# Automatic Identification Methods for Policy Instruments: An Empirical Study (Postprint)

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## Abstract

[Purpose/Significance] The identification and analysis of policy instruments constitute one of the important means in policy research. This work is currently conducted mostly manually. This paper employs deep learning methods for the automatic identification of policy instruments, aiming to improve the efficiency of policy instrument identification. [Method/Process] We design and implement an experimental workflow for automatic policy instrument identification encompassing policy data collection and cleaning, manual annotation of policy instruments, model training, and result interpretation. Using government information disclosure policies from Beijing, Shanghai, Guangzhou, and Guiyang as examples, we compare the performance of traditional machine learning methods and deep learning methods on the policy instrument identification task. Additionally, we propose a scheme that integrates global policy information for paragraph-level policy instrument identification and demonstrate its effectiveness through experiments. [Results/Conclusion] The deep learning model CNN achieves 76.51% accuracy on the full test dataset, while the CNN model integrating global information reaches 77.13% accuracy. When evaluating only the model's high-confidence results, we find that the CNN model integrating global information achieves 95.44% accuracy on 55.63% of the test data. This accuracy already meets practical requirements, indicating that over half of the policy instrument annotations can leverage the model's high-confidence results without manual review. The research on automatic policy instrument identification based on deep learning methods has achieved favorable results, improving the efficiency of policy instrument annotation and providing positive experience for large-scale automatic policy instrument identification.

# Full Text

## Preamble

### Policy Tool Automatic Identification Method and Empirical Research Based on Deep Learning

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**Abstract:** *[Purpose/Significance]* The identification and analysis of policy tools represent an important method in policy research, yet this work is currently performed manually. This study employs deep learning methods for the automatic identification of policy tools to improve efficiency. *[Method/Process]* We designed and implemented an experimental workflow for automatic policy tool identification comprising policy data collection and cleaning, manual policy tool indexing, model training, and result interpretation. Using government information disclosure policies from Beijing, Shanghai, Guangzhou, and Guiyang as examples, we compared the performance of traditional machine learning methods and deep learning methods on policy tool identification tasks. Additionally, we proposed a scheme that integrates global policy information to identify policy tools in each paragraph and demonstrated its effectiveness through experiments. *[Result/Conclusion]* The deep learning CNN model achieved 76.51% accuracy on the full test dataset, while the CNN model integrating global information reached 77.13% accuracy. When evaluating only the model's high-confidence results, the global-information-integrated CNN model achieved 95.44% accuracy on 55.63% of the test data, meeting practical requirements. This indicates that over half of policy tool annotations can leverage the model's high-confidence results without manual review. The deep learning approach to policy tool automatic identification demonstrates promising results, improving annotation efficiency and providing positive experience for large-scale policy tool identification.

**Keywords:** policy tools; deep learning; automatic identification; convolutional neural network
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Policies are specific action guidelines formulated by governments, political parties, and organizations to accomplish tasks during certain historical periods. Governments at all levels issue numerous policies annually, creating authentic records of governmental management and regulation that serve as the foundation for policy analysis. Policy analysis can examine both external characteristics and internal features. As a crucial means of policy implementation and an important perspective for mining internal policy features, policy tools have attracted widespread attention from domestic scholars since the late 20th century. Scholars from different disciplines have conducted extensive empirical research from the policy tool perspective, demonstrating the importance of policy tools in policy analysis.

Policy tools originated from public policy structural theory, and currently there is no unified definition. J.P. Lester et al. consider policy tools as techniques for policy implementation, summarizing two technical paths: command-and-control and economic incentives. O.E. Hughes views policy tools as government behavior patterns and mechanisms for regulating government action. L.M. Salamon defines policy tools as anything that influences the entire process to achieve established goals. Domestic scholar Zhao Xiaoyuan et al. regard policy tools as elements of the policy system—means and measures that the government can employ to achieve policy objectives. Zhang Chengfu sees policy tools as pathways and mechanisms for translating policy goals into concrete actions. Chen Zhenming considers policy tools as specific methods and means adopted to solve social problems or achieve policy goals. Although no consensus exists on the definition of policy tools in academia, common ground can be found. Synthesizing these perspectives, policy tools can be understood as various methods and means adopted by policymakers to achieve specific policy objectives.

In current policy tool research, identification is performed manually, which is time-consuming and labor-intensive, greatly limiting the extensive application of policy tools in policy analysis. Therefore, automatic identification of policy tools holds significant importance. This paper explores methods for automatic policy tool identification based on deep learning and conducts empirical research.

## 1. Overview of Policy Tool Identification Research

### 1.1 Definition of Policy Tools

Policy tools, derived from public policy structural theory, currently lack a unified definition. J.P. Lester and colleagues conceptualize policy tools as techniques for policy implementation, identifying two primary pathways: command-and-control mechanisms and economic incentives. O.E. Hughes defines them as patterns of government behavior and mechanisms for regulating governmental action. L.M. Salamon views policy tools as anything that influences the entire process to achieve established objectives. Domestic scholars Zhao Xiaoyuan et al. consider policy tools as elements of the policy system—means and measures that governments can employ to achieve policy goals. Zhang Chengfu regards them as pathways and mechanisms for translating policy objectives into concrete actions. Chen Zhenming defines policy tools as specific methods and means adopted to solve social problems or achieve policy goals. Although academic consensus on the definition remains elusive, these perspectives share common elements. Synthesizing these viewpoints, policy tools can be understood as the various methods and means that policymakers adopt to achieve specific policy objectives.

### 1.2 Policy Tool Classification Systems

Applying policy tools for policy analysis first requires establishing a classification system. Due to different research objects and purposes, current classification standards vary, resulting in diverse classification systems. E.S. Kirschen first proposed 64 general policy tools without classification. L.M. Salamon developed a classification of regulatory, non-regulatory, expenditure, and non-expenditure tools based on previous work. C.C. Hood proposed a classification of information, authority, finance, and organization tools. M. Lorraine et al. categorized policy tools into four types: command-and-control, incentive, capacity-building, and system-change tools. A. Schneider et al. proposed a classification system comprising authority-based, inducement, capacity-building, persuasive, and learning-oriented tools. R. Rothwell et al. divided policy tools into three categories: supply-side, demand-side, and environment-side. Among these, supply-side tools primarily manifest as government expansion of factor supply (information, technology, infrastructure, funding, talent) to promote development in specific fields. Environment-side tools involve government use of fiscal, tax, and regulatory means to improve the policy environment, remove obstacles, and indirectly promote development. Demand-side tools involve government creation of market demand through procurement, outsourcing, and other measures to reduce uncertainty and stimulate development in relevant fields. This classification system covers most policy tool types and enjoys high authority, being the most widely adopted in China. Based on publicly available literature, Chinese scholars frequently employ this system for analysis, often further subdividing the three categories to clarify tool connotations and extensions.

### 1.3 Current Policy Tool Identification Process

Currently, policy analysis from the policy tool perspective is mostly conducted through manual indexing of complete datasets. The basic workflow involves: policy text collection, policy coding, policy tool identification, and statistical analysis. Using Guangzhou's Government Information Sharing Management Regulations as an example, Table 1 illustrates this process.

**Table 1. Example of Policy Tool Indexing**

| Policy Text Content Unit | Policy Tool | Policy Tool Subcategory |
|---|---|---|
| Article 14: The municipal government information sharing authority is responsible for coordinating the construction of city-wide natural person, legal person, natural resources, and spatial geographic databases, electronic certificate information databases, and other shared information libraries. Each government department shall, according to laws, regulations, and performance requirements, coordinate construction management… | Supply-side | Infrastructure Construction |
| (16) For oral solid dosage forms in the national essential medicine catalog that have passed generic drug consistency evaluation according to national regulations, and for other chemical pharmaceutical preparations that are among the first three nationwide to pass generic drug consistency evaluation, provide financial support of 2 million yuan per variety… | Supply-side | Financial Support |
| —Establish a long-term mechanism for health and medical big data sharing, opening, and operation. Promote graded, categorized, and domain-based management and effective application of health and medical big data. Establish and improve policy systems, operational mechanisms, and management methods… | Environment-side | Regulation |

| Policy Text Content Unit | Policy Tool | Policy Tool Subcategory |
|---|---|---|
| (12) Implement and improve government information disclosure regulations. Revise and promulgate the "Regulations on Open Government Information of the People's Republic of China." All regions and departments shall adjust and improve relevant supporting measures, strictly implement new regulations, and ensure smooth transitions… | Environment-side | Regulation |

The policy coding and manual identification steps in this process are cumbersome and error-prone, making large-volume or long-term policy analysis challenging. Most studies select policy domains with fewer texts for policy tool analysis, such as wind power and photovoltaic industries, limiting the scope of policy tool analysis. Therefore, this paper aims to replace policy coding and manual identification with computer technology to achieve automatic policy tool identification.

### 1.4 Related Work

No publicly available research on automatic policy tool identification methods has been found. Policy tool identification falls under policy text identification, which primarily employs linguistics, statistics, machine learning, and deep learning methods. Ma Feicheng et al. established a semantic structure of policy citation types based on linguistic methods to identify relationships between policies and citation themes. Zeng Wen et al. proposed a two-stage term filtering method based on linguistics and statistics for identifying domain terms in science and technology policies. Liu Xing studied policy text mining methods for automatic identification of tax policy documents using attribute subset-weighted Naive Bayes algorithms and attribute-clustered regular automaton models. Li Binbin used the LDA topic probability generation model for text mining analysis to identify 15 themes in China's cultural policies and analyze their evolution. Gu Jiayi used deep learning models to achieve policy text vectorization and automatic identification of enterprise subsidy conditions, saving time for enterprises seeking suitable preferential policies. Lin Deming et al. matched strategic objectives, guiding policy tools in programmatic documents with policy tools in annual intellectual property strategy implementation plans using semantic similarity calculations to comprehensively analyze China's intellectual property strategy goal adjustments and policy tool selections. Overall, current policy text identification methods primarily rely on traditional machine learning, which requires manual feature extraction and has limited capacity for large policy text volumes. Deep learning methods have demonstrated superior performance in multiple research fields, and although some scholars have explored applying deep learning to policy text identification tasks, no systematic research on deep learning-based policy text identification exists, particularly in the domain of automatic policy tool identification. Therefore, this paper explores deep learning-based methods for automatic policy tool identification based on the characteristics of policy texts.

## 2. Methods and Process for Automatic Policy Tool Identification

The workflow for automatic policy tool identification in this study is shown in Figure 1 [Figure 1: see original paper]. First, policy texts undergo paragraph segmentation, then training datasets are divided for model training, and finally the model infers policy tools used in each paragraph of the target policy.

**Figure 1. Process Framework**

### 2.1 Policy Text Paragraphization

To achieve specific policy objectives, policymakers employ multiple methods and means, which manifest in policy texts as the use of various policy tools, typically expressed through single or adjacent paragraphs. Therefore, this study processes policy texts by paragraph, conducting automatic policy tool identification at the paragraph level.

### 2.2 Model Selection

Chinese governments issue numerous policies annually, making it difficult to exhaustively capture all expression rules in policy texts. Moreover, comprehensive policy lexicons are currently lacking, making rule-based and keyword-based identification approaches challenging. Policy texts possess unique characteristics: (1) paragraph lengths vary significantly, from a few characters to hundreds; (2) features useful for policy tool identification are diverse, including word frequency, vocabulary, and mutual information; and (3) policy language is concise and precise with high terminological specificity, where core vocabulary is crucial for identification. Traditional machine learning classification methods require manual feature extraction, generally limited to statistical features, making it difficult to achieve satisfactory classification results. Deep learning-based classification methods can automatically extract features, including semantic features, more comprehensively. Therefore, we selected deep learning methods for automatic policy tool identification.

Typical deep learning text classification models include Convolutional Neural Networks (CNN), Long Short-Term Memory networks (LSTM), and Gated Recurrent Units (GRU). The CNN model comprises an input layer, convolutional layer, pooling layer, fully connected layer, and output layer. The convolutional layer is the core of CNN, where input matrices and kernel matrices undergo convolution operations to generate feature vectors. The pooling layer extracts important features after convolution, removes irrelevant information, and reduces feature vector dimensions. The fully connected layer maps feature vectors to corresponding classification categories to complete the classification task. CNN models are amenable to parallel operation and effectively capture local text features.

LSTM is an improved Recurrent Neural Network (RNN) model that introduces a "gate" mechanism to control input and output for each unit. The forget gate determines how much of the previous unit state is retained in the current unit state; the input gate determines how much of the current input is saved to the unit state; and the output gate determines the current unit's output. LSTM solves gradient vanishing and explosion problems in long sequence training, enabling it to capture sequential information in language.

GRU is similar to LSTM, also being a recurrent neural network, but modifies the input, forget, and output gates into two gates—update and reset gates—while merging the unit state and output into a single state, making the model simpler with fewer parameters and faster training speed.

This study employs three classic deep learning models—CNN, LSTM, and GRU—for automatic policy tool identification. Since LSTM and GRU focus on capturing sequence information, we introduced an Attention mechanism to the base models to help them concentrate on features beneficial for policy tool classification and improve identification effectiveness. The Attention mechanism assigns different weights to different elements in the input sequence, ultimately selecting more critical information for the current task through parameter learning.

### 2.3 Integrating Global Information to Assist Automatic Policy Tool Identification

The aforementioned methods conduct automatic policy tool identification based on paragraphized policies, ignoring global policy information. Global policy information contains tendencies regarding policy tool usage, providing additional information to assist in paragraph-level policy tool identification. Therefore, this study considers integrating global policy information to aid automatic policy tool identification. Recognizing that policy titles are important summaries of policy content and significant representations of global information, we investigate the impact of adding corresponding policy titles to each policy paragraph on automatic policy tool identification.

## 3. Empirical Research

The empirical research process involves: (1) using automated collection technology to obtain relevant policy texts and preprocess them; (2) manually annotating training data according to the selected policy tool classification system; (3) selecting appropriate text classification models based on the characteristics of the policy tool identification task for model training; and (4) using the optimal model for automatic policy tool classification, as shown in Figure 2 [Figure 2: see original paper].

**Figure 2. Experimental Process**

### 3.1 Policy Collection

Government information disclosure has been a key government priority in recent years and an important measure for building transparent government. Beijing, Shanghai, Guangzhou, and Guiyang have performed well in this area. Therefore, this study uses government information disclosure policies from these four cities as research subjects to empirically validate deep learning-based policy tool identification methods.

Broad government information disclosure includes e-government openness, government information disclosure, and government data openness. Using the Chinese Government website, Peking University Law Database, and government websites of Beijing, Shanghai, Guangzhou, and Guiyang as data sources, we retrieved policies using "government data," "open data," "government affairs resources," "e-government," and "information disclosure" as search terms. Automated collection technology yielded 739 policy documents.

### 3.2 Policy Information Preprocessing

Policy information preprocessing aims to improve data quality and provide accurate experimental datasets for subsequent manual annotation, including:

(1) Removing irrelevant and duplicate policies. Since "information disclosure," "open data," and "e-government" are recent government priorities mentioned in many policies, we removed policies where government information disclosure was not the main content. Additionally, different provinces and cities forward policies from higher-level authorities, creating duplicates.

(2) Standardizing policy metadata. We unified publication date formats from different sources and standardized the names of policy-issuing institutions.

(3) Paragraphizing policy texts. We divided texts by paragraph, merging shorter paragraphs such as "Table of Contents" and "General Provisions" with adjacent paragraphs as they have minimal impact on policy tool identification.

After these three steps, the experimental dataset comprised 449 government information disclosure-related policy documents: 237 from Beijing, 107 from Shanghai, 30 from Guangzhou, and 75 from Guiyang. Paragraphization yielded 19,449 natural paragraphs.

### 3.3 Manual Annotation of Training Set

Manual annotation of policy tools aims to create high-quality training datasets for machine learning model training. The work includes: (1) establishing a complete policy tool classification system, and (2) manually interpreting and annotating policy text paragraphs to create training data. Based on Rothwell and Zegveld's policy tool classification and incorporating characteristics of the government information disclosure domain, we developed the classification system used in this study (see Table 2 ) and conducted two rounds of policy tool annotation on 8,000 policy paragraphs.

**Table 2. Government Information Disclosure Policy Tool Indexing System and Examples**

| Policy Tool | Policy Tool Subcategory | Example |
| --- | --- | --- |
| Supply-side | Infrastructure Construction | "Strengthen frontier and basic research. Accelerate improvement of basic research systems and mechanisms, strengthen enterprises' dominant position in innovation, and increase scientific and technological 攻关 for basic frontier technologies and key common technologies in information and communication…" |

| Policy Tool | Policy Tool Subcategory | Example |
|---|---|---|
| Supply-side | Financial Support/Tax Incentives | "The state establishes an electronic certificate sharing service system to achieve cross-regional, cross-departmental sharing and nationwide mutual trust and recognition of electronic certificates." |
| Environment-side | Regulation | "(12) Implement and improve government information disclosure regulations. Revise and promulgate the 'Regulations on Open Government Information of the People's Republic of China.' All regions and departments shall adjust and improve relevant supporting measures…" |

| Policy Tool | Policy Tool Subcategory | Example |
| --- | --- | --- |
| Demand-side | Government Procurement | "Article 9: Public data and e-government project management should adapt to rapid iterative application development models, actively adopt government purchase-of-service project construction methods, and include data services, e-government network services, and e-government cloud services in the purchase-of-service scope." |

| Policy Tool | Policy Tool Subcategory | Example |
| --- | --- | --- |
| Supply-side | Talent Development | "(4) Strengthen team building. Include government website work in cadre education and training, regularly organize training to continuously improve awareness and capabilities…" |
| Supply-side | Information Support | "Before the end of 2019, the national government service platform will be operational. Provincial and State Council department government service platforms will connect with the national platform…" |

| Policy Tool | Policy Tool Subcategory | Example |
|---|---|---|
| Demand-side | Government Procurement | "Cultivate new growth points for information industry development. Accelerate 攻关 and industrialization of frontier key technologies…" |
| Supply-side | Public Services | "Innovate e-government operation management systems, vigorously promote government purchase-of-services. For outsourced business and matters in government website information content construction, strictly review service providers' qualifications…" |

| Policy Tool | Policy Tool Subcategory | Example |
|---|---|---|
| Environment-side | Strategic Measures | "…establish a long-term mechanism for health and medical big data sharing and operation. Promote graded, categorized, domain-based management and effective application…" |

### 3.4 Baseline Models: Machine Learning Methods

We selected two traditional machine learning models as baselines: Logistic Regression (LR) and Support Vector Machines (SVM). Considering the importance of core vocabulary in policy tool identification, we used TF-IDF vectors as text features. TF represents term frequency—the frequency of a term in a document—with higher TF indicating greater relevance. DF represents document frequency—the number of documents containing the term—with higher DF suggesting a more common term. Therefore, Inverse Document Frequency (IDF) measures term importance, calculated as:

$$IDF = \log \frac{N}{DF} \quad \text{(Formula 1)}$$

where N represents the total number of documents in the collection. The final TF-IDF calculation is:

$$TF\text{-}IDF = (1 + \log(TF)) \times \log \frac{N}{DF} \quad \text{(Formula 2)}$$

We represented each policy paragraph as a vector where each dimension represents the TF-IDF value of the term at that position.

### 3.5 Model Parameter Settings

We divided the dataset into training, validation, and test sets in a 4:1:1 ratio. Models were trained on the training set, parameters were updated, the best-performing model was selected based on the validation set, and final performance was tested on the test set. Key parameter settings were: LR model with inverse regularization coefficient C = 0.5; SVM model with C = 0.6; deep learning models with maximum text length of 130 and publicly available Chinese Wikipedia pretrained word vectors (300 dimensions) for initial word representations. The single-layer CNN model used convolutional kernels of sizes 2, 3, 4, and 5, concatenated vectors after max pooling, and used two fully connected layers with 128 and 11 neurons for classification. In the LSTM+Attention model, the LSTM hidden layer size was 60, and after Attention fusion, two fully connected layers with 64 and 11 neurons performed classification. The GRU+Attention model configuration matched the LSTM+Attention model, with only the LSTM module replaced by GRU.

## 4. Experimental Results and Analysis

### 4.1 Experimental Results

Table 3 presents the results of traditional machine learning and deep learning models on the test set. Accuracy represents the proportion of correct predictions, while Weighted avg F1 represents the weighted macro-average F1 score calculated from precision and recall.

**Table 3. Model Test Results**

| Model | Accuracy | Weighted avg F1 |
|---|---|---|
| LR | 0.6816 | 0.7330 |
| SVM | 0.6373 | 0.7162 |
| CNN | 0.7651 | 0.7554 |
| LSTM+Attention | 0.7599 | 0.7580 |
| GRU+Attention | 0.7547 | 0.7541 |
| CNN+Global Info | 0.7713 | 0.7679 |

Both machine learning and deep learning models achieved 68%+ accuracy, demonstrating the feasibility of applying these methods to automatic policy tool identification. Deep learning methods generally outperformed traditional machine learning methods, attributable to their stronger feature representation capabilities, ability to learn semantic information, and focus on local features. For example, consider this policy paragraph using “regulatory” tools:

“Implement and improve government information disclosure regulations. Revise and promulgate the ‘Regulations on Open Government Information of the People’s Republic of China.’ All regions and departments shall adjust and improve relevant supporting measures, strictly implement new regulations, and ensure smooth transitions.”

Deep learning models (CNN, LSTM+Attention, GRU+Attention) correctly identified this category, while traditional models (LR, SVM) erred. We attribute this to deep learning models' superior ability to learn semantic associations—for instance, the strong semantic link between "regulations" and "regulatory control"—a capability lacking in traditional methods. Additionally, policy tool attributes are often expressed through specific phrases like "disclosure regulations" and "revise and promulgate," which CNN and Attention-based models can better focus on, contributing to their superior performance.

### 4.2 Impact of Global Information on Model Results

The CNN model demonstrated good performance with relatively low training time and overhead. We therefore experimented with adding global information to the CNN model. Results showed that integrating global information achieved 77.13% accuracy and 76.79% weighted macro-average F1, outperforming the standard CNN model and confirming the feasibility of using global information to assist automatic policy tool identification.

### 4.3 Impact of Confidence on Experimental Results

The highest-accuracy model (CNN with global information) achieved 77.13% accuracy, still requiring manual review if used directly. To further improve accuracy and reduce manual review costs, we introduced the concept of confidence—the probability value corresponding to the model's output category. We examined the performance of the global-information-integrated CNN model at different confidence thresholds, with results shown in Table 4 . "Data retention ratio" refers to the proportion of test data where the model's predicted probability meets or exceeds the confidence threshold.

**Table 4. Impact of Confidence on Global-Information-Integrated CNN Model Results**

| Confidence | Data Retention Ratio | Accuracy | Weighted avg F1 |
|---|---|---|---|
| 0.5 | 0.7286 | 0.8946 | 0.8884 |
| 0.6 | 0.7107 | 0.9035 | 0.8939 |
| 0.7 | 0.6696 | 0.9176 | 0.9082 |
| 0.8 | 0.6488 | 0.9253 | 0.9164 |
| 0.9 | 0.5943 | 0.9498 | 0.9449 |
| **0.97** | **0.5563** | **0.9544** | **0.9494** |
| 0.99 | 0.4437 | 0.9815 | 0.9796 |

As confidence increases, data retention ratio decreases while accuracy and weighted macro-average F1 increase substantially. At a confidence threshold of 0.97, the data retention ratio is 55.63% and model accuracy reaches 95.44%, meeting practical requirements. This means that when using this model for automatic policy tool identification, if the confidence exceeds 0.97, there is a 95.44% probability that the data truly belongs to the predicted label, eliminating the need for manual review. Consequently, 55.63% of data would not require manual verification during annotation, significantly improving efficiency.

### 4.4 Existing Limitations

While our model integrates global policy information and achieves practical accuracy under high-confidence conditions, there remains substantial room for improvement on the full dataset. Reviewing policies reveals that some paragraphs require contextual information for accurate tool identification. For example:

"Achieve standardization of government service item lists, guidelines, review details, evaluation metrics, real-name users, and online/offline payments, enabling enterprises and the public to enjoy standardized, transparent, and efficient government services."

This paragraph alone makes classification difficult, but combined with its preceding context "(II) Overall Objectives," it should be classified as target planning. Therefore, incorporating contextual information may improve performance. Additionally, considering the relatively standardized terminology and expressions in policy texts, combining lexicon-based and rule-based methods could further enhance identification accuracy.

## Conclusion

This study explored automatic policy tool identification using deep learning methods, taking government information disclosure policies from Beijing, Shanghai, Guangzhou, and Guiyang as data sources. We proposed integrating global information for policy tool identification and demonstrated model effectiveness through empirical research. Under high-confidence conditions, the global-information-integrated deep learning model achieved practical accuracy on a substantial proportion of data, improving annotation efficiency. However, the model still has considerable room for improvement on the full dataset. Future work will consider incorporating contextual information and combining lexicon-based and rule-based methods to further enhance accuracy. Additionally, this paper focuses on methodological exploration; subsequent research will apply the model to reveal current usage patterns of government information disclosure policy tools in the four cities.

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## Author Contributions

**Li Na:** Conceived research ideas, designed research framework; conducted experiments; collected, cleaned, and analyzed data; wrote the paper.
**Jiang Enbo:** Conceived research ideas, designed research framework; collected, cleaned, and analyzed data; revised the paper.
**Zhu Yizhen:** Annotated data.
**Liu Ting:** Annotated data.

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