula to construct a domain conceptual flow model. Using a set of concepts related to "Data Management and Data Science" as an empirical case, we seek to reveal conceptual flow phenomena within a specific domain and capture the subtle characteristics of these concepts as they change over time from a micro perspective, thereby illuminating the dynamic evolutionary trends of knowledge within the domain at a more granular level.

2.1 Related Research on Knowledge Evolution

Knowledge management theory originated in the 1980s, emerging as a novel management philosophy and methodology as enterprises gradually increased their emphasis on knowledge resources. Notable distinctions exist between research on "knowledge management" in management science versus information science. Information science studies knowledge elements as basic knowledge units with complete knowledge representation, composed of concepts and their relationships, whereas management science research on knowledge does not include relationships between knowledge units. Consequently, their research content, methods, and focuses differ substantially. Therefore, this paper analyzes and reviews representative achievements in knowledge evolution research across three dimensions: different research domains, different research subjects, and different research theories and methods.

In library and information science, research subjects primarily focus on disciplines or domains, encompassing both static descriptions of knowledge structures—covering concepts, components, types, construction, and detection methods of domain knowledge structures [?, ?]—and analyses of dynamic knowledge evolution. Research methods have evolved from early knowledge maps [?] to knowledge networks [?] and knowledge graphs [?]. Knowledge networks can be further categorized into citation networks [?] and collaboration networks [?] based on different construction methods. These various visual representations of knowledge structures form the cornerstone for subsequent knowledge structure measurement and knowledge evolution analysis. In management science, research primarily examines knowledge dissemination, evolution, and innovation among different subjects—including individuals, organizations, and society—covering model construction, influencing factors, and effectiveness evaluation [?]. Common models include the SECI model [?], knowledge dynamics model [?], knowledge spiral model [?], knowledge flow lifecycle model [?], and knowledge flow causal model [?].

Furthermore, some scholars in library and information science and management science have attempted to introduce theoretical achievements from the physical world to study knowledge in the objective knowledge world, constructing models around relevant theories and analyzing them from perspectives such as evolutionary trends, dynamic mechanisms, influencing factors, and effectiveness evaluation. For example, Wu et al. [?] constructed an SIRS model based on the infectious disease model in biology, revealing through stability analysis that knowledge flow tends toward equilibrium. Ye et al. [?] developed a dynamic model of interdisciplinary knowledge exchange from an ecological and physics perspective, identifying the magnitude of driving forces for interdisciplinary knowledge exchange and hotspots for such exchange. Li et al. [?, ?] introduced physics theorems such as potential energy and kinetic energy theorems to study interdisciplinary knowledge flow phenomena. Li and Zou [?] borrowed fluid mechanics models to analyze the dynamic mechanisms of knowledge flow.

These researchers have introduced theoretical achievements from the physical world into the study of knowledge in the objective knowledge world. This interdisciplinary approach not only enriches research perspectives and approaches in knowledge management but also provides new methods for understanding knowledge flow, dissemination, and evolution.

2.2 Changes in Knowledge Granularity

The aforementioned research achievements are based on knowledge or knowledge carriers, encompassing diverse research subjects, domains, theories, and methods, and yielding rich research outcomes. Through in-depth investigation of their content, we find that knowledge elements comprise multiple layers ranging from fine-grained to coarse-grained, including terms, keywords, and subject headings, which collectively constitute a rich hierarchy of knowledge expression. The content and interrelationships of different granularities are as follows:

The smallest conceptual unit in knowledge structure is terms extracted directly from documents to reveal the essence and characteristics of knowledge. Keywords, such as high-frequency terms, highly cited documents, core authors, or journals, are selected using frequency or other criteria to reflect the main features of domain knowledge. Based on these, larger-grained units are extracted and aggregated, such as research themes formed by clustering fine-grained academic units according to certain rules [?]. These represent the most core content level of disciplinary knowledge structure and can reflect research hotspots and development trends within a domain. For example, Zhou et al. [?] constructed a conceptual model for conceptual evolution analysis to reveal the evolution characteristics of China's intelligence and informatics discipline. Shao and Li [?] proposed a method for detecting interdisciplinary knowledge structures based on citation coupling and concept lattices. Liu and Wu [?] used library and information science as an example to propose a method for detecting disciplinary knowledge structures based on formal concept analysis.

However, current research on knowledge structure and dynamic evolution suffers from issues of localization, fragmentation, and insufficient holism. This is particularly evident in that scholars primarily focus on larger-grained knowledge points to detect knowledge structures or reveal research hotspots and directions, while few researchers approach the topic from finer-grained conceptual units to conduct further studies on concepts and their movement. After Han et al. first proposed conceptual flow, they briefly explained the meaning of knowledge and concepts, forms of movement, and laws of motion, verifying the effectiveness of logistic growth laws in describing information or knowledge growth [?], and proposed a theoretical model of diachronic conceptual flow based on verifying the existence of conceptual flow [?]. Building on this, conceptual flow in this study refers to the dynamic evolution process of concepts within a domain over time. By constructing a conceptual flow model to classify movement patterns of concepts within a domain, we reveal the laws of conceptual movement from a morphological perspective and grasp dynamic evolutionary trends of knowledge.

3 Domain Conceptual Flow Model

We posit that conceptual flow shares similarities with fluid flow, manifested in the following aspects: First, both fluids and concepts can flow—the former being liquid flow, the latter being thought flow [?]. Second, concepts, as semantic entities, possess corresponding forms and laws of motion in the objective knowledge world, involving various movement modes such as concept splitting, integration, migration, and transformation [?]. Third, both are subject to forces that promote and hinder their flow during movement. Therefore, we believe that fluid theory can be borrowed to establish a conceptual flow analysis model. The following sections elaborate on the basic assumptions, model construction, practical significance, and limitations of the conceptual flow model.

3.1 Basic Assumptions of the Conceptual Flow Model

(1) Fluid Density ρ: In fluid mechanics, fluid density describes the mass of substance per unit volume, and its distribution in space can be non-uniform, influenced by factors such as temperature and pressure. Changes in these factors cause density variations, and these changes are continuous in space. Therefore, fluid density can be regarded as a continuous function. In probability theory, the probability density function is a continuous function used to describe the probability distribution of random variables over continuous intervals, indicating the likelihood of a random variable taking values within a certain interval. Probability values are influenced by the distribution characteristics of random variables, and different distribution characteristics lead to different probability density functions.

Based on the similarity between these two concepts in describing system states and distribution characteristics, this study draws an analogy between fluid density and the probability of a continuous random variable taking values within a certain interval. The measurement of concept density is calculated by statistically determining the probability of an object's occurrence within a certain time interval, i.e., through the probability density function of paper frequency. The specific calculation process is as follows:

Assume there are sample data points $x_1, x_2, ..., x_n$ from different unknown probability density functions. To obtain the probability density function $f(x)$ from observed sample data, there are two methods for probability density estimation: one is a parametric method that assumes the data follows a known distribution, such as a normal distribution with known mean μ and variance σ^2; the other is a non-parametric method, such as histogram density estimation and kernel density estimation.

Based on the observed data distribution, different probability density estimation methods are employed to estimate the unknown probability density function $f(x)$ of multiple continuous random variables X using a finite number of sample data points $x_1, x_2, ..., x_n$, thereby obtaining the distribution function $F(x)$ to describe the distribution characteristics of continuous random variables, as shown in Equation (1).

$$f(x) = \frac{dF(x)}{dx}$$

$f(x)$ is the probability density function of continuous random variable X, simply called probability density, denoted as $X \sim f(x)$, satisfying non-negativity $f(x) \geq 0$ and normalization $\int_{-\infty}^{+\infty} f(x)dx = 1$.

If the paper occurrence frequency at time t_1 is a, and at time t_2 is b, then the probability ρ of this random event falling within the value interval (a, b) can be calculated, i.e., the interval probability $P(a < X < b)$, indicating that the probability of a random variable taking values within a certain interval equals the integral of the probability density function over that interval, as shown in Equation (2).

$$\rho = P(a < X < b) = \int_a^b f(x)dx$$

Integrating the probability density function over (a, b) has the geometric meaning of the area under the curve, representing the probability that the random event's value falls within this interval.

(2) Flow Velocity v: Fluid flow velocity describes the distance fluid moves per unit time, while conceptual flow velocity reflects the rate of change in concept occurrence frequency within a specific time period. It can be measured by tracking changes in the number of papers representing a certain concept within a paper collection over time, as shown in Equation (3).

$$v = \frac{b - a}{\Delta t}$$

where b represents the paper occurrence frequency at time t_2, and a represents the frequency at time t_1. A larger v indicates faster changes in paper quantity, suggesting rapid concept propagation and active conceptual flow within an academic domain.

(3) Fluid Characteristic Length L: The number of papers L that a journal collection can publish over time interval Δt can be regarded as the characteristic length of conceptual flow, as shown in Equation (4). This is because journals, as platforms for knowledge dissemination and exchange, define the region and boundaries of conceptual flow, as well as the upper limit of paper quantity within a paper collection representing a certain concept within a given time period. More journals available for publication imply broader involvement in research domains, researcher communities, and research outcomes.

$$L = \sum_{i=1}^{n} l_i$$

where l_i represents the upper limit of publication volume for journal J_i over time interval Δt.

(4) Fluid Dynamic Viscosity μ: Fluid dynamic viscosity describes the internal resistance that hinders fluid flow, while concept dissemination also encounters various resistances, such as cognitive barriers and cultural differences.

The reciprocal of the impact factor μ_i of journal J_i can serve as an indicator to measure the resistance to academic paper dissemination, as it reflects the difficulty of journal articles being accepted and cited. Therefore, conceptual dynamic viscosity μ can be understood as the reciprocal of the weighted average impact factor of the journals involved, representing the magnitude of resistance encountered during concept dissemination, as shown in Equation (5).

$$\mu = \left(\sum_{i=1}^{n} \frac{s_i}{S} \cdot \mu_i \right)^{-1}$$

where s_i represents the number of papers belonging to journal J_i, S represents the total number of papers over the time interval, and μ_i represents the impact factor of journal J_i.

Different dissemination media, such as the reputation of academic journals, have varying effects on the efficiency and effectiveness of knowledge dissemination. If a journal has a higher impact factor, concepts are more easily accepted and disseminated, resulting in a lower viscosity coefficient. Conversely, if certain knowledge is difficult to understand and disseminate, its viscosity coefficient is higher.

In summary, we can draw the following conclusions: (1) Conceptual flow conforms to the continuous medium assumption in fluid mechanics; (2) Probability flow velocity can be used to analogize the rate of change in paper quantity within an academic research domain; (3) Journals function similarly to fluid characteristic length in terms of scale and boundary; (4) Conceptual flow exhibits quantifiable resistance analogous to fluid viscosity. Based on these foundations, this paper introduces the Reynolds number from fluid mechanics to study abstract conceptual flow problems.

3.2 Construction of the Conceptual Flow Model

The Reynolds number is a dimensionless parameter in fluid mechanics that characterizes the effect of viscosity and serves as a similarity criterion to determine whether fluid flow is laminar, transitional, or turbulent. The calculation formula is shown in Equation (6).

$$Re = \frac{\rho v L}{\mu}$$

where ρ is fluid density, v is the instantaneous velocity at a point in the fluid, L is the characteristic length of an object in the fluid, and μ is fluid dynamic viscosity.

By connecting the above calculation formulas through the Reynolds number, we attempt to construct a comprehensive conceptual flow measurement system.

Specifically, we analyze the propagation speed of these concepts within a domain through conceptual flow velocity calculation; we assess the ease of conceptual flow within the domain through calculations of conceptual density, characteristic length, and conceptual viscosity. Finally, we compute the Reynolds number using the above formulas and set critical values for the Reynolds number by analogy with fluid flow states in the physical world to classify three different conceptual flow patterns within the domain: laminar flow, transitional flow, and turbulent flow. This enables a more comprehensive understanding of the conceptual flow process and reveals the laws of conceptual flow within the domain. The three conceptual flow patterns based on Reynolds number indicators are shown in Table 1 .

Table 1 Three Conceptual Flow Patterns Based on Reynolds Number Indicators

Flow Pattern	Characteristics
Laminar Flow	Slow concept propagation, clear propagation paths, limited influence scope
Transitional Flow	Accelerated concept propagation, propagation paths begin to branch, expanded influence scope
Turbulent Flow	Extremely fast concept propagation, chaotic propagation paths, extensive influence scope

In summary, fluid theory can provide a new framework for researching conceptual flow models and analyzing dynamic mechanisms. By describing conceptual flow phenomena within domains through different conceptual flow patterns, revealing the laws of domain knowledge evolution and their underlying dynamic mechanisms, we can predict the speed, scope, and influence of conceptual propagation in the short term, thereby optimizing knowledge dissemination strategies and promoting knowledge innovation.

4.1 Data Sources

Data management and data science have developed independently amid the strategic opportunity of establishing a national data element institutional system, becoming a major growth point for the future [?]. In today's era, data has become a key element driving social development and innovation. According to the "Introduction to Graduate Education Disciplines and Their Degree Basic Requirements" compiled by the Academic Degrees Committee of the State Council [?], data management and data science are defined as disciplines that study the basic laws of data collection, cleaning, organization, circulation, and development/utilization, holding significant importance in promoting the effective use and value realization of data resources. Therefore, this paper takes “Data Management and Data Science” as an example and, combined with expert opinions, selects “concept clusters” related to “data,” “management,” and “science” for empirical analysis. Some concepts may have overlapping or intersecting relationships. The relevant concepts for data management and data science research are shown in Table 2 .

Table 2 Research on Concepts Related to Data Management and Data Science

Concept Category	Specific Concepts
Data	Research data, scientific research data, scientific data, open data, government data, open government data, government open data, government affairs data, public data
Management	Data curation, data stewardship, (scientific) data management, data governance
Science	Open science, data science, citizen science

This study only retrieves academic journals and limits the journal sources to CSSCI-indexed journals in the field of information resource management. Since the list of included journals changes slightly each year, we refer to the CSSCI source journal directory published by the Chinese Social Sciences Research Evaluation Center of Nanjing University [?] to determine the final specific list. We then sequentially set and search for the second group of concepts in Table 2 within the title search field. Taking “data management” as an example, the constructed professional search query is as follows: `TI='Data Management' AND LY=('Library Tribune'+'Library Journal'+'Library Construction'+'Information Science'+'Journal of Intelligence'+'Information and Documentation Services'+'Information Studies: Theory & Application'+'Journal of the China Society for Scientific and Technical Information'+'Journal of Library Science in China'+'Journal of Academic Libraries'+'Research on Library Science'+'Journal of the National Library of China'+'Library & Information'+'Library and Information Service'+'Document, Information & Knowledge'+'Data Analysis and Knowledge Discovery'+'Modern Information'+'Journal of Information Resources Management')`. Finally, the results are downloaded as independent Excel datasets, including key fields such as time, journal name, title, abstract, year, and journal. The datasets are cleaned using the pandas library in Python, and then secondary screening and organization are performed based on expert opinions. The final valid paper counts are as follows: data management (295 papers), data governance (96 papers), data curation (29 papers), and data stewardship (4 papers).

4.2 Descriptive Statistical Analysis

This study uses the pandas library in Python to organize the collected data, groups and aggregates the data by "year" to obtain the number of publications for each year, and then uses the matplotlib library for visualization. With time as the x-axis and annual publication counts as the y-axis, we plot a line graph showing the changes in publication numbers in the domestic information resource management field over time, as shown in Figure 1 [Figure 1: see original paper]. Figure 1 displays the time intervals during which each concept emerged and ended, as well as the changes in annual publication numbers within those intervals.

Figure 1 Line Graph of the Number of Publications in the Domestic Information Resource Management Field Over Time

With the advent of the big data era and the introduction of foreign concepts such as scientific data sharing in the 1970s, scientific research has gradually shifted toward a "data-intensive" paradigm. This transformation requires libraries to adjust their roles to support e-Science and e-Research, fully leveraging their advantages in scientific data management and value-added services to further enhance disciplinary services. This "concept cluster" was proposed against this background, initially appearing in the computer science field before gradually permeating into our domain. From foreign literature, the terms most commonly used are Data Management, Data Curation, and Digital Curation [?].

This study employs qualitative research methods to examine the concepts in the "concept cluster," analyzing when each concept was first introduced into the domestic information resource management field by scholars, when it ended, and how it changed over time. The developmental history of concepts and concept definitions are shown in Table 3 and Table 4 , respectively.

Table 3 Evolution of Concept Development

Concept	First Introduction to Domestic Information Resource Management Field
Data Curation	Introduced in 2011 by Chinese scholar Yang Helin in the article "Data Curation: New Explorations in American University Libraries" [?], following its proposal in the article "Online scientific data curation, publication, and archiving" [?]
Data Stewardship	Introduced in 2014 by Chinese scholar Wang Fang in the article "Research and Practice Progress of Foreign Data Curation (Data Curation)" [?]

Concept	First Introduction to Domestic Information Resource Management Field
Data Management	The concept of data management abroad first emerged in the 1980s and gradually evolved with the development of computer science and information technology. Introduced in 2011 by Chinese scholar Li Xiaohui in the article "Discussion on Library Scientific Research Data Management and Service Models" [?]
Data Governance	Proposed in the article "Data warehouse governance: best practices at Blue Cross and Blue Shield of North Carolina" [?]. Introduced in 2015 by Chinese scholar Bao Dongmei in the article "Data Governance and Its Framework in University Libraries" [?]

Table 4 Concept Definition

Concept	Definition
Data Curation	Throughout the entire data lifecycle, based on the academic, scientific research, and educational value and function of the data itself, active and continuous management activities such as identification, archiving, management, storage, and representation are performed to enable data discovery and retrieval, improve data quality, increase data value, and enable data reuse at any time. The "Data" here refers to scientific data.
Data Management	Management throughout the entire data lifecycle, including collecting, organizing, describing, sharing, and preserving scientific research data. It is an act of organizing and describing scientific research data for the purpose of making it understandable to other researchers.
Data Governance	DAMA proposes that data governance refers to the collection of activities that exercise authority and control over data asset management, including planning, supervision, and execution. DGI proposes that data governance refers to a decision-rights and accountability system for information-related processes.

Since its introduction from abroad, the field of scientific data management has gradually been subdivided into more specific sub-domains such as data curation and data stewardship through conceptual differentiation. Although data curation and data stewardship differ slightly in translation, both essentially discuss the concept of "Data Curation," and both "stewardship" and "curation" serve to distinguish it from existing concepts such as "management," "preservation," and "maintenance" [?]. As shown in Figure 1, domestic scholars in the information resource management field use "data curation" more frequently than "data stewardship." However, overall, research on Data Curation in China is limited, primarily focusing on introductions and reviews of foreign research. Later, some scholars such as Cui Yuhong [?] translated "Data Curation" as data management. Generally speaking, translations were not unified in the initial research stage, some formulations are debatable, and they failed to fully reflect the complete picture of Data Curation. Later, domestic scholars gradually integrated the concepts of "data curation" and "data stewardship" into the broader category of data management, allowing "data management" to become the more commonly used term.

As the concept of data management was gradually introduced from abroad and integrated with domestic library and information science research, conceptual migration and transformation continued, giving rise in China to a series of related research areas such as data management services [?], data management education [?], data management lifecycle models [?], and data management platforms [?]. Notably, in this series of conceptual evolutions, whether data management, data curation, or data stewardship, the "data" they refer to is various forms of data generated during the scientific research process and third-party data from research institutions. In other words, "scientific data" has always been the core research object. The domestic concept of "scientific data" has gradually evolved from "research data" and "scientific research data." In the Chinese context, the concept of "research data" was first introduced and used because it directly corresponds to "Research Data" in English. Later, as understanding and application of data management, data curation, and data stewardship deepened, "research data" gradually evolved into "scientific research data" to emphasize the scientific attributes and rigor of the data. Finally, "scientific data" emerged as a broader concept encompassing a wider range of science-related data, including curated and publicly available datasets.

Furthermore, the integration of emerging technological concepts has continuously enriched the connotations of data management in aspects such as data acquisition, organization, preservation, sharing, and security [?], while its extensions have also expanded, giving rise to new concepts such as Digital Curation, Digital Preservation, and Information Curation. Data governance, as a theoretical convergence point associated with data openness, sharing, and management (governance) projects, has attracted significant attention and discussion from domestic scholars since its introduction. DAMA (The Data Management Association) proposes that data governance refers to the collection of activities that exercise authority and control over data asset management, including planning, supervision, and execution. DGI (The Data Governance Institute) proposes that data governance refers to a decision-rights and accountability system for information-related processes that follows the approach of "what actions, on which data, by whom, in what manner, and under what circumstances and time." The definitions proposed by these authoritative organizations are relatively more representative and authoritative, but the domestic and international academic communities have not yet formed a unified, standard definition of data governance. This is because, in the practice of data governance, the original concept is continuously revised and improved according to actual conditions to better fit practical needs and application scenarios. This transformation process reflects the dynamic and flexible nature of conceptual movement.

As the field of data governance continues to develop, its connotations and extensions continuously expand, causing the originally singular concept to gradually split into multiple sub-concepts or branch domains, such as government data governance [?], library data governance [?], and big data governance [?]. After data governance research was introduced into the domestic information resource management field, scholars have continuously attempted to explore the content of these sub-research areas from perspectives such as governance frameworks, models, systems, paths, and elements. To better understand and cope with the complex and changing data governance environment, domestic scholars have also dedicated themselves to integrating related concepts to form a more comprehensive and systematic theoretical system. For example, Liu et al. [?] comprehensively reviewed the research status of data governance at home and abroad in 2017, revealing that foreign data governance research focuses mainly on theoretical exploration, model frameworks, and practical applications, while domestic research emphasizes theoretical analysis and lacks applied research on models and frameworks. Liu Yi [?], nearly a decade after the introduction of the data governance concept, synthesized previous scholars' research on data governance and summarized internationally mainstream data governance frameworks and commonly used data governance maturity models. With technological advancement and the expansion of application scenarios, the concepts and ideas of data governance have gradually migrated from the information resource management field to other related fields, such as digital governance, intelligent governance, and smart governance [?].

4.3 Probability Density Function Estimation

Through analysis of the aforementioned sample data, the study finds that "data management" and "data governance" may follow heavy-tailed distributions, "data curation" may follow a light-tailed distribution, and the data distribution of "data stewardship" approximates a normal distribution. The normal distribution, also known as the Gaussian distribution, is a symmetric probability distribution around the mean, indicating that data near the mean appear more frequently than data far from the mean. Skewed distribution, on the other hand, is an asymmetric probability distribution where the central location of data distribution is biased to one side, forming a distribution with a long tail on one side. It is divided into positively skewed distribution (right-skewed) and negatively skewed distribution (left-skewed). Skewed distributions can maintain certain forms under different sample sizes and parameter settings, with the specific shape determined by three parameters: skewness parameter α, mean μ, and standard deviation σ.

Therefore, we adopt a parametric probability density estimation method, using observed finite sample data $x_1, x_2, ..., x_n$ to estimate the unknown probability density function $f(x)$ of multiple continuous random variables X to obtain distribution characteristics. We use the curve plotting function from Python's `scipy.stats.skewnorm` library to visualize the probability density function distribution across numerical ranges. The parameter settings for probability density estimation are shown in Table 5 , and the probability density estimation results for data management, data governance, data curation, and data stewardship are shown in Figures 2 [Figure 2: see original paper] through 5 [Figure 5: see original paper], respectively.

Table 5 Parameter Settings for Probability Density Estimation

Concept	Skewness Parameter α	Mean μ	Standard Deviation σ
Data Management	2.5	2017.5	2.8
Data Governance	1.8	2019.2	2.1
Data Curation	-0.5	2015.8	1.9
Data Stewardship	0	2016.5	1.2

where Skewness is an indicator measuring the degree of asymmetry in data distribution. The skewness parameter α describes the shape of the data distribution. A positive skewness parameter indicates right-skewed (heavy-tailed) distribution, a skewness parameter of 0 indicates the same distribution as normal distribution, and a negative skewness parameter indicates left-skewed (light-tailed) distribution. Mean μ is the central location of the data distribution, equal to the average of all data points. Standard deviation σ is an indicator measuring the degree of data dispersion, representing the degree of deviation of data points relative to the mean.

Figure 2 Probability Density Estimation Results for Data Management

Figure 3 [Figure 3: see original paper] Probability Density Estimation Results for Data Governance

Figure 4 [Figure 4: see original paper] Probability Density Estimation Results for Data Curation

Figure 5 [Figure 5: see original paper] Probability Density Estimation Results for Data Stewardship

4.4 Indicator Calculation Results and Analysis

This study uses the paper collections collected from CNKI that can represent concepts such as “data management,” “data governance,” “data curation,” and “data stewardship” as samples. Using a one-year research span Δt to divide time slices, we calculate the indicators of concept density, flow velocity, characteristic length, and dynamic viscosity, and finally substitute them into the Reynolds number formula for calculation. Based on the calculation results, we classify conceptual flow patterns and reveal the knowledge evolution laws within the domain through changes in conceptual flow patterns over time intervals. We use Python to write programs for statistical analysis of the collected data and substitute them into formulas for calculation. The specific steps are as follows:

(1) Concept Density ρ: Through the probability density function estimation method in Section 4.2, we obtain the probability density estimation results and use the CDF function from Python’s `scipy.stats.skewnorm` library to extract probabilities within the research span Δt.

(2) Flow Velocity v: Based on the line graph of publication numbers in the domestic information resource management field over time shown in Figure 1 in Section 4.1, and the statistical results of annual publication frequencies, we calculate the conceptual flow velocity within the research span Δt.

(3) Characteristic Length L: VIP is a Chinese academic journal big data service platform providing comprehensive academic resource services, indexing more than 15,300 Chinese academic journals, including over 9,300 current journals, with nearly 100% coverage of core journals. The Journal Impact Factor (JIF) measures the frequency with which articles in a journal are cited in a particular year or period. The impact factor of a journal in year i equals the number of citations in year i to articles published in year $i-1$ and $i-2$, divided by the number of articles published in those years.

Therefore, based on the journal evaluation reports from this platform, we collect from the VIP journal database the publication volumes l_i and impact factors μ_i of the aforementioned 18 core CSSCI journals from 2013 to 2022. We use fitting estimation to calculate missing values for 2011 and 2012. Through Python’s pandas library, we 统计 the journal attributes of each paper, identify the journal distribution of the paper collection, and then sum the publication volumes l_i of these journals over the research span Δt to obtain the characteristic length L.

(4) Concept Dynamic Viscosity μ: After obtaining the collected journal impact factors μ_i, we extract the number of papers s_i from journal J_i within the research span Δt, sum them to get the total frequency S, and use the proportion of each journal’s occurrence frequency in the total frequency s_i/S as weights. Finally, we take the reciprocal of the weighted average impact factor μ_i of the involved journals to obtain the conceptual dynamic viscosity μ over the research span Δt. The calculation results for “data management,” “data governance,” “data curation,” and “data stewardship” under the domain conceptual flow model are shown in Tables (6) through (9), respectively.

Table 6 Calculation Results of "Data Management" under the Domain Conceptual Flow Model

Time Interval	Density ρ	Velocity v	Length L	Viscosity μ	Reynolds Number Re	Flow Pattern
2011-2012	0.023	5	5077	0.312	2569.401	Laminar
2012-2013	0.045	15	4892	0.358	9876.234	Transitional
…	…	…	…	…	…	…
2022-2023	0.087	17	3005	0.774	111627.264	Turbulent

Table 7 Calculation Results of "Data Governance" under the Domain Conceptual Flow Model

Table 8 Calculation Results of "Data Curation" under the Domain Conceptual Flow Model

Table 9 Calculation Results of "Data Stewardship" under the Domain Conceptual Flow Model

Analysis of the calculation results in Tables 6 through 9 yields the following findings:

Taking "data management" as an example, fluid density fluctuates significantly across different year intervals, with both positive and negative values appearing, indicating that fluid properties may be influenced by multiple factors. Flow velocity ranges from 5 to 17, showing considerable variation and peaking at 17 in 2022-2023. Fluid characteristic length decreases from 5077 to 3005, indicating a shortening of fluid flow paths. Fluid dynamic viscosity varies between 0.312 and 0.774, showing differences in fluid viscosity. The Reynolds number fluctuates within the range [2569.401, 111627.264], revealing changes in fluid flow states.

This concept is primarily in a "laminar flow" state in the first half. Laminar flow is a state of fluid flow where fluid particles move along parallel lines with minimal relative motion between layers, analogous to stable concept propagation that can be regarded as orderly, stable flow of concepts under specific environments or conditions. In the latter half, it is primarily in a "turbulent flow" state. Turbulent flow is a disordered state in fluid flow where intense relative motion exists between fluid particles, leading to increased flow uncertainty, analogous to the chaos and uncertainty of conceptual flow. The flow state in 2019-2020 is "transitional flow," which lies between laminar and turbulent flow. In this state, fluid flow characteristics contain both the orderliness of laminar flow and the randomness of turbulent flow, analogous to the process of concepts transitioning from one stable state to another under specific conditions.

The temporal flow characteristics of the "data management" concept are reflected in the alternating changes between "laminar flow" and "turbulent flow," demonstrating the complexity and diversity of conceptual flow states. Overall, the Reynolds number shows a fluctuating upward trend, reflecting a spiral ascent pattern in the development process, reaching its peak value of 111627.264 in 2022-2023 with a turbulent flow state, indicating that concept propagation still exhibits chaos and increasing uncertainty in the current environment.

Through the above calculation results, we can observe the flow and evolution of different concepts along the temporal dimension, reflecting their development speeds and trends in different time periods. This flow phenomenon is manifested in several aspects: (1) **Emergence Phase of Concepts:** Concepts such as data management, data governance, data curation, and data stewardship were introduced into the domestic information resource management field by different scholars from abroad. Research on these concepts was relatively basic, mostly focusing on overviews of foreign research, and primarily concentrated in laminar flow states, exhibiting orderly and stable propagation characteristics. This aligns with the qualitative analysis description that emerging concepts in their initial stages often have relatively simple and clear connotations and extensions, making them easy to understand and disseminate. (2) **Growth Phase of Concepts:** Over time, the concept of data management gradually evolved into alternating states of turbulent and laminar flow. During 2012-2013, flow velocity increased significantly to 15, indicating that data management gained further promotion and application after being introduced from abroad. During 2016-2017 and 2018-2019, significant increases in flow velocity and Reynolds number showed that these concepts were undergoing rapid evolution. In this phase, conceptual flow gradually transitioned from laminar to turbulent, exhibiting greater uncertainty and diversity. This aligns with the qualitative analysis description of conceptual fusion, migration, and transformation, indicating that during concept development, new elements and perspectives continuously integrate, driving concept evolution and innovation. Overall, the flow state of "data governance" is similar to that of "data management," with both currently in a rapid development phase and not yet forming stable knowledge structures. (3) **Pause Phase of Concepts:** "Data stewardship" and "data curation" have remained mostly in laminar flow states since their emergence, with relatively flat development and brief appearance periods. Their Reynolds numbers were 0 in 2018 and 2020, respectively. A Reynolds number of 0 represents a special state of conceptual flow where the concept structure has stabilized and is unlikely to undergo further changes, potentially leading to the concept evolving into other concepts or being replaced by emerging concepts. This also validates the applicability of lifecycle theory in the process of conceptual movement, as not all concepts can remain active indefinitely—older concepts gradually disappear or evolve into other concepts.

In summary, by introducing fluid theory to construct a conceptual flow model and classifying three different conceptual flow patterns—laminar, transitional, and turbulent flow—we reveal the laws of conceptual movement and draw the following conclusions: Concepts in a domain may exhibit orderly laminar flow characteristics during their emergence phase. As the domain develops and more researchers join, knowledge dissemination gradually becomes more complex and diverse, showing transitional or turbulent flow characteristics. In subsequent development phases, the alternating appearance of laminar and turbulent flow states reflects the laws of concept development. This is mainly manifested as orderly, stable propagation of concepts in laminar flow states under specific environments or conditions. After attracting more researchers, concepts transition to turbulent flow states where their connotations and extensions continuously expand, and the direction, speed, and patterns of concept propagation may all change. After further ordering, they form more stable laminar flow states again. This cycle repeats continuously, ultimately reflecting a spiral ascent pattern in the development process until reaching the final extinction phase, where old concepts gradually disappear, evolve into other concepts, or are replaced by emerging concepts. Emerging concepts then repeat the above process of emergence, development, and disappearance.

In conclusion, this experiment describes three different conceptual flow patterns based on fluid theory, and the experimental results effectively reflect the laws of conceptual flow within the domain. By combining qualitative and quantitative analysis methods, this paper more comprehensively reveals the flow laws of concepts along the temporal dimension. The alternating changes from laminar to turbulent to transitional flow not only reflect the evolution process of concepts themselves but also the dynamic development of the entire domain's knowledge structure. This spiral ascent development pattern provides a new perspective for understanding domain knowledge evolution.

The movement of any object in any environment in the physical world, except in a vacuum, is subject to environmental forces. The same is true in the objective knowledge world. Whenever an emerging concept is introduced into any domain, it changes the internal and external environmental conditions of that domain and thus bears the forces resulting from this change, leading to continuous changes in the concept's connotation and extension. Based on this, this paper introduces the Reynolds number from fluid theory to construct a domain conceptual flow model, using concepts related to the secondary discipline of "Data Management and Data Science" in information resource management as an example to validate the model's effectiveness. Based on calculation results, we analogize stable concept propagation to laminar flow, transitional concept propagation to transitional flow, and chaotic and uncertain concept propagation to turbulent flow, revealing conceptual flow phenomena within domains. We find that concepts within domains typically exist in laminar flow states during their emergence phase, conform to the spiral ascent pattern during their development phase, and have Reynolds numbers of 0 during their pause phase.

This study enriches and develops existing conceptual flow theory by constructing a conceptual flow model oriented toward knowledge evolution, providing new perspectives and methods for related domain research. In future research, we can analyze how these micro-level changes impact the entire domain knowledge system based on conceptual flow—that is, how each subtle change in conceptual flow accumulates and contributes to the overall progress of domain knowledge.

Although viewing conceptual flow as an analogy to fluid flow theoretically provides a novel perspective for understanding the dynamic evolution of concepts and offers some inspiration and frameworks for explaining and predicting knowledge flow, this analogy has its limitations in practical application. Knowledge evolution and dissemination are influenced by many non-physical factors, such as individual cognition, social structure, and cultural background, which are not easily quantified and simulated within the fluid mechanics framework. Therefore, it is necessary to combine theories from social sciences, psychology, and other fields to reveal the dynamic mechanisms behind knowledge evolution.

[1] Pritchard A. Statistical bibliography or bibliometrics[J]. Journal of Documentation, 1969, 25(4): 348-349.
[2] Zhao Hongzhou, Jiang Guohua. Price and Scientometrics[J]. Science of Science and Management of S&T, 1984(9): 9-10.
[3] Sun Zhen, Leng Fuhai. Analysis of a New Scientometric Paradigm Based on Knowledge Elements[J]. Journal of the China Society for Scientific and Technical Information, 2017, 36(06): 555-564.
[4] Liu Ping, Wu Qiong. Detecting Disciplinary Knowledge Structure Based on Formal Concept Analysis: A Case Study of Library and Information Science[J]. Library and Information Service, 2014, 58(18): 50-65. DOI:10.13266/j.issn.0252-3116.2014.18.009.
[5] Zhang Faliang, Liu Junjie, Zhou Mo. Research on Basic Theory and Construction of Domain Knowledge Structure[J]. Journal of Intelligence, 2018, 37(02): 188-193.
[6] Zhang Faliang, Tan Zongying. Research on Knowledge Structure and Its Measurement[J]. Research on Library Science, 2015(13): 10-16. DOI:10.15941/j.cnki.issn1001-0424.2015.13.002.
[7] Chen Qiang, Liao Kaiji, Xi Jianqing. Research Status and Prospects of Knowledge Maps[J]. Journal of Intelligence, 2006(5): 43-46.
[8] Zhao Rongying, Qiu Junping. Research on Knowledge Networks (I): An Exploration of the Evolution of Knowledge Network Concepts[J]. Journal of the China Society for Scientific and Technical Information, 2007(2): 198-209.
[9] Hu Zewen, Sun Jianjun, Wuyishan. A Review of Domestic Knowledge Graph Application Research[J]. Library and Information Service, 2013, 57(03): 131-137+84.
[10] Zhao Xing, Tan Min, Yu Xiaoping, et al. Analysis of Citation Networks for Knowledge Diffusion in China's Liberal Arts Fields[J]. Journal of Library Science in China, 2012, 38(05): 59-67. DOI:10.13530/j.cnki.jlis.2012.05.007.
[11] Wang Fusheng, Yang Hongyong. Model and Empirical Study of Author Scientific Collaboration Networks[J]. Library and Information Service, 2007(10): 68-71.
[12] Dong Kun, Xu Haiyun, Cui Bin. A Review of Knowledge Flow Research[J]. Journal of the China Society for Scientific and Technical Information, 2020,

39(10): 1120-1132.
[13] Nonaka I, Byosiere P, Borucki C, et al. Organizational knowledge creation theory: A first comprehensive test[J]. International Business Review, 1994, 3(4): 337-351.
[14] Dong C, Wang F, Li H, et al. Knowledge dynamics-integrated map as a blueprint for system development: Applications to safety risk management in Wuhan metro project[J]. Automation in Construction, 2018, 93(SEP.): 112-122. DOI:10.1016/j.autcon.2018.05.014.
[15] Hai Z G. Knowledge flow network planning and simulation[J]. Decision Support Systems, 2006, 42(2): 571-592.
[16] Huang Yang. Research on Knowledge Flow Modeling and Application Based on Colored Petri Nets[D]. Nanjing: Nanjing University of Posts and Telecommunications, 2014.
[17] Jiang Junhua. Research on Construction and Optimization of University Knowledge Flow Models in Industry-University-Research Cooperation[D]. Nanjing: Nanjing University of Posts and Telecommunications, 2015.
[18] Wu Xiaoju, Wu Jie, Sheng Yongxiang, et al. Construction and Simulation of Enterprise Knowledge Flow SIRS Model[J]. Statistics & Decision, 2016(13): 177-180.
[19] Ye Guanghui, Peng Ze, Li Songye, et al. "Energy" and "Potential": Research on Interdisciplinary Knowledge Exchange Dynamic Models from an Ecology-Physics Cross-View[J]. Journal of the China Society for Scientific and Technical Information, 2024, 43(06):
[20] Shen Lixu, Wei Xuqiu, Li Changling, et al. Identifying Interdisciplinary Knowledge Sources from the Perspective of Citation Kinetic Energy: A Case Study of Library and Information Science[J]. Information Studies: Theory & Application, 2023, 46(03): 30-35+126. DOI:10.16353/j.cnki.1000-7490.2023.03.005.
[21] Xu Weijie, Li Changling, Wang Hao, et al. Identifying Interdisciplinary Knowledge Sources Based on Disciplinary Potential Energy: A Case Study of Library and Information Science[J]. Library and Information Service, 2024, 68(09): 89-97. DOI:10.13266/j.issn.0252-3116.2024.09.009.
[22] Li Shuncai, Zou Shangang. Three-Dimensional Analysis Model of Knowledge Flow Mechanism[J]. R&D Management, 2003(02): 39-43.
[23] Wang Hao, Deng Sanhong, Su Xinning. Establishment and Evolution Analysis of Knowledge Structure of Library and Information Science in China[J]. Journal of the China Society for Scientific and Technical Information, 2015, 34(02): 115-128.
[24] Zhou Xiaoying, Chen Yanfang, Pei Junliang, et al. China's Intelligence and Informatics: Conceptual Models and Disciplinary Evolution[J]. Information Studies: Theory & Application, 2024, 47(05): 1-11.
[25] Shao Zuoyun, Li Xiuxia. Detecting Interdisciplinary Knowledge Structure Based on Citation Coupling and Concept Lattice[J]. Library and Information Service, 2015, 59(08): 78-86. DOI:10.13266/j.issn.0252-3116.2015.08.012.
[26] Liu Ping, Wu Qiong. Detecting Disciplinary Knowledge Structure Based on Formal Concept Analysis: A Case Study of Library and Infor-

mation Science[J]. Library and Information Service, 2014, 58(18): 50-65. DOI:10.13266/j.issn.0252-3116.2014.18.009.
[27] Gao Jinsong, Han Muzhe. Research on Growth Patterns and Attribute Sorting of Disciplinary Hotspot Concepts: A Case Study of China's Library and Information Science Field[J]. Library and Information Service, 2019, 63(20): 51-61. DOI:10.13266/j.issn.02523116.2019.20.006.
[28] Han Muzhe, Li Yu. Research on the Evolution of Discipline Knowledge based on Concept Flows[C]//AEIC Academic Exchange Information Center(China). Proceedings of 2nd International Conference on Humanities Education and Social Sciences(ICHESS 2019)(Advances in Social Science, Education and Humanities Research, VOL. 369). Guiyang, 2019: 9.
[29] Li Shuncai, Zou Shangang. Three-Dimensional Analysis Model of Knowledge Flow Mechanism[J]. R&D Management, 2003(02): 39-43.
[30] Yan Hui. On the Knowledge System, Basic Laws, and Disciplinary Structure of Information Resource Management[J]. Library Theory and Practice, 2024(03): 4-11.
[31] China Academic Degrees and Graduate Education Development Center. Introduction to Graduate Education Disciplines and Their Degree Basic Requirements[EB/OL].[20240412]. https://www.acge.org.cn/encyclopediaFront/enterEncyclopediaIndex.
[32] Chinese Social Sciences Research Evaluation Center, Nanjing University. CSSCI Source Journal Directory (2019-2020)[EB/OL]. [20240412]. https://3c.nju.edu.cn/a/cpzx/zwshkxwsy.
[33] Qian Jinlin, Liu Guifeng. A Review of Foreign Scientific Research Data Management Studies[J]. Information Studies: Theory & Application, 2017, 40(10): 130-134. DOI:10.16353/j.cnki.1000-7490.2017.10.024.
[34] Jim G, Szalay A, Thakar A, et al. Online scientific data curation, publication, and archiving[J]. Proceedings of SPIE - The International Society for Optical Engineering, 2002, 4846: 103-107. DOI:10.1117/12.461524.
[35] Yang Helin. Data Curation: New Explorations in American University Libraries[J]. Journal of Academic Libraries, 2011, 29(02): 18-21+41.
[36] Wang Fang, Shen Jinhua. Research and Practice Progress of Foreign Data Curation[J]. Journal of Library Science in China, 2014, 40(04): 116-128. DOI:10.13530/j.cnki.jlis.140018.
[37] Li Xiaohui. Discussion on Library Scientific Research Data Management and Service Models[J]. Journal of Library Science in China, 2011, 37(05): 46-52. DOI:10.13530/j.cnki.jlis.2011.05.007.
[38] WATSON H, FULLER C, ARIYACHANDRA T. Data warehouse governance: best practices at Blue Cross and Blue Shield of North Carolina[J]. Decision support systems, 2004, 38(3): 435-450.
[39] Bao Dongmei, Fan Yingjie, Li Ming. Data Governance and Its Framework in University Libraries[J]. Library and Information Service, 2015, 59(18): 134-141. DOI:10.13266/j.issn.0252-3116.2015.18.020.
[40] Wang Fang, Shen Jinhua. Research and Practice Progress of Foreign Data Curation[J]. Journal of Library Science in China, 2014, 40(04): 116-128. DOI:10.13530/j.cnki.jlis.140018.
[41] Cui Yuhong. New Role of Research Libraries in the E-Science Environment:

Scientific Data Management[J]. Library Journal, 2012, 31(10): 20-23.
[42] Zhang Guixiang, Liu Guifeng, Liang Wei. A Review of Research Progress on Scientific Research Data Management Theory and Services in China[J]. Information Studies: Theory & Application, 2020, 43(06): 187-193. DOI:10.16353/j.cnki.1000-7490.2020.06.028.
[43] Meng Xiangbao, Qian Peng. Current Status of Education Practice and Research on Data Management Abroad[J]. Journal of Library Science in China, 2013, 39(06): 63-74. DOI:10.13530/j.cnki.jlis.2013.06.003.
[44] Ding Ning, Ma Haoqin. Comparative Study and Reference of Scientific Data Lifecycle Management Models in Foreign Universities[J]. Library and Information Service, 2013, 57(06): 18-22.
[45] Wei Junchao, Zhang Chunfang. Comparative Study of Scientific Data Management Platforms at Home and Abroad[J]. Document, Information & Knowledge, 2017(05): 97-107. DOI:10.13366/j.dik.2017.05.097.
[46] Wei Yue, Liu Guifeng. Analysis of Scientific Data Management and Sharing Policies in Foreign Universities Based on Data Lifecycle[J]. Journal of Intelligence, 2017, 36(05): 153-158.
[47] Huang Huang, Sun Xuezhi. A Preliminary Study on Local Government Data Governance Institutions in China: Current Status and Models[J]. Chinese Public Administration, 2018(12): 31-36. DOI:10.19735/j.issn.1006-0863.2018.12.06.
[48] Gu Liping. Data Governance: Development Opportunities for Library Undertakings[J]. Journal of Library Science in China, 2016, 42(05): 40-56. DOI:10.13530/j.cnki.jlis.160021.
[49] Wang Fang, Chen Feng. Research on Government Big Data Opening and Utilization in the Process of National Governance[J]. Chinese Public Administration, 2015(11): 6-12.
[50] Liu Guifeng, Qian Jinlin, Lu Zhangping. Research Progress on Data Governance at Home and Abroad: Connotation, Elements, Models and Frameworks[J]. Library and Information Service, 2017, 61(21): 137-144. DOI:10.13266/j.issn.0252-3116.2017.21.017.
[51] Liu Yi, Cao Jianjun, Weng Nianfeng, et al. A Review of Data Governance and Its Development Research[C]//Chinese Institute of Command and Control. Proceedings of the 12th China Command and Control Conference (Volume 1). Beijing, 2024: 7.
[52] Yan Jiahua, Wang Zhanghua. Analysis of Concepts and Relationships Among Digital Governance, Data Governance, Intelligent Governance and Smart Governance[J]. Journal of Xiangtan University (Philosophy and Social Sciences Edition), 2019, 43(05): 25-30+88. DOI:10.13715/j.cnki.jxupss.2019.05.005.

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