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How Policies Influence Academia: Evolution and Influencing Factors Based on Knowledge Flow

Siluo Yang, Tianxiu Chen, Longfei Li, Xiaojuan Liu, Yi Liang

Abstract: Existing studies rarely examine, at a fine-grained level, the specific effects generated when policy texts are cited by academic papers. This study aims to provide decision support for policymakers seeking to enhance policy influence and policy-to-knowledge translation efficiency, while offering academia a new perspective for understanding the diffusion of policy knowledge and promoting synergy between policy communication and knowledge innovation. Focusing on the academic dissemination of policy within policy–academia interactions, this study takes artificial intelligence (AI) policies and the academic papers citing them as samples. More than 4,000 sentence-level citation chains containing policy knowledge elements were extracted. Using citation analysis, the thematic evolution, diffusion characteristics, and influencing factors of differences in policy knowledge flow were examined from the perspective of knowledge diffusion. In thematic terms, policy topics such as AI education, AI ethics, and AI justice receive concentrated scholarly attention and citations, and thus constitute key channels through which policy affects academia. Analysis of differences in knowledge flow shows that the dissemination power of policy knowledge elements follows a long-tail distribution: a small number of policy elements exert substantial influence, whereas most have only limited impact. The major drivers of differences in knowledge flow include policy topic and the administrative level of

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the issuing body, while institutional co-authorship and the time lag of secondary citation also show potential associations. Temporally, policies generally trigger scholarly responses in the short term (usually within three years), although some also exhibit delayed resurgence in knowledge flow, often in connection with national strategies or industrial development. It is therefore recommended that future policy design emphasize thematic focus and inter-organizational coordination, innovate policy activation mechanisms, and renew policy communication approaches.

Keywords: citation analysis; policy text; knowledge diffusion; knowledge evolution; knowledge flow; influencing factors

Author Biographies: Siluo Yang, Ph.D., Professor, and Ph.D. Supervisor. Research interests: bibliometrics and science evaluation. **Tianxiu Chen**, Master's student. Research interests: scientometrics and science evaluation. **Longfei Li**, Doctoral student. Research interests: scientometrics and science evaluation. **Xiaojuan Liu**, Ph.D., Professor, and Ph.D. Supervisor. Research interests: informetric and science evaluation. **Yi Liang (translator)**, Ph.D., Associate Professor, currently at Hebei GEO University. His research interests include low-carbon energy management, machine learning and intelligent algorithms, and big data analytics in logistics. E-mail: lianglouis@126.com.

1. Introduction

Scientific decision-making depends on forward-looking and effective theoretical guidance, and academic research provides theoretical support for policymaking by examining and responding to real-world issues. Within this interaction, policy offers research agendas and practical materials to academia, while academic outputs in turn inform the formulation, evaluation, and refinement of policy. Academic citation of policy is not only an important manifestation of this virtuous interaction, but also a crucial pathway through which policy knowledge is re-disseminated, reinterpreted, and recreated within the academic system (Zhai Yujia et al., 2023). The dissemination of policy knowledge in the academic domain is, in essence, a process of knowledge diffusion. According to Chen Baitong and Zhang Bin (2014), knowledge diffusion proceeds along two principal routes: knowledge sharing among members within an organization, and knowledge transmission among different actors in scientific activity. This study focuses on the latter and defines it more precisely as inter-institutional diffusion of scientific knowledge, whose core lies in cross-boundary knowledge flow and innovation-oriented evolution. Citation analysis serves as a key means of tracing and evaluating this process.

Existing research on knowledge diffusion covers multiple levels of analysis. At the macro level, scholars have explored knowledge diffusion through journal relationships and disciplinary linkages (Zhang Hui et al., 2020), disciplinary exchange and interdisciplinarity (Ye Ying et al., 2020), and factors affecting journal citations and knowledge flow, including impact-factor-related characteristics (Yao Zheng et al., 2014). Citation-based bibliometrics is a core method for uncovering such trajectories of knowledge flow (Chen Chaomei and Hicks D, 2004). By analyzing patent citation networks (Ho M H C et al., 2014) and large-scale bibliographic databases (Zhao Xing et al., 2012; Tan Chunhui and Wang Yiwen, 2023), previous studies have successfully traced transnational diffusion of technological knowledge and disciplinary knowledge propagation. At the micro level, research has increasingly shifted toward finer units of analysis, moving from documents and sentences to "knowledge elements," understood as the smallest indivisible units in the recombination of knowledge (Wang Pingping and Wang Yi, 2018). Such studies either verify citation relationships through content similarity (Zhao Weiting and Shan Donghong, 2014) or quantify knowledge flow through topic terms in order to reveal diffusion mechanisms (Peng Ze et al., 2020; Yue Zenghui and Xu Haiyun, 2016). Overall, research on knowledge diffusion is evolving toward increasingly fine granularity (Yang Siluo and Chen Zhiling, 2024).

Within this broader field, the interaction between policy and academia has become a distinctive topic of interest, mainly reflected in the bidirectional citation relationships between the two. Existing studies have examined three major forms of citation linkage. First, policy-to-policy citation focuses on diffusion mechanisms, routes, and directions, often using methods such as social network analysis (Wei Ping et al., 2025; Huang Cui et al., 2015; Liu Fengchao and Xu Qian, 2012) and co-word analysis (Wang Chunmei et al., 2014), and has generated analytical chains such as "structure–relationship–mechanism–result" (Qiu Yiming and Shi Ce, 2023) as well as several typologies of diffusion patterns (Wang Puqu and Lai Xianjin, 2013). Second, policy citation of academic papers has been treated as an indicator of research translation, with studies examining the factors (Ren Chao et al., 2023) and motivations (Cao Zhe et al., 2025) behind policy citation of scholarly work. Third, academic citation of policy has mainly been discussed in terms of citation motivation and strategy, including what parts of policy are cited and where they are cited in papers (Zhai Yujia et al., 2023). However, this line of research largely remains at the level of citation behavior itself and has not yet systematically revealed the diffusion characteristics and influence mechanisms of policy knowledge within academic literature.

Although existing studies have made progress in the study of policy citation, several problems remain in research on academic papers citing policy, especially from the fine-grained perspective of policy knowledge elements. First, most studies rely on indirect indicators such as citation frequency to assess policy influence and lack a direct measure of the dissemination intensity of knowledge elements; methods for quantifying knowledge flow in the diffusion process remain relatively underdeveloped. Second, prior work has mainly discussed citation content, with little attention to thematic evolution and temporal characteristics; the thematic and temporal evolution of policy knowledge within academic papers therefore lacks systematic analysis. Third, the factors that shape differences in knowledge flow across repeated citation processes have not been systematically explored, particularly at the level of policy knowledge elements. Accordingly, this study adopts a fine-grained perspective centered on policy knowledge elements, applies a knowledge-flow measurement approach, selects representative AI policies, and systematically analyzes the diffusion of policy knowledge in academic literature. It addresses the following questions: How can knowledge flow be measured at the level of policy knowledge elements so as to quantify their dissemination intensity in academic citation? What evolutionary paths and time-lag characteristics emerge in first- and second-round citation? Which factors influence differences in knowledge flow across multiple rounds of citation, and which of them exert substantive effects?

2.Research Design and Methods

The study develops a “policy–first citation–second citation” analytical framework. The analysis is limited to second-order citation so as to avoid exponential growth in data volume and excessive computational complexity. First, target policy texts and their first- and second-order citing academic papers were collected to construct the basic dataset. Second, policy knowledge elements and corresponding citation sentences were extracted; after data cleaning and semantic matching, knowledge flow was measured. Finally, the study conducts a systematic analysis from three dimensions — topic evolution, time-lag characteristics, and influencing factors. The overall research process is shown in Figure 1.

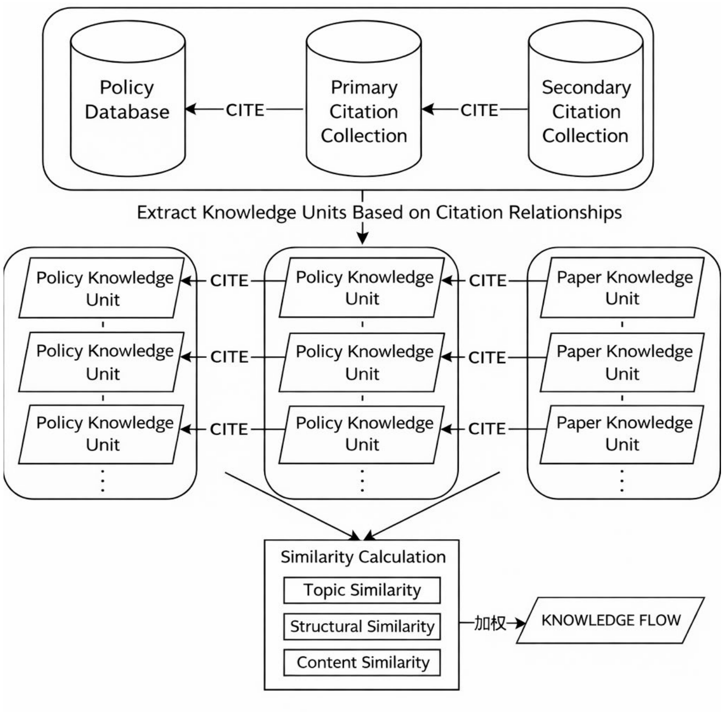

Fig. 1. Policy knowledge element extraction and knowledge flow calculation

1) Each clause in a policy text is operationally defined as an independent policy knowledge element, which serves as the basic unit of analysis. Although the definition and extraction of knowledge elements have not yet been fully unified (Bi Chongwu et al., 2023), rule-based extraction remains one

of the most commonly used approaches (Ye Guanghui et al., 2023; Hua Bolin, 2013).

2) Knowledge flow is defined as the total amount of knowledge entering and leaving a knowledge entity within a given period (Bi Chongwu et al., 2023). Drawing on existing measurement models (Ye Guanghui et al., 2020; Chen Yongyue et al., 2024; Li Changling et al., 2024), this study operationalizes knowledge flow as the weighted similarity between a cited policy knowledge element and a citing sentence. This similarity is obtained by weighting topic similarity (θ_1), structural similarity (θ_2), and content similarity (θ_3). Following prior research (Bi Chongwu et al., 2023), the coefficients are set as $\sigma_1 = 0.6$, $\sigma_2 = 0.3$, and $\sigma_3 = 0.1$. The final weighted similarity is calculated as follows:

$$\theta = \sigma \theta + \sigma \theta + \sigma \theta \quad (1)$$

3) For the thematic evolution of policy knowledge, a BERT-LDA model is used to cluster policy knowledge elements and their citation sentences into topics, while the BAAI/bge-large-zh-v1.5 model is employed for semantic representation. Combined with knowledge-flow data, a Sankey diagram is used to visualize topic divergence, convergence, and transfer paths in the first- and second-order citation process (Yang Siluo and Wu Lijuan, 2024; Yang Siluo and Yu Yonghao, 2024).

4) For time-lag analysis of policy knowledge flow, statistical analysis is conducted on the relationships among first citation lag, second citation lag, and knowledge flow. The measures are defined as follows:

First citation lag = year of first citation − year of policy issuance (2)

Second citation lag = year of second citation − year of policy issuance (3)

5) To examine factors influencing differences in policy knowledge flow, the study draws on general citation-impact factors (Fu Zhu et al., 2024) and includes policy knowledge topic, policy knowledge element type, first citation lag, second citation lag, administrative level of the issuing body, and institutional co-authorship. ANOVA and related statistical analyses are then used to test their effects on knowledge flow differences.

3.Data Collection and Preprocessing

Pkulaw (“Beida Fabao”) was used as the policy retrieval tool, with “artificial intelligence” as the main keyword for searching relevant policy texts and metadata on April 1, 2025. To ensure both scientific validity and representativeness of the dataset while balancing citation volume and policy diversity, ten AI-related policy documents issued between 2018 and 2022 were finally selected to constitute Policy Set A. Details are presented in Table 1.

The corpus of first-order citing papers (Set B) was constructed using the advanced search function of CNKI. Using the titles of the policies in Set A as search terms in the “References” field, academic papers citing the policy texts were retrieved, yielding 837 papers in Set B. On this basis, the corpus of second-order citing papers (Set C) was obtained by searching, one by one, the titles of papers in Set B with the same method and retrieving the academic papers that cited them. This produced 4,571 papers in Set C. To ensure that each knowledge element had both first- and second-order citations, 4,141 policy knowledge citation chains were finally extracted. These chains can be traced back to 186 independent policy knowledge elements.

Policy No.	Policy Title	Document No.	Issuing Body	Citations	Date Issued	Legal / Administrative Status	No. of Knowledge Elements	No. of Citation Chains
Policy 1	Opinions of the Supreme People's Court on Regulating and Strengthening AI Applications in the Judiciary	Fa [2022] No. 33	Supreme People's Court	577	Dec. 8, 2022	Judicial interpretive document	17	113
Policy 2	Notice of the Ministry of Education on Issuing the Action Plan for AI Innovation in Higher Education Institutions	Jiao Ji [2018] No. 3	Ministry of Education	503	Apr. 2, 2018	Departmental normative document	57	3177
Policy 3	New Generation AI Ethics Code	—	National New Generation AI Governance Expert Committee	222	Sept. 25, 2021	Departmental normative document	15	300
Policy 4	Notice of the Ministry of Science and Technology on Issuing the Guidelines for the Construction of National New Generation AI Innovation and Development Pilot Zones	Guo Ke Fa Gui [2020] No. 254	Ministry of Science and Technology	131	Sept. 29, 2020	Departmental normative document	12	50
Policy 5	Notice of the Department of Degree Management and Postgraduate Education of the Ministry of Education on Issuing the Guiding Training Program for Graduate Education in the Field of AI (Trial)	Jiao Yan Si [2022] No. 6	Ministry of Education	94	July 27, 2022	Departmental working document	17	61
Policy 6	Notice of the Secretariat of the National Information Security Standardization	Xin An Mi Zi [2021] No. 2	National Information Security Standardization Technical	74	Jan. 5, 2021	Departmental normative document	9	33

	Technical Committee on Releasing the Cybersecurity Standards Practice Guide—Guidelines for the Prevention of Ethical and Security Risks in Artificial Intelligence		Committee					
Policy 7	Notice of Six Ministries Including the Ministry of Science and Technology on Issuing the Guiding Opinions on Accelerating Scenario Innovation to Promote High-Level AI Applications and High-Quality Economic Development	Guo Ke Fa Gui [2022] No. 199	Ministry of Science and Technology; Ministry of Education; Ministry of Industry and Information Technology; Ministry of Transport; Ministry of Agriculture and Rural Affairs; National Health Commission	65	July 29, 2022	Departmental normative document	15	107
Policy 8	Notice of the Ministry of Education, the National Development and Reform Commission, and the Ministry of Finance on Issuing Several Opinions on Promoting Interdisciplinary Integration in Double First-Class Universities and Accelerating Postgraduate Training in AI	Jiao Yan [2020] No. 4	Ministry of Education; National Development and Reform Commission; Ministry of Finance	54	Jan. 21, 2020	Departmental normative document	27	243
Policy 9	Announcement of the Center for Medical Device Evaluation of the National Medical Products Administration on Issuing the Guiding Principles for Registration Review of AI Medical Devices	Center for Medical Device Evaluation Announcement No. 8 [2022]	National Medical Products Administration	37	Mar. 7, 2022	Departmental working document	11	49
Policy 10	Notice of the Ministry of Science and Technology on Supporting the	Guo Ke Fa Gui [2022] No. 228	Ministry of Science and Technology	36	July 27, 2022	Departmental normative document	6	8

	Construction of Demonstration Application Scenarios for the New Generation of AI							

Table 1. Policy sample information

Note: Policy 3 is a non-mandatory policy document and therefore has no official document number.

4. Results and Discussion

4.1 Evolutionary Characteristics of Policy Knowledge Themes

To explore the thematic evolution paths between policy texts and their two levels of citations, the BERT-LDA method was used to summarize the themes of the knowledge elements in each dataset, and the optimal number of topics was selected according to topic coherence so as to ensure semantic distinctiveness and stability. The clustering results show that the policy texts were divided into 15 topics, the first-order citation texts into 30 topics, and the second-order citation texts into 25 topics. Selected results are shown in Table 2.

From the ten policy texts, fifteen principal topics were identified. Except for policy documents closely aligned with legal and medical topics (e.g., Policy 9 and the cluster "medical assistance and intelligent decision-making systems"), most policies exhibited complex many-to-many mappings with topics. On the one hand, some key issues, such as "research integration and talent cultivation mechanisms," recur across multiple policy documents (e.g., Policies 2, 8, and 10). On the other hand, single content-rich policies — especially top-level strategic plans — often cover multiple themes. For example, Policy 2 contains topics such as "research integration and talent cultivation mechanisms" and "policy implementation and support for university governance."

Policy Topics	First-Order Paper Topics	Second-Order Paper Topics
P1. AI risk and protection of individual rights	F1. Ethics and AI governance	S1. Reading and library service experience
P2. Research integration and talent cultivation mechanisms	F2. AI education and talent cultivation	S2. Smart eldercare and information technology applications
P3. Major research platforms and special-project construction	F3. Enterprises in central and western China and career development	S3. Optimization of university curriculum goals and teaching conditions
P4. Multidisciplinary theoretical permeation and general research	F4. AI and university curriculum design	S4. Employment management systems and exploration of creative output
P5. Intelligent education and innovation in modern teaching	F5. Digital intelligence and the development of economics- and management-related majors	S5. Virtual teaching and experimental construction in teaching and research offices

Table 2. Selected clustered themes for each dataset

On the basis of the clustering results, and by combining the semantic mapping relationships among policy citation sentences, first-order citation sentences, and second-order citation sentences, a Sankey diagram of policy-theme diffusion was constructed using the knowledge flow of the two citation rounds as the flow weight (Figure 2). This visualization reveals the dissemination paths and evolutionary tendencies of policy themes within the knowledge network.

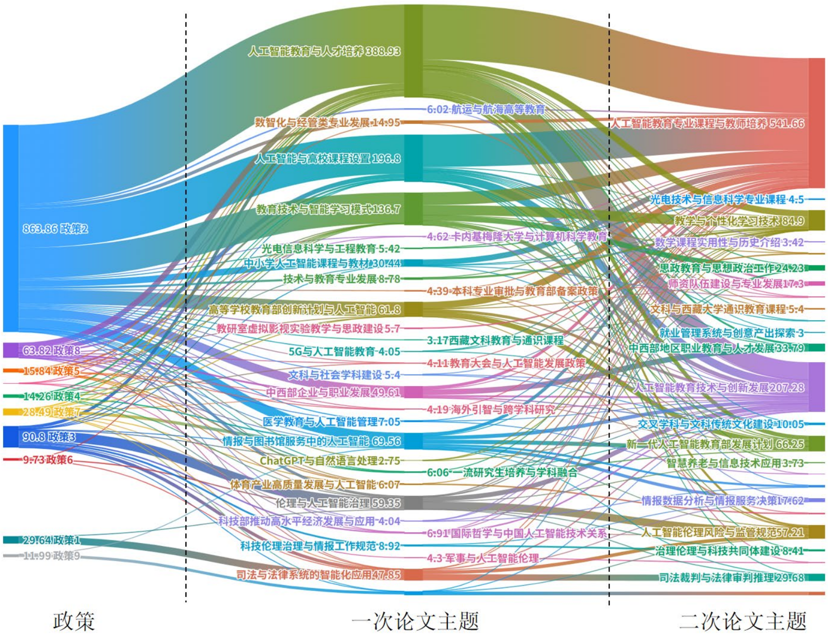

Fig. 2. Sankey diagram of policy knowledge theme evolution

First, the results show a pronounced divergent diffusion pattern, in which a single high-impact policy drives innovation across multiple areas. Policy 2 is a representative case. Its knowledge elements display strong radiating capacity. In the first-order citation stage, it gives rise to broad research agendas such as "AI talent cultivation" and "university curriculum design." In the second-order citation stage, these topics further differentiate and deepen into more specific and frontier subfields such as "teacher training" and "personalized learning technologies." This evolutionary path — from conceptual guidance to application-oriented deepening — demonstrates that high-quality policy can not only direct academic agendas but also stimulate continuing theoretical and methodological innovation. The same policy also shows a degree of cross-domain spillover into non-core areas such as intelligent justice.

Second, individual policies contribute substantial knowledge flow to the themes most closely related to themselves. For example, Policy 1 contributes 61.3% of the knowledge flow to the theme "intelligent applications in judicial and legal systems" (29.32/47.85). Similarly, Policy 9 contributes 67.7% of the knowledge flow to the theme "medical devices and AI assistance" (11.74/17.34). This indicates that specialized policies within a given sector or field constitute the primary sources of knowledge input into the corresponding academic research domains.

Third, from the perspective of thematic convergence, several key themes show clear aggregative characteristics. Themes related to "AI + education" — such as "talent cultivation," "curriculum design," and "intelligent learning modes" — act as knowledge hubs in both citation stages. At the first-order citation stage, they absorb knowledge inputs from multiple policies; at the second-order citation stage, they become nodes of renewed aggregation, giving rise to new focal areas such as “teacher training” and “educational technology innovation.” This pattern of multi-source input and multi-level convergence confirms that, under the joint impetus of a national policy cluster, “AI + education” has crystallized into a core academic research agenda, highlighting the critical role of policy combinations in guiding scholarly agenda setting.

4.2 Time-Lag Analysis of Policy Knowledge Diffusion

4.2.1 Time Lag and Evolution of Policy Knowledge Flow

By comparing the heatmaps of first citation lag and first-round knowledge flow (Figure 3) with those of second citation lag and second-round knowledge flow (Figure 4), this study identifies several characteristics of the temporal diffusion of policy knowledge.

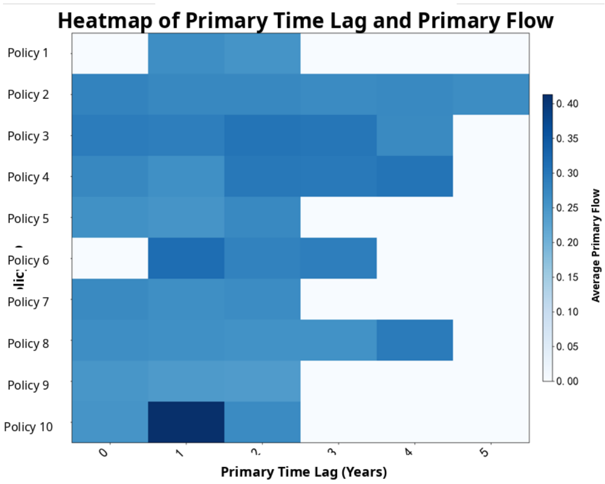

Fig. 3. Heatmap of first citation delay and first citation knowledge flow

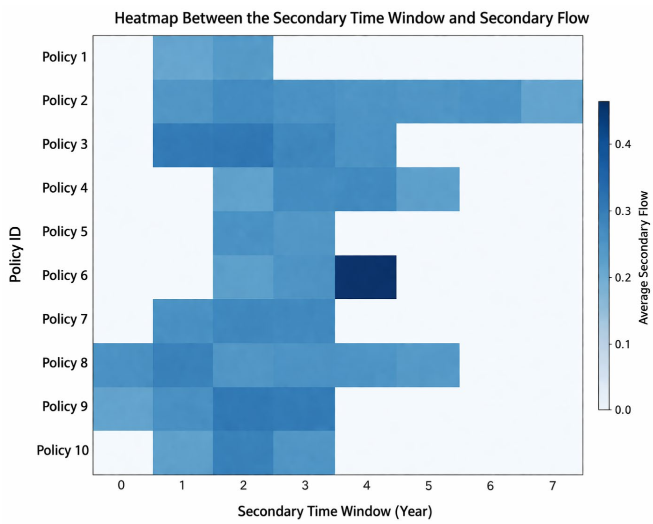

Fig. 4. Heatmap of second citation delay and second citation knowledge flow

First, most policies generate immediate responses within three years after issuance, and their knowledge flow typically peaks during this initial three-year period. For instance, Policies 2 and 3 both achieve relatively high knowledge flow within the first three years, while Policy 10 reaches a marked peak as early as the second year, indicating that academia responds to these policies quickly and follows them in a timely manner.

Second, domestic policies as a whole display strong persistence of influence. Although the first response is concentrated in the early period, the policies selected in this study generally show considerable academic vitality. As of the date of data collection, almost all policies still maintained active first- and second-order citations, demonstrating their continuing influence in academia.

However, the averaging effect of the heatmaps masks major differences in absolute influence across policies. A small number of key policies far outperform others. As shown in Table 3, which reports the peak knowledge flow values and their timing, Policy 2 reaches a first-order knowledge-flow peak of 38.470 and a second-order peak of 49.766. This phenomenon, revealed by absolute values, is strong evidence that Policy 2 constitutes a highly influential policy that has been internalized as part of the knowledge base of the field.

Policy	Months to 1st Peak	1st-Peak Value	Months to 2nd Peak	2nd-Peak Value
Policy 1	3	6.783	16	16.323
Policy 2	51	38.470	66	49.766
Policy 3	4	10.061	29	11.481
Policy 4	22	3.684	37	3.108
Policy 5	4	9.588	19	6.748
Policy 6	28	2.324	33	2.067
Policy 7	18	4.600	28	4.265
Policy 8	23	6.801	60	10.043
Policy 9	14	6.089	23	4.340
Policy 10	4	1.010	31	0.251

Table 3. Peak knowledge flow and occurrence month for each policy

Third, some policies exhibit a clear delayed effect. The first-order citation of Policies 4, 5, and 8, and the second-order citation of Policies 6 and 9, all show noticeable growth in knowledge flow several years after policy issuance. Table 3 provides quantitative support: for these delayed-effect policies, the peaks of second-order knowledge flow generally occur more than one year later than the peaks of first-order knowledge flow. Policy 8 is particularly notable, with the second-order peak occurring nearly three years later than the first-order peak. This delayed effect can be driven both by endogenous policy content — for example, the alignment between Policy 6 and the academic focus on AI ethics — and by external catalysts such as emerging industries (e.g., the low-altitude economy) and subsequent policy environments, including the 2024 World Digital Education Conference and related supporting policies (The 2024 World Digital Education Conference was held in Shanghai, 2024; Notice of the General Office of the Ministry of Education on announcing the list of AI education bases for primary and secondary schools, 2024; The Ministry of Education released four actions to promote AI-empowered education, 2024).

Fourth, some policies exhibit very low knowledge flow in the year of issuance, suggesting barriers to initial diffusion. This is mainly due to two types of factors. One is timing: Policy 1, for example, was released at the end of the year, which objectively compressed the window in which it could be cited during its first year. The other is the administrative level of the issuing body: because the issuing body of Policy 6 is relatively low in rank, its early authority and diffusion breadth were constrained, delaying the academic response.

4.2.2 Knowledge Flow Difference and Time Lag

Knowledge flow difference is introduced as an important indicator of the sustained influence of policy knowledge elements. A positive knowledge-flow difference indicates continued diffusion between the two citation stages and thus stronger dissemination power, whereas a negative value suggests limited influence and weaker diffusion capacity. In general, when the overall time lag is short and the knowledge-flow difference is substantially positive, the policy exerts a sustained positive influence across the complete citation chain, rapidly triggering consecutive responses; such elements can be regarded as important and high-quality policy knowledge units. Table 4 lists the average citation lag and average knowledge-flow difference for each policy.

Policy	**Avg. 1st Citation Lag**	**Avg. 2nd Citation Lag**	**Avg. Knowledge-Flow Difference**	**Maximum Difference**	**Minimum Lag (1st / 2nd)**	**Year Issued**
Policy 1	1.1770	1.9735	-0.0021	0.3971	1 / 1	2022
Policy 2	2.7016	4.6944	0.0094	0.5660	0 / 1	2018
Policy 3	1.5133	2.5933	0.0112	0.4073	0 / 1	2021
Policy 4	1.6600	3.7800	-0.0007	0.2701	0 / 2	2020
Policy 5	0.5574	2.1967	0.0182	0.4773	0 / 2	2022
Policy 6	1.9091	2.8182	-0.0151	0.3903	1 / 2	2021
Policy 7	1.3832	2.1028	0.0291	0.2863	0 / 1	2022
Policy 8	1.7366	3.4403	0.0117	0.2847	0 / 0	2020
Policy 9	0.8571	1.8980	0.0677	0.5579	0 / 0	2022
Policy 10	0.8750	2.0000	0.0009	0.2251	0 / 1	2022

Table 4. Average citation lag and knowledge-flow difference for each policy

By analyzing the association between citation lag and knowledge-flow difference (Figures 5 and 6), the following characteristics can be identified.

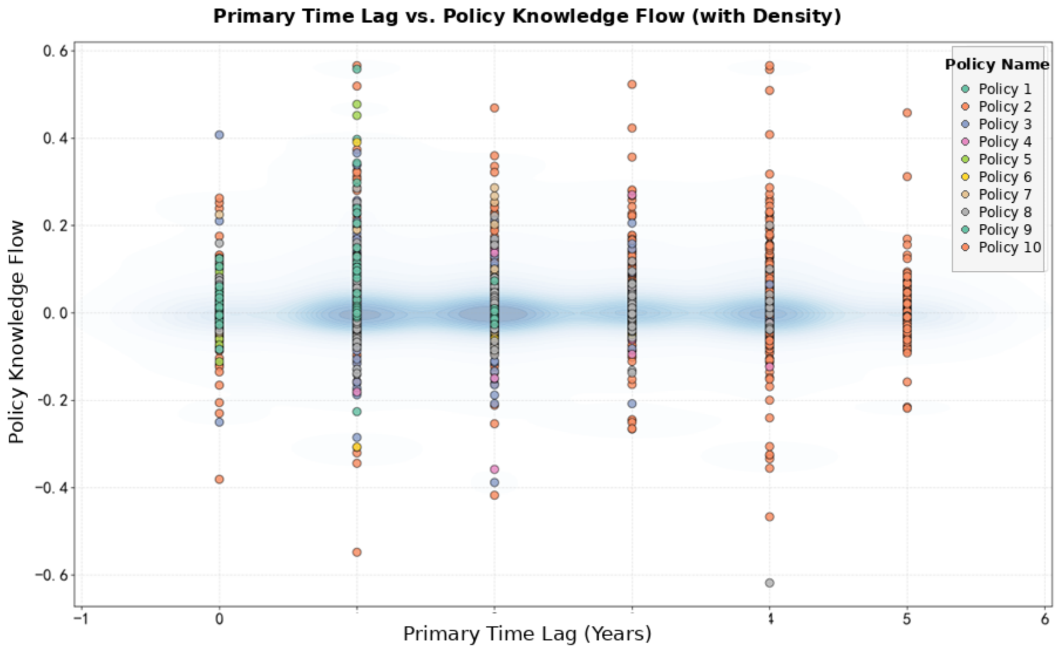

Fig. 5. Relationship between first citation delay and knowledge-flow difference

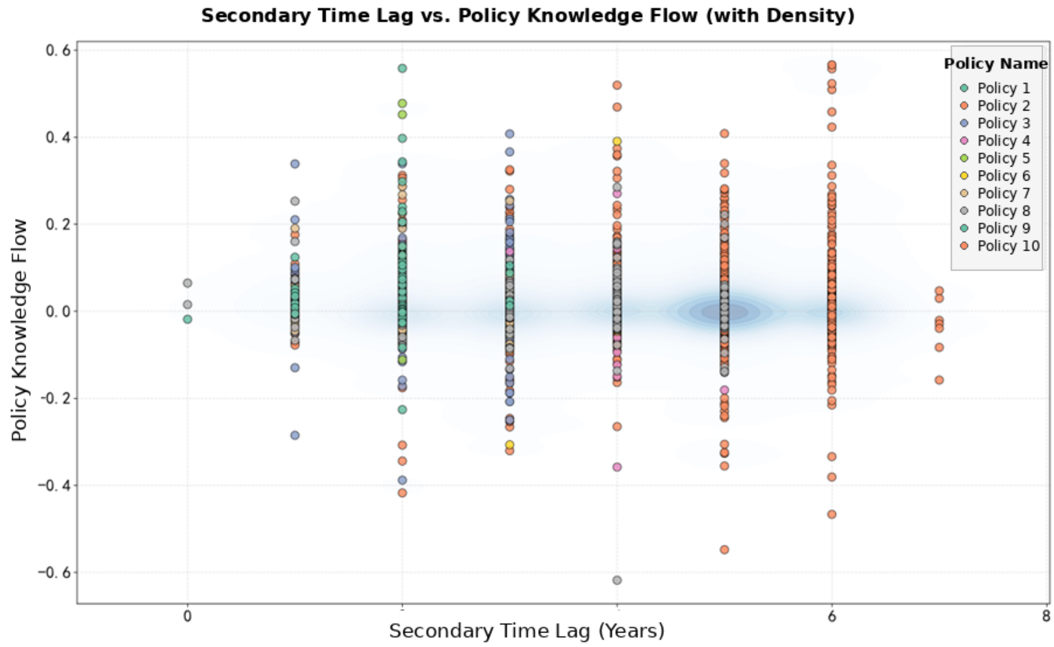

Fig. 6. Relationship between second citation delay and knowledge-flow difference

(1) The policy knowledge elements as a whole exhibit positive knowledge-flow differences, but the degree of differentiation is substantial and conforms to a long-tail pattern. Most policy knowledge elements show positive differences, indicating that policy knowledge continues to generate output in academia. However, only a small number of core elements account for most of the increase in knowledge flow, demonstrating strong and durable dissemination power, whereas the impact of most elements remains limited. For example, although some knowledge elements in Policy 2 are highly influential, they constitute only a limited share of all the elements in that policy.

(2) Policy knowledge elements generally trigger academic response within three to four years.

Combined with the time-lag analysis, the positive knowledge-flow differences of most policies begin to become prominent during this period. This suggests that academia not only responds quickly to policy, but that the knowledge influence of policy enters a key fermentation stage of growth and re-innovation three to four years after release.

(3) Some high-quality policies possess exceptional sustained influence. Since its release in 2018, Policy 2 has displayed not only high first-order knowledge flow but also a clearly positive knowledge-flow difference, demonstrating strong output capacity throughout the entire citation chain. Similarly, Policies 5 and 9, with relatively high average and peak knowledge-flow differences, also confirm continued and substantial knowledge output.

4.3 Influencing Factors of Differences in Policy Knowledge Flow

Policies display different dissemination power in the process of knowledge diffusion, as reflected in the difference in knowledge flow between two rounds of citation. To investigate the mechanisms behind these differences, this section examines the concrete effects of policy knowledge topic, policy knowledge element type, first citation lag, second citation lag, administrative level of the issuing body, and institutional co-authorship on knowledge diffusion outcomes. The categories of policy knowledge elements follow Wang Junxia et al. (2023) and are listed in Table 5.

Type	Definition
Plans and action measures	Plans, schemes, and actions requiring specific tasks to be completed within a defined period.
Regulations and norms	Standards, regulations, and similar provisions applicable over a relatively long period.
Interpretive and guiding elements	Opinions, notices, and similar documents that explain or guide major issues.
Guiding ideology	Statements of overall guiding principles or policy spirit.
Background information	Descriptions of the background from which the policy arose.

Table 5. Types and definitions of policy knowledge elements

For the categorical variables — policy knowledge element type, administrative level of the issuing body, institutional co-authorship, and policy topic — one-way ANOVA was used. For the continuous variables, first citation lag and second citation lag, regression analysis was performed to test the relationships between these factors and differences in knowledge flow. The statistical results show that, among the independent variables examined, "administrative level of the issuing body" and "policy topic" are significantly associated with knowledge-flow difference ($p < 0.05$). Although "institutional co-authorship" ($p = 0.071$) and "second citation lag" ($p = 0.066$) do not reach conventional significance levels, their p-values are close to the threshold and suggest potential effects. Other variables, including "policy knowledge element type," do not show significant relationships ($p > 0.05$). The results are presented in Table 6.

Independent Variable	F value	Coefficient	Std. Error	p value
Continuous variables				
Second citation lag	—	-0.002	0.001	p = 0.066

First citation lag	—	-0.001	0.001	p = 0.156
Categorical variables				
Institutional co-authorship	F = 3.257	—	—	p = 0.071
Policy knowledge element type	F = 0.939	—	—	p = 0.440
Administrative level of issuing body	F = 11.929	—	—	p < 0.001**
Vice-ministerial level		0.068		
National level		0.009		
National-level coordinating body		0.011		
Bureau / department level		-0.015		
Policy topic	F = 6.727	—	—	p < 0.001**

Table 6. Statistical analysis of influencing factors for policy knowledge-flow difference

*Note: ** indicates significance at the 1% level.*

A closer examination of the four factors that are statistically significant or potentially influential yields several findings.

First, the administrative level of the issuing body is a key factor affecting the continued diffusion of knowledge. Among issuing bodies, policies released by vice-ministerial bodies tend to have higher knowledge-flow differences. Policies issued by national-level bodies and national-level coordinating bodies also show positive effects, but their overall impact is comparatively smaller. By contrast, policies issued by bureau-level and lower-level bodies tend to exert negative effects on knowledge-flow difference. This difference can be interpreted in terms of policy importance. Policies issued by higher-level bodies usually possess stronger authority and directional force and therefore attract more academic citations. However, larger citation volume may also bring more heterogeneity in citation quality, including both high- and low-level studies, which can increase volatility in subsequent knowledge-flow differences and weaken sustained dissemination power. That said, low-level bodies are not necessarily devoid of academic influence. Policy 6 is a good example: although issued by a lower-level body, it achieved relatively rapid first citation and displayed a certain delayed effect. This suggests that ethical issues emerging in the development of AI can align closely with academic concerns and thereby enable rapid uptake even for lower-ranked issuing bodies.

Second, policy topic significantly affects dissemination efficiency. In thematic terms, topics such as “AI ethical institutional design and social consensus,” “policy implementation and support for university governance,” “medical assistance and intelligent decision-making systems,” and “financial intelligence and credit modeling” all show positive knowledge-flow differences (Table 7). This indicates that policy knowledge elements connected with current academic hotspots and broader social and environmental concerns possess stronger sustained dissemination power.

Policy Topic	Coefficient
AI ethical institutional design and social consensus	0.033
AI risk and protection of individual rights	0.010
Ethical governance and behavioral norm systems	0.001
Medical assistance and intelligent decision-making systems	0.064

Macro-level strategic planning and pilot implementation	0.025
Policy implementation and support for university governance	0.033
Intelligent judicial services and trial assistance	0.000
Intelligent discipline construction and regional development	-0.022
Intelligent education and innovation in modern teaching	0.001
Multidisciplinary theoretical permeation and general research	0.002
Research integration and talent cultivation mechanisms	0.011
Trends in intelligent socio-economic transformation	0.016
Major research platforms and special-project construction	0.015
Financial intelligence and credit modeling	0.022
Mission of higher education and connotative innovation-driven development	-0.019

Table 7. Influence coefficients of policy themes

Finally, institutional co-authorship and second citation lag also show potential effects. On the one hand, policies jointly issued by multiple departments generally have a higher knowledge-flow difference (coefficient = 0.017) than those issued by a single department (coefficient = 0.009). This may stem from the cross-disciplinary characteristics of such jointly issued policies, which attract more diverse research perspectives and thereby strengthen the continued dissemination of knowledge. On the other hand, second citation lag is negatively related to knowledge-flow difference, suggesting that policies receiving more timely follow-up responses tend to maintain more durable knowledge influence, which is consistent with general intuition.

5. Conclusion and Prospects

Focusing on policy citation within policy–academia interactions, this study takes AI policies as samples and, based on sentence-level citation extraction and knowledge-flow analysis, systematically examines the dissemination characteristics of policy knowledge elements from the perspective of knowledge diffusion. Specifically, it analyzes thematic evolution, temporal diffusion, and the key factors affecting differences in knowledge flow across citation stages.

(1) At the thematic level, the analysis of citation topics shows that themes such as “AI education and talent cultivation,” “AI and university curriculum design,” “AI education curricula and teacher cultivation,” and “AI educational technology and innovative development” attract concentrated scholarly attention and citation. These therefore constitute important channels through which policy influences academia, which also reflects China’s increasing emphasis on AI talent cultivation and digital literacy education.

(2) Analysis of differences in knowledge flow indicates that the influence of policy knowledge elements follows a typical long-tail pattern. A small number of key policy elements display pronounced and persistent dissemination power, whereas the vast majority of elements remain relatively weak in influence.

(3) In temporal terms, policy response in academia combines immediacy with delayed effects.

Most policies are quickly taken up within three years after issuance and generate peaks in knowledge flow. Yet some policies — especially those related to scenario applications or aligned with subsequent industrial hotspots — show strong delayed effects, with their knowledge influence rising significantly several years after release, thereby demonstrating substantial academic vitality.

(4) Regarding influencing factors, the dissemination power of policy knowledge elements mainly depends on policy topic and the administrative rank of the issuing body. The rank of the issuing body is a foundational factor determining the breadth and depth of knowledge diffusion; among the categories examined, policies issued by vice-ministerial bodies show especially strong knowledge-gain effects. Meanwhile, policy topics that are tightly linked to social concern and industrial frontiers, such as AI ethics and medical assistance, are also more likely to generate stronger dissemination power. In addition, policies characterized by multi-department co-authorship and shorter second citation lag show a tendency toward larger knowledge-flow differences, suggesting potentially stronger dissemination capacity.

These findings not only provide, at the theoretical level, a new quantitative analytical framework for understanding the mechanisms of policy knowledge diffusion, but also offer practical implications for policymakers seeking to enhance the academic influence and translation effectiveness of policy.

(1) Policy design should strive for thematic focus and actor coordination. To improve sustained policy influence, policy formulation should move from grand narrative toward more concrete and forward-looking issues, thereby consolidating the practical foundation for knowledge diffusion. At the same time, cross-institutional and cross-departmental coordination in policymaking should be encouraged so as to broaden the knowledge coverage and interdisciplinary appeal of policy.

(2) Policy design can also innovate policy activation mechanisms. Policy management departments should establish dynamic tracking mechanisms. When methods such as knowledge-flow analysis identify that a policy has regained academic attention due to technological or social changes, this should be treated as an important feedback signal. At that point, policy managers can convene thematic workshops or launch special research programs to gather new insights from academia and industry. The core purpose is to excavate the policy's renewed potential and practical significance in the current environment, explore pathways for further implementation, and provide decision support for policy revision, optimization, or the development of a new round of supporting measures.

(3) Policy communication methods should be renewed. Policymakers should move beyond the single mode of formal document release and explore diversified approaches such as graphic interpretation, case-based dissemination, and online seminars, thereby promoting deeper academic understanding of policy content and facilitating higher-quality citation and knowledge translation.

This study still has limitations and leaves room for future extension. Owing to data availability constraints, only the knowledge flow between policy texts and their first two citation stages was analyzed. In addition, within second-order citation, the motivations for citing first-order papers may also affect the eventual policy-citation influence. Future research may rely on larger-scale and more precise data, cover more policies, and extend to longer citation chains in order to obtain a more accurate and comprehensive picture. At the same time, the study of influencing factors of policy knowledge elements constitutes a complex topic worthy of more independent, systematic, and in-depth research, so as to provide new perspectives and findings for the study of policy knowledge diffusion mechanisms.

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ORCID

Liang Yi[ID]https://orcid.org/0000-0003-3760-4433

References

The 2024 World Digital Education Conference was held in Shanghai. (2024, January 30). Retrieved from https://www.gov.cn/yaowen/tupian/202401/content_6929182.htm#1

The Ministry of Education released four actions to promote AI-empowered education. (2024, March 28). Retrieved from https://www.moe.gov.cn/jyb_xwfb/xw_zt/moe_357/2024/2024_zt05/mtbd/202403/t20240329_1123025.html

Notice of the General Office of the Ministry of Education on announcing the list of AI education bases for primary and secondary schools. (2024, February 20). Retrieved from https://www.moe.gov.cn/srcsite/A06/s3321/202402/t20240223_1116386.html

Bi, C., Peng, Z., Shen, X., et al. (2023). Research on the academic value of knowledge element from the perspective of knowledge diffusion. *Information Studies: Theory & Application*, 46(5), 75-83. DOI: https://doi.org/10.16353/j.cnki.1000-7490.2023.05.009

Cao, Z., Shang, Y., & Zhang, L. (2025). What kinds of research are more likely to generate policy impact: Taking classification and multidimensional characteristics of academic articles as pathways. *Documentation, Information & Knowledge*, 42(1), 6-17, 28. DOI: https://doi.org/10.13366/j.dik.2025.01.006

Chen, B., & Zhang, B. (2014). A research framework for scientific knowledge diffusion. *Library and*

Information Service, 58(15), 48-57. DOI: https://doi.org/10.13266/j.issn.0252-3116.2014.15.007

Chen, C., & Hicks, D. (2004). Tracing knowledge diffusion. *Scientometrics*, 59(2), 199-211.

Chen, Y., Xu, C., & Xu, T. (2024). Mechanism of knowledge fusion and value transmission in structural unit of citation-network knowledge fusion. *Journal of the China Society for Scientific and Technical Information*, 43(10), 1182-1198.

Fu, Z., Zhang, Q., & Liu, P. (2024). Difference of influencing factors of citation in scientific papers from the perspective of subject theme: An empirical study of library and information science. *Digital Library Forum*, 20(9), 16-26.

Ho, M. H. C., Lin, V. H., & Liu, J. S. (2014). Exploring knowledge diffusion among nations: A study of core technologies in fuel cells. *Scientometrics*, 100(1), 149-171.

Hua, B. (2013). Knowledge extraction by sentence level for academic papers [Doctoral dissertation, Nanjing University].

Huang, C., Ren, T., Li, J., et al. (2015). Responsibilities and interests: An evolutionary study of intergovernmental cooperation in China's science and technology innovation policy based on quantitative analysis of policy documents. *Journal of Management World*, (12), 68-81. DOI: https://doi.org/10.19744/j.cnki.11-1235/f.2015.12.007

Li, C., Luan, K., Wang, H., et al. (2024). Analysis of the current situation of disciplinary knowledge innovation growth from the perspective of knowledge variation: Taking the field of citation analysis as an example. *Information Studies: Theory & Application*, 47(12), 89-96. DOI: https://doi.org/10.16353/j.cnki.1000-7490.2024.12.011

Liu, F., & Xu, Q. (2012). Research on the evolution of Chinese S&T policy makers' cooperation networks. *Studies in Science of Science*, 30(2), 241-248. DOI: https://doi.org/10.16192/j.cnki.1003-2053.2012.02.011

Peng, Z., Ye, G., Bi, C., et al. (2020). Analysis of citation network's knowledge flow path from the perspective of citation content. *Information Studies: Theory & Application*, 43(12), 19-25, 10. DOI: https://doi.org/10.16353/j.cnki.1000-7490.2020.12.004

Qiu, Y., & Shi, C. (2023). The operational logic of China's policy diffusion from an intergovernmental relations perspective: A case study of urban talent attraction policies. *Jiangxi Social Sciences*, (10), 183-191.

Ren, C., Yang, M., Li, K., et al. (2023). Analysis of factors in citing scientific papers in policies against COVID-19 pandemic. *Journal of the China Society for Scientific and Technical Information*, 42(3), 341-353.

Tan, C., & Wang, Y. (2023). Quantitative analysis of interdisciplinary knowledge flow in the field of humanities and social sciences in China. *Library and Information Service*, 67(1), 131-143. DOI: https://doi.org/10.13266/j.issn.0252-3116.2023.01.016

Wang, C., Huang, K., & Guo, L. (2014). Nanjing's innovation policy based on the social network analysis. *Science and Technology Management Research*, (15), 25-28.

Wang, J., Ding, L., & Chu, S. (2023). Quantitative analysis of the policies on the DRG payment reform from the perspective of policy tools. *Health Economics Research*, 40(6), 50-53. DOI: https://doi.org/10.14055/j.cnki.33-1056/f.2023.06.018

Wang, P., & Lai, X. (2013). Analysis of the patterns and mechanisms of public policy diffusion in China. *Journal of Peking University (Philosophy and Social Sciences)*, (6), 14-23.

Wang, P., & Wang, Y. (2018). The characteristics of knowledge components and its effect on inventors' knowledge combination behavior: From the knowledge network perspective. *Business and Management Journal*, 40(5), 92-107. DOI: https://doi.org/10.19616/j.cnki.bmj.2018.05.006

Wei, P., Cai, R., & Yan, J. (2025). Network characteristics and dynamic mechanism of policy diffusion in digital economy: SNA analyses based on 533 policy texts. *Journal of Management*, 38(1), 97-113. DOI: https://doi.org/10.19808/j.cnki.41-1408/F.2025.0007

Yang, S., & Wu, L. (2024). Research progress of foreign information resource management: An analysis based on the BERTopic model. *Information Studies: Theory & Application*, 47(2), 189-197. DOI: https://doi.org/10.16353/j.cnki.1000-7490.2024.02.025

Yang, S., & Chen, Z. (2024). The model analysis of knowledge communication system research based on full-text bibliometric analysis perspective. *Knowledge Management Forum*, 9(4), 380-393. DOI: https://doi.org/10.13266/j.issn.2095-5472.2024.028

Yang, S., & Yu, Y. (2024). Topic mining and evolution analysis of information resource management research based on BERTopic model. *Information Science*, 42(8), 12-21.

Yao, Z., Peng, X., Zhang, L., et al. (2014). Modeling nonuniversal citation distributions: The role of scientific journals. *Journal of Statistical Mechanics: Theory and Experiment*, (4), P04029.

Ye, G., Peng, Z., Bi, C., et al. (2020). Research on citation network knowledge flow from the perspective of citation content. *Information Studies: Theory & Application*, 43(12), 11-18. DOI: https://doi.org/10.16353/j.cnki.1000-7490.2020.12.003

Ye, G., Peng, Z., Chen, G., et al. (2023). Research on knowledge element extraction in academic literature and its distribution feature recognition. *Information Studies: Theory & Application*, 46(4), 90-98. DOI: https://doi.org/10.16353/j.cnki.1000-7490.2023.04.012

Ye, Y., Zhang, J., & Zhang, H. (2020). The association between knowledge flow and interdisciplinary research. *Library & Information*, (3), 29-33.

Yue, Z., & Xu, H. (2016). Research on the process of knowledge diffusion among scientific disciplines: Taking the field of social network as an example. *Library and Information Service*, 60(9), 106-115. DOI: https://doi.org/10.13266/j.issn.0252-3116.2016.09.015

Zhai, Y., Xu, J., & Liang, Y. (2023). The interaction and relevance between Chinese government information disclosure policy and related research from the perspective of academic citation. *Journal of the China Society for Scientific and Technical Information*, 42(6), 690-701.

Zhang, H., Zhang, J., & Ye, Y. (2020). An exploration of disciplinary knowledge flows via CSSCI. *Library & Information*, (3), 41-48.

Zhao, W., & Shan, D. (2014). Research on the evolving model of complex networks based on node similarity. *Information Technology*, (8), 163-166. DOI: https://doi.org/10.13274/j.cnki.hdzj.2014.08.101

Zhao, X., Tan, M., Yu, X., et al. (2012). Exploring the citation networks for knowledge diffusion of humanities and social sciences in China. *Journal of Library Science in China*, 38(5), 59-67. DOI: https://doi.org/10.13530/j.cnki.jlis.2012.05.007