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A Framework to Analyze the Coordination of Policy Objectives Using Topic Modeling

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Abstract: ***The effective implementation of policies lies in coordinating objectives across different governments. Latent Dirichlet Allocation (LDA) models are crucial for analyzing the thematic content of policy texts. However, a single LDA model struggles to capture the richness of policy topics and content from different policy actors, and its output consists of probabilistic word clusters, which significantly reduces interpretability. These issues result in ineffective policy coordination objective measurement models. We first constructed multi-LDA model to retain the unique characteristics of different policy actors, and developed a policy objective framework to facilitate an effective association between LDA topics and policy objectives. Finally, semantic information was captured using the Word2Vec model, measuring policy objective coordination through a " word - topic - document" hierarchy. Analyzing 112 Chinese New Energy Vehicles (NEVs) policy documents from 2009 to 2022, this approach assessed the central-local coordination and provided both theoretical and practical insights for policy implementation.***

Keywords: Policy Coordination, Text Mining, Latent Dirichlet Allocation, New Energy Vehicles Policy.

1. Introduction

The success factors of policy implementation and the harmonious operation of policy actors lie in coordination of policies (Van Den Bergh et al., 2021). Coordination encompasses both the equilibrium among various components within a policy and the strategic alignment among different policy actors towards a common goal, promoting better performance (Borrás & Edquist, 2013). Especially in terms of coherence of goals, consistency of means, and congruence between goals and means across policies, different combinations of consistency can impact effectiveness in various ways (Van Geet et al., 2021). Therefore, to achieve a common goal, effective coordination between policies is crucial. Relevant agencies can promote the integration and support of various policies by focusing on the degree of policy coordination, thereby ensuring the successful attainment of policy objectives.

The performance of policy coordination measurement largely depends on the ability of the topic model to mine textual information. When addressing topic modeling tasks involving multiple policy actors, the influence of the multi-actor structure of government organizations (Jungblut & Rexe, 2015) must be considered. Even when different policy actors develop policies for the same policy issue, there are differences in their terminology and the thematic focuses they emphasize. These differences are further amplified in topic modeling, affecting the accuracy of thematic information identification, particularly in terms of thematic richness and content variation. A single, parameter-fixed topic modeling method struggles to comprehensively capture the key semantic information in policies (Nie et al., 2022).

The textual information to be extracted also includes the latent semantic information within policy texts. Recent research has employed neural network models and bag-of-words models to measure policy coordination (Biesbroek, Badloe & Athanasiadis, 2020), quantifying the coherence of policy documents by analyzing the proportions of annotated labels in policy paragraphs. Although this approach improved upon the limitations of traditional methods in utilizing textual features, it operated primarily at the paragraph and lexical levels (Biesbroek et al., 2020; Liu & Wang, 2022), resulting in insufficient attention to the latent semantics within policy texts. Conversely, LDA topic models can automatically extract key information and features from policy texts (Li, Jiao, Xu & Chen, 2021; Xu, Chang & Zhang, 2024), identifying differences in key topics and viewpoints, thereby further uncovering hidden patterns within policy texts. Despite its significant support role, LDA model exhibits performance variability when handling different types of data (Altarturi, Saadoon & Anuar, 2023) or complex conceptual data (Prince-Tritto & Ponce, 2023). Additionally, the topics generated by the model are composed of probabilistic distributions over multiple words, and the ambiguous meaning of word combinations, combined with subjective interpretation, often presents challenges to the interpretability of LDA results (Fang & Partovi, 2021). Simultaneously, policy texts are highly specialized and context-dependent, and relying solely on LDA models can limit semantic capture capabilities. Consequently, the integration of natural language processing techniques is often necessary to enhance context semantic recognition and feature extraction efficiency. Therefore, this study proposes a model that combines topic modeling with natural language processing techniques to measure policy coordination.

In this study, the primary objective is to develop a measurement model for assessing the degree of policy coordination in various policy scenarios. Initially, policy text data from different actors within a given policy scenario are collected according to specified criteria. Subsequently, a multi-LDA model is employed to create latent topic structures for each policy actor, resulting in multiple sets of topic-word distributions that reflect the unique characteristics of each policy actor. A policy objective framework is then constructed to aid in naming the topics, designating word clusters as specific policy objectives to address the limitations of weak interpretability. Finally, based on the results from the previous stage, coordination measurement is conducted using the Word2Vec model to leverage its superior ability to capture semantic information, enabling a three-tiered "word-topic-document" policy coordination measurement and determining the level of coordination between pairs of policies.

The new energy vehicles (NEVs) sector has been recognized by the Chinese government as a powerful driver of energy reform, achieving remarkable growth over the past decade (Li et al., 2023). In this study, the rapid development of the NEVs industry has been significantly influenced by policy measures, with incentives and subsidies steering the industry in various directions. Therefore, it is crucial to minimize discrepancies in policy formulation and implementation among different policy stakeholders targeting the same policy objectives. However, existing research on NEVs policies has primarily focused on regional policy practices and evaluations, exploring development strategies and lessons learned (Åhman, 2006; Lee and He, 2017), or comparing multiple regional policies to develop indicator systems for assessing NEVs development across different regions (Ma et al., 2019). There has been limited exploration of policy coordination in NEVs policies. This study uses NEVs policies as a case study and applies a developed coordination model to analyze policy coordination within this policy scenario. In summary, this study has developed a model for assessing policy coordination and successfully applied it within the NEVs policies. The contributions of this paper are as follows: (1) A multi-actor multi-LDA model was constructed to capture the complexity of policy objectives of different policy actors. Independent LDA models were constructed for different policy actors to identify their unique focal points and behavioral patterns. (2) A policy objective framework combined with thematic naming rules was developed to enhance result interpretability. By integrating a seven-dimensional policy objective framework with the thematic naming rules, an effective correlation between policy objectives and topics was achieved, making the results of the LDA model more interpretable. (3) Semantic information was introduced to refine the policy objective coordination measurement model. A three-tiered policy objective coordination measurement model was proposed, utilizing the Word2Vec embedding model to quantify the coordination of central and local policy objectives in NEVs policies at a deeper semantic level.

2. Related Work

2.1 Research on Policy Coordination

Policy coordination is a critical issue that modern governments urgently need to address. Borrás and Edquist et al. (2013) define policy coordination as the consistency among elements such as policy actors, policy objectives, policy instruments, and policy objects, either internally or across elements. Since modern governments are inherently multi-actor organizations, planning conflicts may arise in policy formulation and collaborative implementation (Jungblut & Rexe, 2015). The perspective of policy coordination emphasizes coordination among different actors to achieve consistency and synergy in overall policy objectives. Several researchers have confirmed that policy coordination plays a crucial role in the successful implementation of public policies (Chudnovsky & Trujillo, 2019), establishing cross-sectoral policy objectives (Meijers & Stead, 2004), and curbing the dispersion of government actions (Cejudo & Michel, 2017).

In order to accelerate the promotion of policy coordination in public policies, recent research related to policy coordination has gradually been incorporated quantitative studies on coordination. Traditionally, policy coordination has focused more on describing and analyzing the processes and mechanisms of policy coordination, often using Qualitative Comparative Analysis (QCA) to identify mechanisms and drivers of policy coordination. However, the binary processing method of QCA reduces the interpretability of the results (Tanner, 2014). Therefore, an increasing number of researchers have begun to incorporate intuitive and universally applicable quantitative tools to measure the degree of policy coordination. Schmitz and Eimer (2019), combining social network analysis, explanatory narratives, and expert interviews, analyzed relevant documents from the European Commission, revealing the impact of the Commission's attitudes on policy coordination through a combined qualitative and quantitative approach. Nevertheless, the reliance on subjective data limits the depth and breadth of policy coordination research. Christensen et al. (2019) further employed a data-driven approach, using Ordinary Least Squares (OLS) to process survey data and assess the collaborative and cooperative administrative capabilities of public administration departments. However, this method detached from the original text, is prone to introducing subjective biases, and is limited by the reliance of OLS regression analysis on variables and measurements, failing to capture subtle differences and complexities in the coordination process. To overcome the limitations of traditional quantitative methods in utilizing textual data, Biesbroek et al. (2020) combine neural network models and bag-of-words models, taking paragraphs of policy texts as the minimum unit of analysis, calculating the proportion of text blocks labelled as "adaptation", and proposed a quantifiable measurement standard for policy coordination. This approach strengthens the utilization of textual features and improves the accuracy of policy coordination research. Building upon this, Liu and Wang (2022) further subdivided the minimum unit of analysis into words, calculated the policy coordination of China's coal capacity reduction policy through segmentation and statistical word frequency methods, supplementing the policy coordination from the lexical perspective. Nie et al. (2022) also pointed out that the scale and complexity of policy data will continue to increase, and the focus of future policy coordination research will shift to quantitative analysis and machine learning, emphasizing the semantic features of policy texts and policy scale, and delving deeper into policy coordination.

Although quantitative analysis and machine learning methods have been applied in policy coordination research, improving the efficiency and accuracy of model analysis, existing studies mostly focuses on descriptive text features such as word frequency or paragraphs organization, oversimplifying the complexity of text construction, especially in terms of the relationship between vocabulary, topics, and the overall structure of the text. Therefore, a comprehensive text analysis model should be conducted, which includes a multi-level computational framework that can identify and parse different levels of features and their relationships, providing a richer and more detailed text interpretation. On the other hand, existing research has not given sufficient attention to the policy objective framework. The core of policy implementation lies in achieving established policy objectives, which not only reflect policy efficacy but also encompass comprehensive considerations of policy subjects, policy tools, and policy content. This requires in-depth exploration of latent information and associations in policy coordination processes. Traditional analysis methods struggle to capture indirectly expressed semantic information or overlook contextual language contexts when dealing with semantic information. Therefore, fully exploring different levels of textual connotations requires policy coordination research to grasp complete contexts and global semantic information. This can be achieved by introducing natural language processing techniques to capture semantic information between words, combined with topic modeling to identify the latent thematic structure of texts, improving the model's ability to semantically segment and infer texts from a semantic perspective.

2.2 Application of Topic Models in Text Analysis

Topic models are essential models for identifying and extracting significant thematic information from large-scale textual data. The most representative LDA model was initially proposed by Blei, Ng, and Jordan (2003) and introduced a Bayesian model by Griffiths and Steyvers (2004) to provide a more flexible method for determining the number of topics. Due to its excellent handling capabilities and high scalability on large-scale corpora, the LDA model, has been widely utilized in studies such as thematic identification and sentiment analysis, and has extended into variant models applicable to different types of texts.

Among the numerous applications of topic models, latent thematic identification and textual sentiment analysis constitute a significant proportion. For instance, Valdez, Thij, Bathina, Rutter, and Bollen (2020) employed LDA model to trace the thematic evolution of the timelines of 354,738 American Twitter users, detecting implicit thematic concerns and emotional transitions over time in user tweets. Similarly, researchers have utilized topic models on social media platforms such as Twitter in the Arab region (Alshalan, Al-Khalifa, Alsaeed, Al-Baity, & Alshalan, 2020) and China's Sina Weibo (Wang, Zhou, Zhang, Evans, & Zhu, 2020; Zhu, Zheng, Liu, Li, & Zhu, 2020) to propose automated solutions for COVID-19-related thematic identification and sentiment analysis. A review of research tasks in topic models over recent years reveals that, the emphasis remains on thematic identification, with a primary focus on short texts from social media, however, with only a few studies addressing policy-oriented texts.

In latent thematic identification, the presentation of topic modeling results in the form of word lists can lead to comprehension barriers. How to give a topic a reasonable and interpretable name based on topic keywords has always been an important challenge faced by topic model applications (Fang & Partovi, 2021). To improve the interpretability of results, thematic labeling based on phrases is commonly adopted to label generated topics, in accordance with criteria such as relevance, coverage, and distinguishability. Therefore, for specific textual data, important information can be extracted from authoritative texts to form labels, combined with standardized thematic naming rules, to associate different topics into a unified information structure, thus enhancing the interpretability of model results.

There are also studies involving policy texts with long textual characteristics, such as Song, Guo, Gholizadeh, and Zhuang's (2022) study on China's food safety policies, and Shirota, Hashimoto, and Sakura's (2019) analysis of Japanese financial policies. The application of topic models in multi-actor environments must recognize that different subjects have different understandings and focuses on policy objectives. Although researchers have recognized the characteristics of multi-actor organizations in governments, the application of multi-actor multi-topic models remains narrow and often leads to varying degrees of information loss due to the inability of a single-topic model to adapt to different text subjects. Due to the potential limitation of semantic capture capability due to relying solely on LDA modeling techniques (Belford & Greene, 2020), it is often necessary to integrate LDA techniques with other natural language processing techniques (such as Word2Vec models) in order to improve the efficiency of contextual semantic recognition and feature extraction.

2.3 Research on NEVs Policies

In China, as one of the seven strategic emerging industries, the construction of the new energy vehicle industry has received strong support from national policies. In recent years, the construction of China's new energy vehicle industry has begun to take shape, and new energy vehicle policies have begun to form a system. With the implementation of many policies related to new energy vehicles (NEVs), research on NEVs policies has also been carried out, but existing research mainly focuses on policy evaluation. NEVs policies can mainly be divided into fiscal policies, infrastructure promotion, and research and development investment policies (Li, Yang & Sandu, 2018), among which fiscal policies have the greatest direct impact on the NEVs industry, attracting the most research attention. However, since 2017, China's fiscal policies regarding NEVs have gradually decreased due to their unsustainability. In this context, Ye, Gao, Fang, Liu and Chen (2021) constructed a System Dynamics (SD) model to propose insights into the shift towards endogenous development of NEVs after subsidy stimulation. Additionally, some studies utilize topic modeling methods, combining LDA modeling and econometric methods, to explore the relationship between policy actors and NEVs sales data (Li et al., 2021). Xu et al. (2024), mainly employing LDA modeling and quantitative textual analysis, social network analysis, and other methods to evaluate NEVs policies. Although these studies have made some progress in analyzing depth, there are still limitations in the deep semantic mining of NEVs policy texts.

There is a trend of diversification in research on the policy field of new energy vehicles in China, but there are still some limitations. With the successive introduction of various NEVs policies by both the central and local governments, the improvement of the policy system, especially the coordination of policy objectives, will significantly affect the healthy and stable development of China's NEV industry. However, there is relatively little research on the coordination between the new energy vehicle policies issued by the central and local governments.

3. Model

This study combines machine learning and natural language processing techniques to construct a model for analyzing policy coordination among different policy actors. It employs a multi-LDA model to capture the thematic complexity inherent in the discourse of multiple policy actors, and incorporates Word2Vec model to process semantic information. Ultimately, it develops a three-tiered policy objective coordination measurement model to assess and analyze the level of objective coordination among different policy actors and policy texts.

3.1 Multi-LDA Model

To accurately extract and grasp the topics of different policy texts, precise methodologies are essential. However, given the significant differences among policy actors in terms of issue priorities, policy preferences, and language usage, a single thematic model may fail to effectively distinguish and identify these differences. Therefore, this study constructs multi-LDA models, ensuring a thorough analysis and accurate grasp of each stakeholder's unique focal points and priority policy objectives. Additionally, when using LDA models to capture themes within texts, the challenge of naming topics often arises. This study focuses on policy objectives and addresses this challenge by constructing a policy objective framework, which guides the naming of topics based on the policy objectives, thereby resolving the challenge of thematic naming. The process of topic modeling is illustrated in Figure 1.

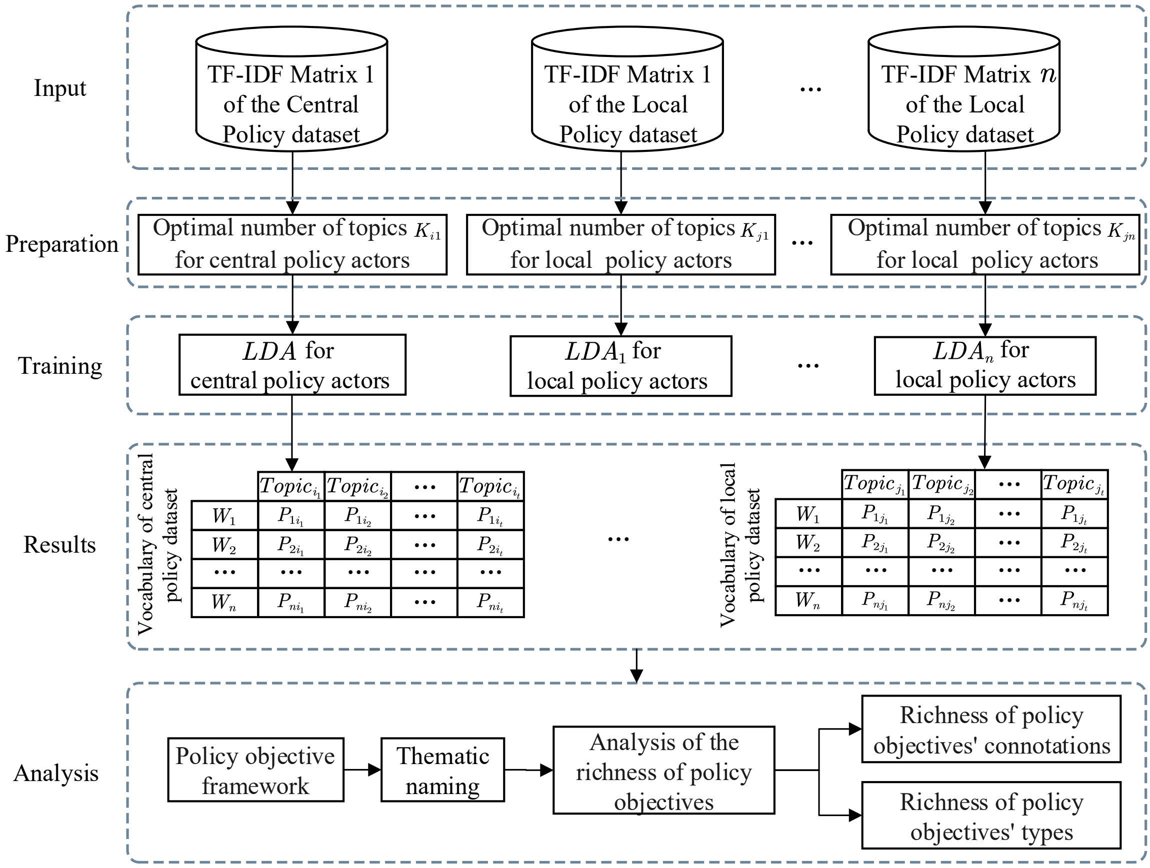

Figure 1: Topic modeling with LDA and document representation for each actor

For the LDA models of different policy actors, it is necessary to determine the optimal number of topics for each LDA model. Subsequently, the models are trained to combine the topic-word distribution with the policy objective framework, and after thematic naming, the diversity and richness of policy objectives are analyzed.

3.1.1 Model Construction

The LDA model, short for Latent Dirichlet Allocation, is an unsupervised Bayesian generative model commonly used to identify latent topic structures within a corpus of text. It takes a corpus containing multiple documents as input and outputs the distribution of topics for each document as well as the distribution of words for each topic. Therefore, use the LDA model to obtain the topics for each policy actor.

Given that different policy actors, such as the central government and local governments, having different priority issues, policy preferences, and linguistic preferences, a single LDA model has difficulty representing the diverse topics and content of policies from various policy actors. It is essential to construct independent LDA models for different policy actors to accurately capture the topics of interest and priority policy objectives in policy texts, and to provide a foundation for analyzing the richness of policy goals in central and local policy documents.

The construction of the LDA model follows the following procedure: Initially, policy texts are categorized into central and local policy texts based on their sources, and then topic modeling is performed on the text sets of different policy actors to adapt to the specific policy domains and expression styles of different actors. When constructing LDA models, it is necessary to determine the appropriate number of topics which can be achieved by using the coherence score, a measure of the model's effectiveness, to determine the optimal number of topics for different LDA models. Coherence score evaluates the coherence between words in a topic, with a higher coherence score indicating better topic quality, implying fewer ambiguities and more coherent semantics within the topics. The formula for coherence calculation is shown in Equation 1(Mimno, Wallach, Talley, Leenders, and McCallum, 2011).

$$C_{UMASS} = \frac{2}{N\times(-1)}\sum_{i=1}^{N}\sum_{j=1}^{i-1}\log\frac{p(w_i,w_j)}{p(w_j)} \qquad (1)$$

Coherence score calculates the average conditional likelihood of word co-occurrences, simultaneously, taking into account the correlation between two words in context, thus better reflecting contextual features. Therefore, the number of topics with the highest coherence score is chosen as the optimal selection during the topic optimization process.

3.1.2 Construction of Policy Objective Framework

A framework links two concepts to highlight their connection, thereby enhancing the relevance of certain dimensions of complex issues. In the process of analyzing the policy themes and objectives coordination between the central and local governments, disparities in expression or emphasis may exist for the same policy points among different policy actors. Such discrepancies hinder the understanding and categorization of policy topics. Therefore, to ensure consistency between policy objectives and the overall policy framework, it is essential to construct an association framework between policy objectives and thematic terms. Starting from the word clusters of LDA topics, a stable and unified information structure is constructed to associate topic terms under different policy actors with policy objectives. This approach strengthens the connection between LDA topics and policy objectives, providing a theoretical basis for the subsequent naming of LDA topics.

The key to develop a policy objective framework lies in identifying the relationship between LDA topics and policy objectives, and then categorizing and synthesizing the identified topics and terms. Policy objectives are the specific anticipated outcomes or effects of policy implementation, which generally guide policy formulation and evaluation. By considering the intentions and motivations behind the policy, one can infer the expected goals and implementation methods included within the policy. This requires a precise understanding of authoritative policy information and guidance from relevant research findings and summary reports. Specifically, constructing a policy objective framework involves focusing on the categorization of policies in research-based annual reports, integrating conclusions from researchers, the characteristics of the policy itself, its expected effects, and implementation requirements. Finally, distill terms related to policy objectives to create a representative policy objective framework.

In conclusion, the construction of a policy objective framework in a particular field can determine the key areas and focal points of policies, serving as the basis for topic naming and result interpretation. The framework consists of multiple policy goals, which are derived from summary reports of policy subjects and distilled into a series of phrases related to policy objectives. By analyzing LDA topic distributions in conjunction with the policy goal framework, different policy objectives can be matched with themes, thereby facilitating thematic naming. Through the policy objective framework, stable connections between information structures of central and local policy texts are established, providing a basis for evaluating the richness of policy topics.

3.1.3 Thematic Naming

Thematic naming involves concretizing the relationship between LDA topics and the policy objective framework, and renaming the word clusters obtained from the LDA model according to thematic naming conventions. Thematic naming entails associating high-frequency thematic terms with core conceptual elements of topics to align with the policy objective framework, thereby assigning interpretable labels to learned topics. Specific naming rules are outlined as follows:

Thematic terms Count: The count of thematic terms within each topic containing policy-relevant terms or synonyms. For terms not present in the policy objective- thematic terms association list but suspected to be relevant to policy objectives, specific text references are consulted for further analysis.

Topic Classification: The classification of topics based on the predominant policy objective category to which the thematic terms within a topic belong. In cases where multiple topics belong to the same policy objective category, prioritize the first term with the highest probability.

Thematic Naming: Naming topics based on policy objective categories. In instances where topics within the same topic model pertain to two identical policy objectives, naming is based on the associated thematic terms.

Thematic naming is a process of assigning policy objective labels to topic categories and classifying objectives. LDA model outputs typically consist of sets of thematic terms, which do not directly reflect specific issues addressed by the topics. Thus, transforming LDA model results into distributions of policy objective-thematic terms and policy text-policy objective distributions, combined with specific experimental results and general rules during the experimental phase, enhances the interpretability of topic outcomes, emphasizing implicit policy objectives of each topic and reflecting the focal points and policy orientations of policy texts.

3.2 Policy Objective Coordination Measurement Model

Measuring the coordination of policy objectives across different policy actors is crucial for ensuring consistency, efficiency, and effectiveness in policymaking. However, differences in how these actors articulate similar objectives can make it challenging for traditional analytical methods to accurately identify and quantify the similarities between policy objectives. To address this, this study introduces semantic information recognition technology, employing the Word2Vec model to capture semantic relationships between terms. Furthermore, we propose a three-level measurement method — "word-topic-document" — which specifically includes: semantic similarity of thematic terms, semantic similarity of topics, coordination of policy objectives between central and local governments, and objectives coordination among specific local policy texts regarding central policy actors. It not only assesses similarity at the lexical level but also extends to broader semantic analyses at the topic and document levels. This approach enables a comprehensive evaluation of policy coordination by considering the various dimensions and levels of policy objectives.

3.2.1 Semantic Similarity of Thematic Terms

Semantic similarity of thematic terms refers to the degree of semantic consistency between two thematic terms. The Word2Vec word embedding model is an effective method for measuring semantic similarity. It uses neural networks to map words into vectors in a high-dimensional space. These word vectors can capture both semantic and grammatical relationships between words, with semantically similar words being close together in the vector space, thus facilitating the computation of semantic relationships between words. To measure the semantic similarity of policy thematic terms, the Word2Vec model is employed to map the topic-word distributions generated by the LDA model into word vectors, allowing for the calculation of semantic similarity from a semantic perspective. In the LDA models, topics are composed of related thematic terms. For any two thematic terms, their semantic similarity can be represented by the cosine of the angle between their word vectors, resulting in the semantic similarity of thematic words $SIM(V_i, V_j)$ between thematic terms $\vec{V_i}$ and $\vec{V_j}$ as shown in Equation 2.

$$SIM(V_i, V_j) = \cos(\vec{V_i}, \vec{V_j}) = \frac{\sum_{i=1}^{n} V_i V_j}{\sum_{i=1}^{n} (V_i)^2 \sum_{j=1}^{n} (V_j)^2} \quad (2)$$

Where $\vec{V_i}$ and $\vec{V_j}$ represent the n-dimensional word vectors of different thematic terms calculated by Word2Vec, namely $\vec{V_i} = (V_1, \dots, V_n)$ and $\vec{V_j} = (V_1, \dots, V_n)$. $cos(\vec{V_i}, \vec{V_j})$ denotes the cosine value of the angle between vectors $\vec{V_i}$ and $\vec{V_j}$. Influenced by the properties of word vectors, the cosine value ranges between 0 and 1, and the closer the cosine similarity value is to 1, the higher the similarity between the two word vectors.

3.2.2 Semantic Similarity of Topics

The semantic similarity of topics is obtained through the calculation of semantic similarity between thematic terms within topics. By pairwise computing the similarity of thematic terms V_{im} and V_{jn} between different topics, and accumulating the similarity of all pairs of topic terms, the overall similarity of topics is obtained. Finally, a normalization term is utilized to constrain the value range, avoiding being influenced by the number of words. The semantic similarity $SIM(T_i, T_j)$ between topics T_i and T_j is computed as shown in Equation 3.

Where N represents the number of words, $TOP-N$ represents the top N words with the highest probabilities in each topic. To ensure that words adequately describe the topics, this paper uniformly sets the number of words in all topic models as N=20. V_{im} and V_{jn} respectively denote the mth word in topic T_i and the nth word in topic T_j, i.e., $T_i = (V_{i1}, \dots, V_{im}, \dots, V_{iN})$ and $T_j = (V_{j1}, \dots, V_{jm}, \dots, V_{jN})$.

$$SIM(T_i, T_j) = \frac{\sum_{m=1}^{N} \sum_{n=1}^{N} SIM(V_{im}, V_{jn})}{N \times N} \quad (3)$$

3.2.3 Objective Coordination of Policy Actors

Objective coordination of policy actors refers to the similarity between two policy actors Ω_i and Ω_j, which is accumulated from the semantic similarity of all topics involved by the two policy actors. Since policy actors involve multiple topics, if there exists a high semantic similarity between the topics of two policy actors, it indicates that they share similar content or focus on similar issues semantically. Therefore, comparing the semantic similarity between the topics involved by two policy actors can infer the coordination of objectives between them. By comparing the similarity of paired topics in two topic models and selecting the maximum topic similarity as the cumulative term, and introducing the optimal number of topics K in the LDA model for normalization, the coordination between different policy actors is finally obtained. The coordination measurement of different policy actors Ω_i and Ω_j is shown in Equation 4.

$$SIM(\Omega_i, \Omega_j) = \frac{\sum_{k=1}^{K_j} \max_{i \in [1, K_i]} (SIM(T_i, T_k))}{K_j} \quad (4)$$

Where K_i and K_j respectively represent the optimal number of topics in the topic models of two policy actors Ω_i and Ω_j, and i, j represent the index numbers of different policy actors. In general, a specific topic in one policy actor's topic model is highly similar to only one topic in another policy actor's topic model. Therefore, the maximum value is used to extract the similarity between topics.

3.2.4 Local Textual Coordination Regarding Central Policy Actors' Objectives

The coordination of objectives between specific policies of local governments and policies issued by central policy actors is based on the text-topic probability distribution of specific policy texts of local governments, combined with the overall similarity between topics of local government policy texts and central government policy texts. The specific calculation is shown in Equation 5. The text's topic model incorporates a probability distribution mixed with multiple topics, where named topics are associated with policy objectives, linking central policy actors and local policy actors. Therefore, the relevance of text-topic distribution is introduced to adjust the similarity between specific local policy texts and central policy actors through a weighting mechanism.

$$SIM(\Omega_1, D_{jk}) = \frac{\sum_{k=1}^{K_j} p_k \times \max_{i \in [1, K_1]} (SIM(T_i, T_k))}{K_j} \quad (5)$$

Where Ω_1 represents central policy actors, D_{jk} represents the kth policy text of the jth local policy actors, p represents the text-topic probability distribution output based on the topic model, and the policy text D_{jk} of the local policy actors belongs to topics $[T_1, \ldots, T_{K_j}]$ with probabilities $[p_1, \ldots, p_{K_j}]$. K_j represents the optimal number of topics in the topic model constructed for the local policy actor Ω_j.

4. Experiments

The research process comprises three phases: (i) Data collection and preprocessing; (ii) Multi-LDA modeling and policy objective analysis; and (iii) Policy objective coordination measurement. The research framework, as depicted in Figure 2, will be implemented in Section 4, with detailed procedures elucidated below.

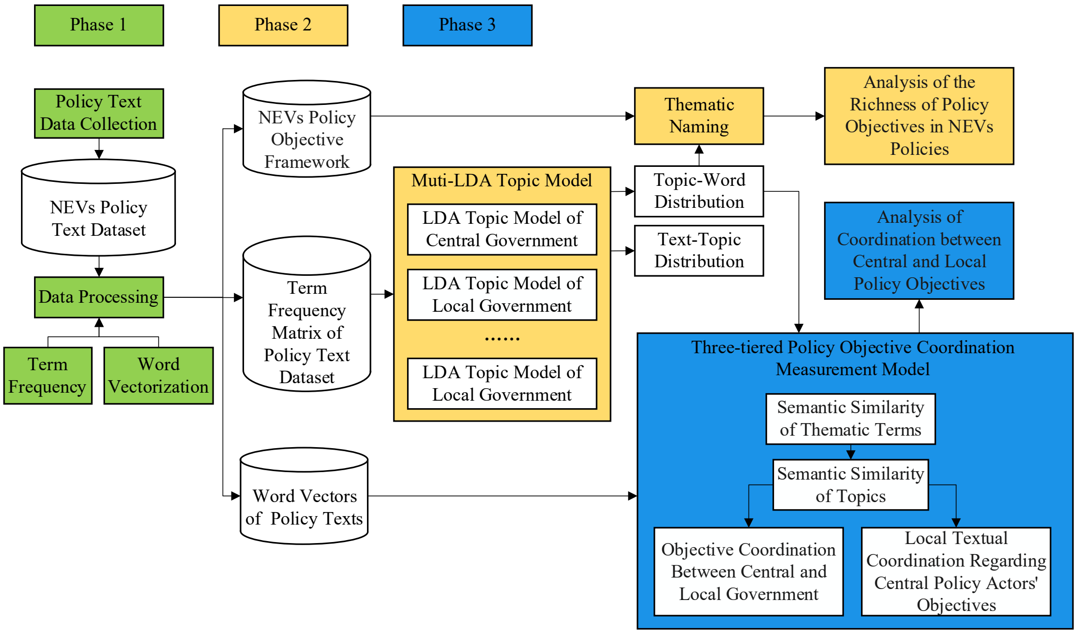

Figure 2: Overall methodology pipeline

4.1 Phase 1: Data Collection and Processing

Figure 3 is the process of data collection and preprocessing used to conduct topic modeling about policy.

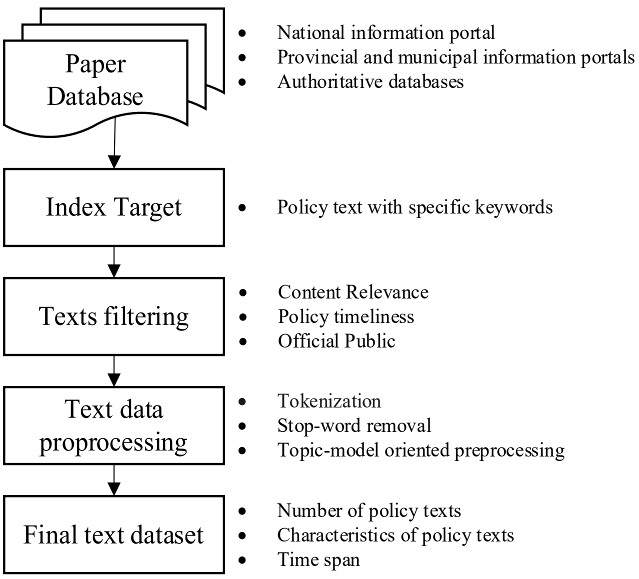

Figure 3: Process of data collection and preprocessing

The paper focuses on the analysis of NEVs policy texts, employing the methodology proposed in Section 3. The rationale for selecting this particular subject is delineated as follows:

(1) NEVs have garnered significant global attention and received substantial support and guidance from national and regional governments, thereby shaping an industrial policy environment that profoundly impacts the relevant industry chains.

(2) NEVs policy encompasses multiple levels, including national regulatory policies and local support measures, rendering it applicable to the proposed three-tiered policy objective coordination measurement model.

(3) There is still insufficient research on textual analysis of NEVs policies, necessitating an enhancement in analytical depth to unveil policy directions and pivotal concerns of governments, thereby offering novel insights for future research endeavors and policy formulation.

4.1.1 Data Collection

Information Sources

We searched for relevant articles in the following databases: Chinese Government Website, National Development and Reform Commission, National Energy Administration, Ministry of Industry and Information Technology, Provincial and Municipal Government Office Websites, Provincial and Municipal Energy Administration, Provincial and Municipal Economic and Information Commission, Provincial and Municipal Development and Reform Commission, Peking University Law Information Database. These databases are highly authoritative, credible, comprehensive in literature, and timely, providing a scientifically reliable basis for research.

Selection Criteria

To select the literature suitable for analysis, a series of inclusion and exclusion criteria were established.

Inclusion criteria

- Policy type: public documents, bulletins, notices, mainstream official media reports and policy interpretations
- Policy language: Chinese articles
- Policy publication time: policies within the timeframe
- Policy main content: NEVs policies issued by the central and provincial governments

Exclusion criteria

- Policy type: unofficial information
- Policy language: articles in other languages
- Policy publication time: expired policies
- Policy main content: Policies not directly related to China's NEVs

Screening of Research Materials

The process of searching for and selecting policy documents was divided into four stages, as delineated below:

(1) Keyword determination: policies were searched for in electronic databases using the keywords *Electric vehicle, Electric-driven vehicle, Pure electric vehicle, New energy vehicle*.

(2) Preliminary review: identified policies were sorted by authority, relevance, and timeliness. Titles and introduction contents were reviewed to select important documents according to the selection criteria.

(3) Further review: policies that passed the preliminary review were thoroughly read.

(4) Material determination: compile and consolidate all policy documents, including document numbers, policy names, types, issuance dates, issuing authorities, policy levels, policy sources, and URLs. As a result, a total of 112 policy documents, including plans, outlines, and notices, were obtained, covering a time span from November 2009 to September 2023.

4.1.2 Data Preprocessing

For the collected policy text data, preprocessing tasks, including tokenization, stop-word removal, and topic-oriented preprocessing, are conducted.

Firstly, leveraging the Python jieba library and custom dictionary matching method, the policy texts related to NEVs were tokenized. A representative custom dictionary highly relevant to the NEVs industry was constructed based on NEVs policy texts, which was combined with the default dictionary and part-of-speech tags. This facilitated the accurate segmentation of NEVs industry-specific terms. For instance, by default, "charging pile" might be segmented into "charging" and "pile", and "charge and swap" into "charge" and "swap." However, the addition of a custom dictionary could prevent the segmentation of specialized terms.

Next, based on multiple popular stop-word lists, several experiments were conducted to remove stop words from the segmentation of NEVs policy texts. The Chinese stop-word lists from sources such as the Chinese stop-word list, the Harbin Institute of Technology stop-word list, the Baidu stop-word list, and the stop-word list from the Sichuan University Artificial Intelligence Laboratory were compiled as the corpus. This corpus was utilized to remove both Chinese and English alphanumeric characters, symbols, and high-frequency meaningless words from the NEVs policy texts. Additionally, after each experiment, words with high frequencies but minimal analytical significance in NEVs policy texts, such as "opinion", "summary", and "formulate", were added to adjust the stop-word corpus. Continual adjustments were made to the stop-word corpus until an appropriate version tailored to NEVs policy texts was obtained for precise stop-word removal.

Finally, data preprocessing was conducted for topic modeling and objective coordination measurement modeling. The input for the LDA model was the TF-IDF word frequency matrix, implemented using the gensim library in Python. For the objective coordination measurement modeling, the skip-gram algorithm model, which is more sensitive to low-frequency words, was trained for preprocessing. Again, this was also implemented based on the gensim library in Python. The trained model could output word vectors for all words in the dictionary, the similarity between two words in the dictionary, synonyms for a specific word, etc., providing textual quantification support for subsequent calculations of pairwise cosine similarity.

4.2 Phase 2: Topic Modeling and Analysis of NEVs Policies Texts

4.2.1 Multi-LDA Training

Multi-LDA models were independently constructed for each policy actor based on data segmentation. Among the 112 texts of NEVs policy texts, they were divided into six major policy actor text sets according to the differences in policy sources: Central government, State Council, Zhejiang government, Shanghai government, Anhui government, and Jiangsu government. For each policy actor, a separate LDA model with parameter independence was constructed to extract NEVs policy topics specific to each policy actor.

To train the LDA models for the six major policy actors, the optimal number of topics for different LDA models needed to be determined based on a coherence metric. To ensure the stability of the models, the optimization of the number of topics was conducted by averaging results from multiple repeated experiments, and the optimal number of topics was automatically searched for through code traversal. The procedure for optimizing the number of topics is as follows:

(1) Set the maximum number of topics, K, from 1 to K, and calculate the coherence of the models.

(2) Repeat step 1 for x times and calculate the average coherence for different numbers of topics.

(3) Select the model with the highest coherence score as the

optimal number of topics, K.

Considering the characteristics of the sample size and the research objectives of NEVs policies in terms of content dimensionality, this paper set the maximum number of topics, K, to 10, and the number of repeated experiments, x, to 50. The distribution of coherence scores is shown in Figure 4.

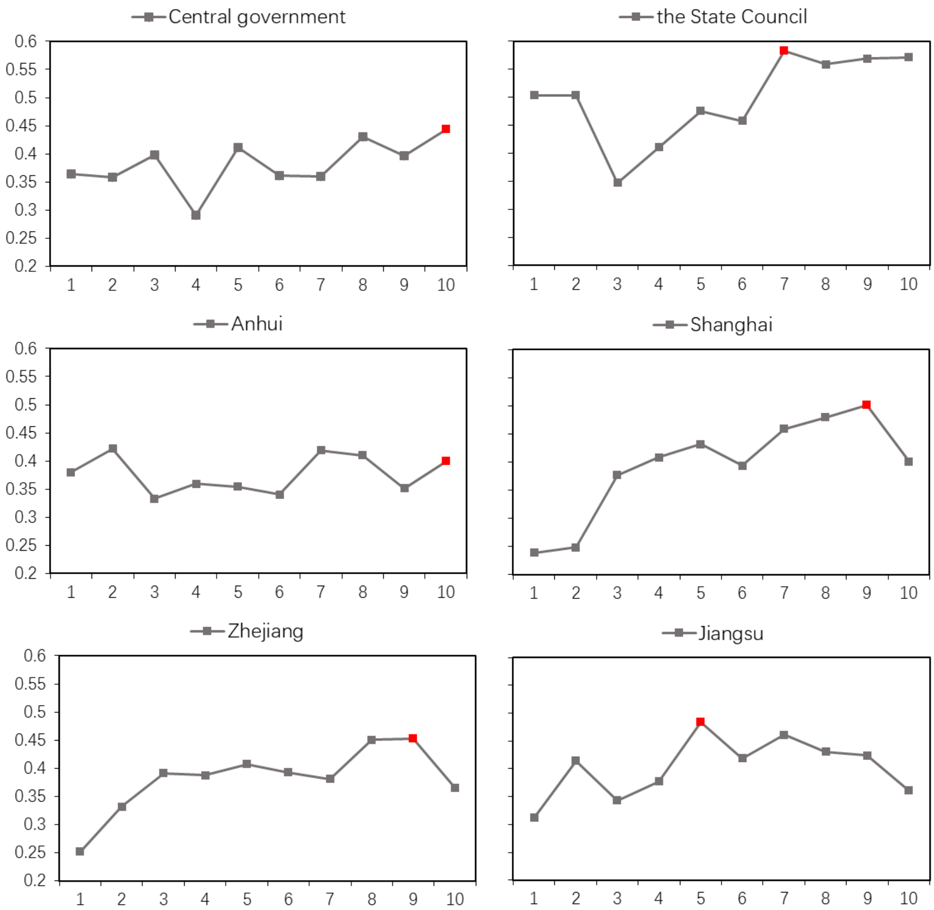

Figure 4: Consistency distribution of LDA models for different subjects

The coherence distribution graph illustrates the maximum coherence scores attainable within the range of topic numbers for the six LDA models. The number of topics corresponding to the maximum value represents the optimal number of topics for each model. The results of the optimal number of topics for LDA models of different policy actors are presented in Table 1.

Table 1: Evaluation results of the optimal index of LDA model of different subjects

Actors	The optimal number of topics	Coherence scores
Central government	10	0.4435
the State Council	7	0.5835
Anhui	2	0.4216
Shanghai	9	0.5014
Zhejiang	9	0.4529
Jiangsu	5	0.4832

Furthermore, the LDA model generated topic distributions for policy texts and topic-word distributions for each policy actor.

4.2.2 Policy Objective Framework Construction

Chen, Zhang, Wang and Ou started from the perspectives of enterprise demand and policy measures, categorized and statistically analyzed policy texts concerning the development of NEVs at different stages, based on enterprise demand and policy measures. According to the "Blue Book on New Energy Vehicles (2015)" issued by the China Automotive Technology and Research Center (CATARC), Nissan (China) Investment Co., Ltd. (NCIC), and Dongfeng Motor Co., Ltd. (DFL) (2015), NEV-related policies in China are categorized into six categories: macro policies, demonstration policies, tax incentives policies, technological innovation policies, industry management policies, and infrastructure policies (CATARC, NCIC & DFL, 2015). Among these, demonstration policies not only encompass policies aimed at increasing the penetration rate of NEVs but also include policies establishing corresponding purchase subsidy standards. Although these two policies share consistency in objectives, their contents exhibit significant differences. To distinguish these policies more clearly, Zhang, Rao, Xie, and Liang (2014) categorized them into pilot policies and fiscal subsidy policies as two independent policy categories. Similarly, Yuan, Liu, and Zuo (2015) conducted in-depth analyses by categorizing them into demonstration policies and financial support policies. Building upon the classification system of the China Automotive Technology Research Center (CATARC) and combining the aforementioned two relevant studies, Li, Long, and Chen (2016) further divided NEVs-related policies into seven directories: macro policies, demonstration policies, subsidy policies, tax incentive policies, technical support policies, industry management policies, and infrastructure policies. This classification is more detailed, allowing for a more comprehensive coverage of the main objectives of current NEVs-related policies in China.

Based on the aforementioned studies and by analyzing the characteristics, demands, and interest mechanisms of NEVs policies themselves, coupled with the supporting situations for the effective implementation of NEVs policies, a framework related to the objectives of NEVs policies is constructed. Emphasis is placed on exploring the promotion strategies for NEVs from the perspective of implementing measures, emphasizing the expected effects in areas such as industry, finance, technology, management, and infrastructure, including implementation of industrial planning, demonstration role of industries, adjustment of financial subsidies, promotion of rational taxation, strengthening of technical support, enhancement of industry management, and promotion of infrastructure construction. The policy objective framework is illustrated in Figure 5.

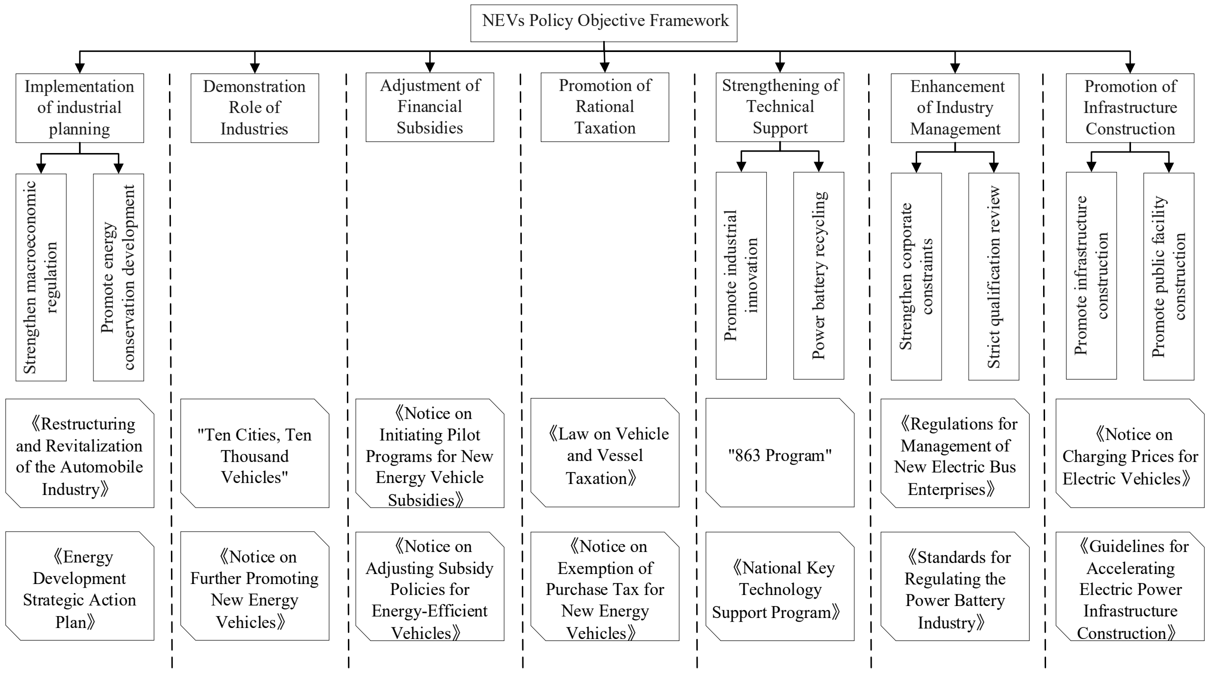

Figure 5: NEVs Policy Objective Framework

Table 2: Correlation table between policy objectives and thematic terms

Policy objectives	Thematic terms
Implementation of industrial planning	“meet the standard”, “long-term”, “plan”, “renewable energy”
Demonstration role of industries	“pilot”, “demonstration”, “promote”, “industrialization”
Adjustment of financial subsidies	“subsidies and incentives”, “financing”, “loan”, “finance”, “subsidy”, “finance”
Promotion of rational taxation	“exemption”, “tax”, “taxation”
Strengthening of technical support	“power battery”, “grading”, “fuel cell”, “power”, “recycling”, “innovation”, “battery”
Enhancement of industry management	“points”, “consumption volume”, “fuel”, “production capacity”, “restrict”, “threshold”, “accountability”, “illegal”, “rated power”, “quality inspection”, “review”, “access”, “enterprise”, “accident”, “security”, “informatization”, “Property rights”
Promotion of infrastructure construction	“charging”, “facilities”, “construction”, “plan”, “parking”, “power grid”, “land use”, “residential area”

4.2.3 Thematic Naming Based on Policy Objectives

Based on the probability distribution of topic-word in the LDA model, combined with the framework of policy objectives related to NEVs, the seven -dimension of NEVs policy objectives were associated with relevant thematic terms. For thematic terms with overt attributes, such as “subsidy”, “taxation”, and “pilot”, corresponding policy objectives could be directly linked. For thematic terms with more ambiguous definitions, such as “credits” and “gradation”, determinations were made by referring to texts most relevant to the topic and incorporating specialized terminologies in the NEVs industry. For example, the term ‘credits’ in the corresponding policy text indicates its association with the credit system for NEVs in passenger car enterprises. It refers to the calculation of the total quantity of new energy passenger cars produced or imported by a company within a fiscal year, multiplied by the production or import volume of each car model. On the other hand, “gradation” is a specialized term in the NEVs field, representing graded utilization, specifically the optimal solution for power battery recycling. Through the delineation and categorization of thematic terms, a table of associations between policy objectives and their matched thematic terms is obtained (see Table 2).

After establishing the relationship between policy objectives and thematic terms, the method outlined in section 3.2.3 for thematic naming was utilized to classify topics based on thematic terms relevant to policy objectives. Subsequently, thematic naming was applied to categorize the topics for each policy actor, thereby emphasizing the essence of each topic. The obtained results are presented in Online Resource.

4.2.4 Analysis of the Richness of Policy Objectives in NEVs Policies

Upon linking policy topics with policy objectives through thematic naming, the results analysis will focus on the richness of policy objectives from different perspectives, comprehensively discussing the types and connotations of policy objectives from the perspective of policy objective types and contents. Additionally, as central policies guide the development of various aspects at the local level, this paper will analyze the types and contents of policy objectives of local policy actors with reference to the richness of policy objectives of central policy actors.

The thematic naming provides interpretability for the analysis of the richness of policy objectives in the policy text. The richness of policy objectives reflects the comprehensiveness of NEVs policies and serves as the basis for analyzing policy coordination. Therefore, attention should be paid to the role of policy objectives to ensure that policies address a broad range of needs and anticipated outcomes, providing multi-level solutions for diverse issues. Based on the distribution of the aforementioned topics, the analysis of the richness of policy objectives is mainly discussed from the following two perspectives:

(1) Richness of Policy Objectives' Connotations

The richness of policy objective connotations is assessed from the distribution of words constituting policy objectives, observing the breadth of areas involved in each objective. Words are the basic units of policy texts, and their interactions constitute the overall meaning of policy texts. Therefore, the scope of fields covered by objective terms can highlight the inherent intentions of policy texts, inferring the comprehensiveness and inclusiveness of policy deployment and focal points.

The central policy actors exhibit the highest number of policy themes, with more diverse thematic content covering a wide range of domains. Using the thematic domains covered by the central policy actors as a reference, the connotations of policy objectives of local policy actors were analyzed. The thematic terms of central policy actors include "finance", "environmental protection", "facilities", "construction", "transportation", "logistics distribution", "renewable energy", "system security", "residents", "tax exemption", among others, involving various domains such as finance economics, infrastructure, environment, transportation, innovative technologies, and public welfare. The comprehensive policy support from the central policy actors is crucial for the perfection of the NEVs industry system, and the synergy with the central policy actors is essential for achieving a comprehensive NEVs industry chain and enhancing the core competitiveness of the national NEVs industry. The distribution of TOP-20 thematic terms in the thematic model provides insights into the domains covered by different policy actors, as shown in Table 3.

Table 3: Domains involved in the NEVs policies

	Central government	Anhui	Shanghai	Zhejiang	Jiangsu
Finance economics	√		√	√	√
Infrastructure	√	√	√	√	√
Environment	√			√	
Transportation	√				
Innovative technology	√	√	√	√	√
public welfare	√		√	√	√

Policy thematic terms of different local policy actors exhibit varying degrees of domain focus, with local policy actors generally covering fewer thematic domains. Taking Anhui as an example, its thematic terms cover "infrastructure" and "intelligent connected vehicles", focusing more on infrastructure construction and innovative technology fields. In contrast, Shanghai's thematic terms are more diverse, including "tax", "facilities", "construction", "investment", "electricity price", "high-tech", among others, covering multiple domains such as finance economics, infrastructure, public welfare, and innovative technologies, demonstrating the richness of policy objectives. However, there still exists a certain gap in full synergy with central policies. Thematic terms in Zhejiang cover "innovation", "financial subsidies", "tax", "research institutes", "residents", "geographical environment", "additional construction", etc., involving domains such as finance economics, infrastructure, environment, innovative technology, and public welfare. In terms of coordinated collaboration among domains, Zhejiang performs exceptionally well in the Yangtze River Delta region, preliminarily achieving multi-domain collaboration in the NEVs industry planning. Thematic terms in Jiangsu include "financial subsidies", "facilities", "electricity price", "intelligent connected vehicles", covering domains such as finance economics, infrastructure, public welfare, innovative technology, yet lacking richness in the connotations of policy objectives. Overall, the richness of policy objectives in the NEVs sector in the Yangtze River Delta region is relatively high. Among them, Shanghai and Zhejiang, with better economic development, demonstrate outstanding performance in multi-domain coordination, while Anhui and Jiangsu still need to focus on multi-domain coordination in the issuance of NEVs policies.

(2) Richness of Policy Objectives' Types

The richness of policy objective types refers to whether policy texts contain diverse and extensive policy objectives. The multiple-topic probability distribution of the topic models determines the probability that a policy text is classified into a certain objective, providing information on the types of policy objectives covered by the policy text. By identifying the types of policy objectives contained in policy actors, the diversity of policy objective types can be revealed.

According to the thematic classification and thematic naming (see Online Resource), the richness of policy objectives' types is shown in Table 4, with numbers representing the frequency of involvement of policy objectives. Based on the results in the table, it can be observed that the central policy actors cover the most diverse types of policy objectives, using the richness of policy objectives of the central actor as a reference to analyze the richness of types of policy objectives of local policy actors. The central policy actors encompass all seven dimensions of NEVs policy objectives, which include implementation of industrial planning, demonstration role of industries, adjustment of financial subsidies, promotion of rational taxation, strengthening of technical support, enhancement of industry management, and promotion of infrastructure construction. The State Council, as part of the central policy actors, mainly focuses on implementing practical measures, with policy objectives including demonstration role of industries, promotion of rational taxation, enhancement of industry management, strengthening of technical support, and promotion of infrastructure construction.

Table 4: The objectives involved in the NEVs policies

	Central government	The State Council	Anhui	Shanghai	Zhejiang	Jiangsu
Implementation of industrial planning	1					1
Demonstration role of industries	1	1			1	2
Adjustment of financial subsidies	1			3	3	1
Promotion of rational taxation	1	1		1		
Strengthening of technical support	2	1	1		2	
Enhancement of industry management	3	1		2	2	
Promotion of infrastructure construction	1	3	1	3	1	1

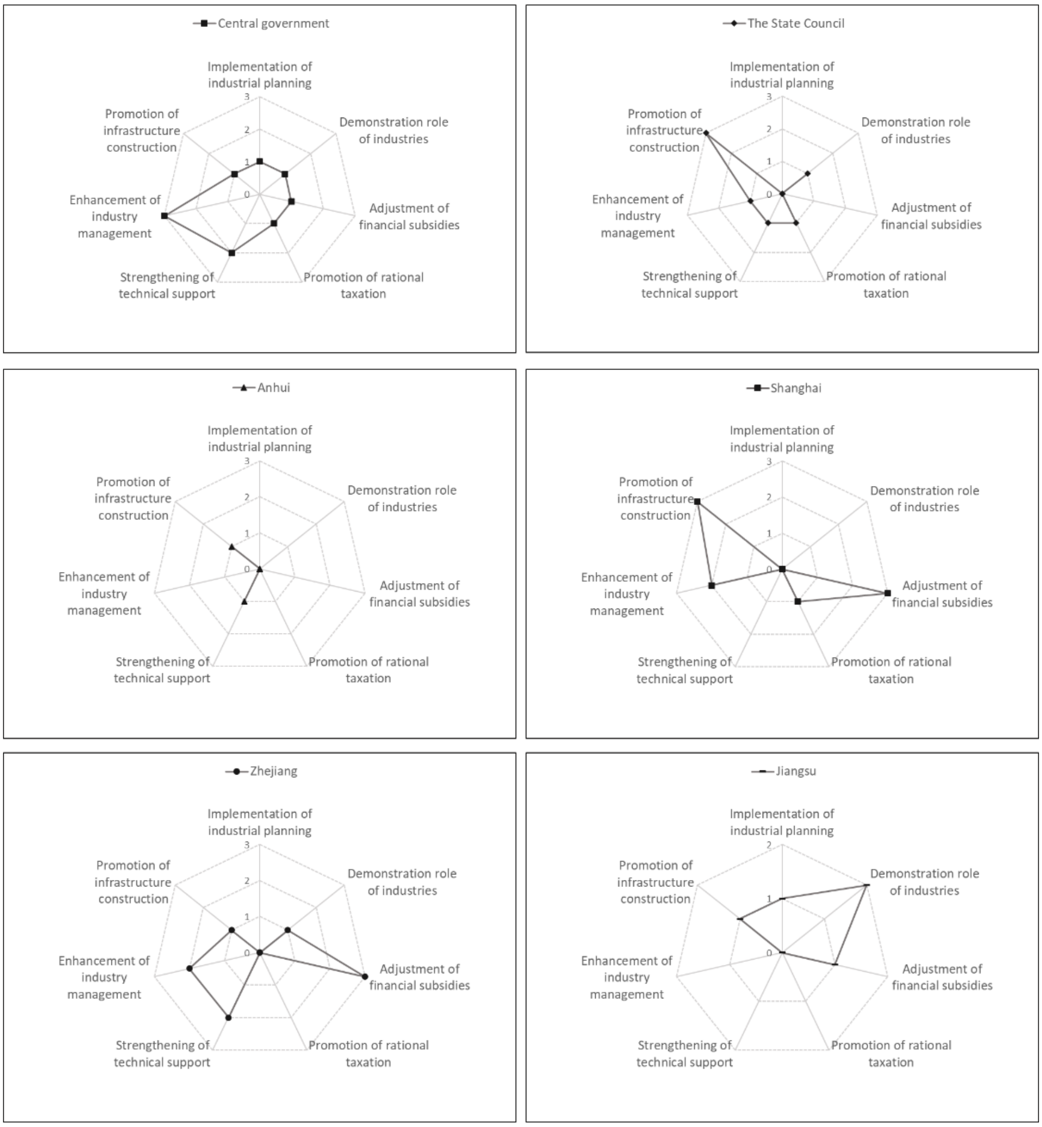

Figure 6: Comparison of the attention of different policy subjects to policy actors

As shown in Figure 6, the central policy actors demonstrate attention to all seven dimensions of policy objectives, while the types of policy objectives involved by local actors are not comprehensive. Among local actors, Zhejiang covers the most diverse types of policy objectives, being the most comprehensive in terms of policy objectives, only omitting the objectives of implementation of industrial planning and promotion of rational taxation among the seven dimensions of policy objectives. Shanghai and Jiangsu respectively cover policy objectives from five dimensions, showing relatively comprehensive policy objectives. Anhui covers the fewest types of policy objectives, only focusing on enhancement of industry management and promotion of infrastructure construction.

The central policy actors emphasize the policy objectives of “strengthening of technical support” and “enhancement of industry management” while local policy actors exhibit differences in policy focus. From the perspective of policy focus, the policy objectives covered by Zhejiang and Shanghai have achieved preliminary coordination with those of the central policy actors. The central policy actors emphasize the objectives of strengthening of technical support and enhancement of industry management, while the policies enacted by Zhejiang include adjustment of financial subsidies, strengthening of technical support, and enhancement of industry management, three key policy objectives, aligning with the focus of the central policy actors. In addition to focusing on policy subsidies and enhancement of industry management, Shanghai also focuses on promotion of infrastructure construction as a policy objective. However, Anhui and Jiangsu have significant deviations in the focus of key policy objectives. Anhui only includes two-dimensional policy objectives, synchronizing with the central policy actors in strengthening of technical support; the NEVs policy of Jiangsu focuses on demonstration role of industries, lacking emphasis on the key objectives of central policy actors, requiring strengthened interpretation of the core points of central policy texts to implement the policy directives effectively.

In conclusion, the analysis of the richness of policy objectives reveals that compared to the connotations and types of policy objectives of central policy actors, those of local policy actors are relatively scattered. Measures should be taken to improve the comprehensiveness of policy objective types, policy transmission, and implementation. Despite having the least amount of text, the State Council contributes significantly to the number of topics, indicating that the optimal number of topics is not directly related to the amount of text. Therefore, in promoting the development of the NEVs industry, both central and local governments should not solely pursue the quantity of policy issuance, but also aim to enrich policy objectives and enhance the coherence of policy concerns. This will facilitate the comprehensive development of the NEVs industry and mitigate policy gaps. Consequently, local governments at all levels should intensify the interpretation of policy documents, align with the central policy actors, and effectively implement important NEVs policies while regulating policy execution behaviors, thus ensuring the orderly advancement of the NEVs industry.

4.3 Phase 3: Coordination Measurement and Analysis of Central and Local NEVs Policies

Following the output of text-topic distribution and topic-word distribution via the LDA model, the results of the second phase were transformed into Word2Vec word vector format. Based on cosine distance, the similarity between words, topics, and texts is measured step by step. To adapt text characteristics, a skip-gram model, sensitive to low-frequency words, is employed for Word2Vec word embedding. With a word frequency filter set to 1, the maximum distance between the current word and the target word was set to 5, taking into account the lengths of proprietary terms in the NEVs policy. Finally, following the policy objectives coordination measurement model, three step-by-step computational steps were undertaken, including semantic similarity calculation of thematic terms, semantic similarity calculation of topics, and coordination degree calculation of policy objectives between central and local policy texts, subsequently, local policy text coordination degrees concerning central policy actors were computed. A Python function was developed to iteratively calculate the coordination degree of central and local NEVs policy objectives.

4.3.1 Analysis of Coordination between Central and Local Policy Objectives

This paper evaluates the coordination level of other policy actors or texts concerning central policy actors using the coordination degree of the State Council as the threshold. The relationship between central policy actors and the State Council is inclusive, with policies issued by the State Council being the core implementation measures in the macro policy of NEVs, thus they hold certain reference value in terms of semantic similarity. If the coordination degree of local actors regarding central policy actors is higher than or equal to the standard threshold, it is considered to have a higher coordination level and is labeled as 1; otherwise, it is regarded as having a lower coordination level and labeled as 0, thereby achieving the classification of central and local policy coordination levels. The results of central and local policy objectives coordination are presented in Table 5 and Figure 7.

Table 5: Policy objectives coordination between central and local actors

Central government-the State Council	**0.6383**		
Local policy actors	Degree of coordination	Level of coordination	Discrepancy
Central government -Anhui	0.5676	Low	-0.0707
Central government -Shanghai	0.6881	High	+0.0498
Central government -Zhejiang	0.6786	High	+0.0403
Central government -Jiangsu	0.6350	Low	-0.0033

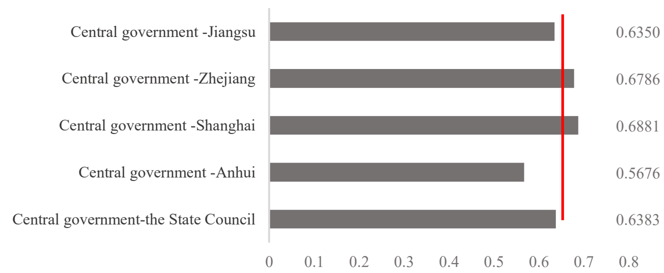

Figure 7: Central and local policy objective synergy level chart

The overall average semantic similarity (coordination degree) between policy actors of Anhui, Shanghai, Zhejiang, and Jiangsu, regarding central policy actors, is 0.5675, 0.6881, 0.6786, and 0.6350, respectively. The coordination degree of policy objectives from high to low is ranked as follows: Shanghai, Zhejiang, Jiangsu, and Anhui. From the perspective of policy objective coordination, it is argued that the governments of Zhejiang and Shanghai exhibit a relatively high level of coordination in the content dimension of NEVs policies. This is evidenced by the coordination level of the two actors surpassing the coordination threshold, indicating a high degree of consistency and cooperation in the formulation and implementation of NEVs policy objectives. However, the coordination between the governments of Anhui and Jiangsu in the construction of NEVs policies requires to be strengthened, as their coordination level falls below the coordination threshold. This suggests significant differences between the two local policy actors in the formulation and implementation of NEVs policy objectives, indicating a lack of consistency and cooperation from the perspective of policy objective coordination, thus necessitating further enhancement of collaborative efforts to facilitate the achievement of policy objectives.

In comparing the objectives and measures of the central government's policy on NEVs with local policy actors, further analysis was conducted on the coordination of NEVs policy objectives among the governments of Anhui, Jiangsu, Zhejiang, and Shanghai. Anhui exhibits a characteristic of dispersed policy objectives regarding NEVs, with insufficiently comprehensive policy measures. Particularly in incentive-oriented objectives, such as fiscal subsidies, tax adjustments, and incentive mechanisms targeting consumers and relevant enterprises, there are evident shortcomings. Moreover, the construction of the NEVs industry system in Anhui has not yet reached an ideal level, lacking some necessary macro planning. In contrast, Jiangsu has shown outstanding performance in policy innovation and achieved certain coordination with the central policy actors. However, compared to the central government, Jiangsu lacks sufficient utilization of infrastructure construction means in policy measures and insufficient allocation of resources for the technological development of the NEVs industry. Zhejiang has excelled in coordinating and implementing policies in line with the central policy objectives, issuing macro planning policies such as the "14th Five-Year Plan" and "Three-Year Action Plan" at the provincial level, as well as specific fiscal subsidy policies and various promotion pilot programs at the municipal level. This practice provides a good example for other provinces and cities to follow. Shanghai ranks high in terms of coordination, being one of the earliest regions to implement NEVs industry development policies, with more focused policy objectives and more comprehensive content. However, there is still room for improvement in macro planning for the future development of NEVs in the city area, which need to be strengthened in future efforts. Overall, while local policy actors have the subjective initiative in policy innovation, it is essential for policy objectives to align with the central policy actors. Continuous efforts are needed to enrich and optimize policy measures based on local development realities, ensuring the effectiveness of local policies and organic alignment with central policies to promote the coordinated development of the national NEVs industry.

The policy coordination between the central and local governments regarding NEVs exhibits uneven levels of synergy. To address this issue comprehensively, suggestions are proposed from both a nationwide perspective and individual regional viewpoints, aiming to strengthen the synergy of policy objectives between the central and local governments to promote the orderly development of the national NEVs industry. To improve the coordination between central and local policies, it is recommended, from a nationwide perspective, to establish a closer central-local policy coordination mechanism. Through regular joint meetings, working groups, and other forms of collaboration, the central and local governments can engage in more frequent and in-depth communication and cooperation. This can help ensure that all levels of government have a clearer and consistent understanding of the NEVs policy objectives, thereby enhancing the effectiveness of coordinated implementation. Regarding specific suggestions for various regions, for Anhui, advocating for more incentivized policy measures is recommended, with a focus on encouraging comprehensive financial subsidies, tax adjustments, and incentive mechanisms to drive more concentrated NEVs policy objectives. Additionally, emphasis should be placed on formulating clearer macro-planning and strengthening the construction of the NEVs industry system to ensure that policy objectives align with future macro-planning. For Jiangsu, it is proposed to enhance the use of infrastructure construction means to ensure that policy innovation not only has foresight but also contributes to the comprehensive development of the NEVs industry. In terms of resource allocation, it is suggested to pay more attention to targeted support for the technological development of the NEVs industry to ensure the comprehensiveness and operability of policies. For Zhejiang, encouraging other regions to learn from its successful experience. Especially in terms of macro-planning, specific "14th Five-Year Plans" and "Three-Year Action Plans" should be formulated to enhance policy coordination. Additionally, it is emphasized to continue releasing specific financial subsidy policies and promotion pilot programs to make local policies more specific and operational. As for Shanghai, it is suggested to conduct in-depth research and formulate more forward-looking macro-plans for the future development of urban NEVs to ensure that policy objectives align with the future development direction of the city. In implementation, emphasis should be placed on the comprehensiveness of policies to ensure that not only are the objectives concentrated but also the policy content is more comprehensive. These series of suggestions aim to collectively promote the enhancement of policy coordination between local policy actors, thereby driving the orderly development of the NEVs industry nationwide.

4.3.2 Objectives Coordination of Local Policy Texts with Central Policy

Policy coordination is not only reflected among policy actors but also focuses on the precise implementation of central policy objectives at the local policy text level. Therefore, this section delves into the coordination of local policy texts with central policy objectives, seeking solutions to enhance the quality of policy implementation. From the perspectives of the discreteness and volatility of objective coordination, this paper analyzes the stability of local policy texts regarding the coordination of policy objectives with central policy actors. Table 6 presents the data indicators of local policy texts regarding the coordination of central thematic policy objectives.

Table 6: Local textual data metrics

Metrics		Anhui	Shanghai	Zhejiang	Jiangsu
Discreteness	Mean deviation	1.28E-08	0.0011	0.0013	0.0017
	Coefficient of variation	0.000181	0.052581	0.053478	0.063187
Volatility	Variance	1.28E-08	0.001106	0.001282	0.001726
	Range	0.000421	0.105204	0.132654	0.196842

Firstly, from the perspective of data discreteness, the average deviation of policy texts among the four local policy actors is ranked from high to low as Jiangsu, Zhejiang, Shanghai, and Anhui. The overall coordination level of Anhui policy texts is relatively concentrated, with minimal deviation from central policy objectives, indicating a higher consistency between local policies and central policies in terms of thematic alignment. The LDA model results for Anhui policy actors show that among the 17 concentrated policy documents, both "promotion of infrastructure construction" and "strengthening of technical support" are presented consistently, with high thematic weights and significant importance in central policy objectives. These local policies exhibit a high level of consistency with central policy objectives, consistent with the results of dispersion levels. In contrast, Jiangsu policy texts demonstrate relatively large fluctuations in coordination, with policy objective coordination being more dispersed, indicating significant inconsistency between local policies in Jiangsu and central policies. Although Jiangsu policy texts are concentrated, showing high consistency in thematic focus across all documents, they predominantly focus on specific topics, such as "demonstration role of industries", which does not hold the same priority in central policies. This phenomenon is consistent with the distribution of policy texts-policy topics, further confirming the coordination relationship between local policy texts and central policy actors.

Under the volatility indicator, different policy texts of the Jiangsu government exhibit significant variations in coordination with central policy actors, displaying high volatility and diversity in policy objective coordination. Observing its LDA model results, although individual documents focus on a single topic in the distribution of policy text-policy topics, from the perspective of the entire text collection, the types of topics covered by these policy texts have a considerable dispersion, which is the main reason for the significant fluctuations in coherence. This may also be influenced by various factors such as local economic structure and cultural background, leading local governments to consider local characteristics and specific needs more extensively when formulating policies, resulting in diverse characteristics of policy texts across different regions and domains, thereby affecting coordination with central policies. In comparison, Anhui government demonstrates relatively stable coordination in policy texts, with minor fluctuations, which correlates with the high consistency of each Anhui policy text in terms of thematic coverage and thematic weight. However, its stability and discreteness may also be influenced by the small data volume and limited coverage of policy objectives.

To further enhance the objective coordination of central and local policy, it is recommended to focus on policy texts or local governments with significant fluctuations and analyze the issues and improvement spaces therein. For the Anhui, establishing incentive mechanisms or strengthening the interpretation and dissemination of central policies could be considered to enhance coordination. Establishing a sound data sharing mechanism to promote the exchange and integration of data among governments at all levels, or strengthening the supervision and evaluation mechanism of policy implementation, could enhance tracking and evaluation of policy implementation effects and improve the coordination level between central and local policies. For the Jiangsu government, ensuring coordination and consistency between central and local policies require an in-depth research into the causes of fluctuations to ensure high coordination while reducing volatility and improving overall stability. Through in-depth data analysis and policy interpretation, key factors causing fluctuations can be identified for precise intervention in factors that may lead to low coordination levels.

5. Discussion

This study constructed a policy coordination measurement model and successfully applied it in the field of NEVs policies. The model integrated topic modeling and natural language processing techniques and consists of two sub-models: the multi-LDA model and the objective coordination measurement model.

The multi-LDA model built independent topic models for different policy actors to explore their unique thematic patterns. The optimal number of topics for each LDA model was determined based on the corresponding consistency distribution, followed by parameter updates and iterations to extract and analyze thematic patterns from each independent LDA model. This approach preserved the richness and variability of important themes and content from different policy entities, reduces information loss, and provided a more accurate data foundation for semantic association calculations and result interpretability. To enhance the interpretability of the final results, an innovative "Policy Goal Framework + Theme Naming" approach was proposed. This method linked policy objectives to LDA topics using a series of representative policy objective frameworks, making the distribution of thematic terms more understandable and recognizable as policy topics rather than simple word clusters. The objective coordination measurement model then built upon the LDA results. This model combined Word2Vec word embedding technology to process the results into word vector forms, capturing semantic relationships among thematic terms. Subsequently, three sequential calculations are performed: semantic similarity of thematic words, semantic similarity of topics, and coordination degree of policy objectives between different policy actors, including the coordination degree between local policy texts and central policy actors.

The policy objective coordination measurement model is adaptable to different policy scenarios and has been validated for feasibility in the NEVs policies context. In this application, 112 policy documents from various policy actors were used. Multi-LDA models were independently constructed for six major policy entities: the central government, the State Council, the governments of Zhejiang, Shanghai, Anhui, and Jiangsu. This approach extracted different thematic patterns from each actor, preserving thematic complexity, and used the framework-based thematic naming method to connect policy objectives with LDA topics. By actively linking goals and themes, this approach strengthened the relationship between policy objectives and topics, revealing differences in policy objective types and content richness among different policy actors, and providing more explanatory basis for result analysis. Finally, semantic similarity calculations based on the three-level policy objective coordination measurement model yielded coordination degrees of 0.5675, 0.6881, 0.6786, and 0.6350 for Anhui, Shanghai, Zhejiang, and Jiangsu, respectively, regarding central policy actors. Relevant recommendations were provided for each local policy actor.

In summary, this study explores unique thematic patterns of different policy actors through multi- actor multi-LDA modeling and uses Word2Vec word embedding technology to identify semantic relationships at the word level. The proposed policy objective framework successfully links policy objectives with topics, enhancing the interpretability of the model results. This measurement approach improves the effectiveness of the policy objective coordination measurement model. Although this study has improved the interpretability of the LDA results, machine learning continues to exhibit ‘black box’ opacity and may lack a certain level of transparency in policy decision-making. Nonetheless, from the perspectives of the model and its results, the policy objective coordination measurement model still holds significant reference and guidance value for policy formulation and implementation.

5.1 Theoretical Implications

This paper contributes in three main aspects:

5.1.1 A multi-actor multi-LDA model was constructed to capture the complexity of policy actors.

This paper constructed six independent LDA models to explore the latent thematic structure of policy regarding NEVs policies texts from six different policy actors: the central government, the State Council, Anhui, Shanghai, Zhejiang, and Jiangsu. While existing research has acknowledged the organizational characteristics of modern government with multiple actors, previous studies have still relied on a single LDA model to identify prominent topics within central and local policies (Song, 2022), struggling to identify inter-entity topic differences when analyzing policy texts from different policy actors. We employed a multi-LDA model in this study to avoid the loss of information and ambiguity caused by applying the same topic model across different policy actors. It enables the recognition of information disparities across different policy actors and their varying focal points and priorities regarding policy objectives. In terms of model accuracy, providing a more comprehensive perspective to capture the richness and diversity of policy themes and their underlying nuances.

5.1.2 A policy objective framework combined with thematic naming rules was developed to enhance result interpretability.

This paper proposed a “policy objective framework + thematic naming” scheme, constructing a seven-dimensional policy framework for NEVs and universal thematic naming rules. By linking the framework structure with policy objectives and LDA topics, the study translates topic word distributions into more comprehensible policy objective names, resulting in more interpretable outcomes. Since LDA topics do not provide names but are constructed through word distributions, using the framework to assign names based on different policy objectives allow for a stable association between policy objects and policy texts. This approach converted LDA topics into policy objectives - thematic terms and policy texts - policy objectives distributions, making LDA topics more meaningful. The research integrated a unified framework and thematic naming rules to handle topic the results model, emphasizing policy coordination and addressing interpretability challenges (Fang & Partovi, 2021) compared to general text analysis methods.

5.1.3 Semantic information was introduced to refine the policy objective coordination measurement model.

This paper proposed a policy objective coordination measurement model to assess the coordination degree of NEVs policies between central and local governments. The model utilized the latent thematic structure discovered by multi-LDA model and integrated Word2Vec model to measure the semantic similarity between thematic terms, specific local policies, and groups of local policies. The Word2Vec model captured semantic associations between words in the form of word vectors, allowing for a deeper exploration of hidden semantic information within policy texts. The combination of LDA model and Word2Vec model strengthens the analysis of semantic relevance in the measurement model, surpassing the limitations of surface structures such as paragraphs and vocabulary (Biesbroek, 2020; Liu, 2022). Moreover, by incorporating multi-level analyses from word to topic and text levels, the model provides a more comprehensive information basis for assessing policy objective coordination at various levels of granularity.

5.2 Practical Implications

The proposed policy objective coordination measurement model in this paper has two main advantages in analyzing the central-local policy coordination of NEVs policies: First, the multi-LDA model provides more comprehensive topic structure on the thematic structure of different policy actors and enhances interpretability by adhering to the policy objective framework and thematic naming rules. Second, the LDA models deconstruct policy texts into “text-topic-thematic term” layers and combines the semantic relevance analysis of the Word2Vec model to explore the implicit information of NEVs policies at a finer granularity. These two aspects enable the analysis of textual themes from a policy objective perspective and facilitate in-depth semantic interpretation of policy texts, ensuring richness of research perspectives and utilization of semantic information.

5.2.1 Facilitating improvement in the allocation of resources and policy coordination among local governments.

This paper establishes a three-tiered policy objective coordination measurement model by combining multi-LDA model and the Word2Vec model to conduct semantic analysis of the coordination between central and local governments in NEVs policies. The measurement results can assist policymakers gain a clearer understanding of the policy orientation of various government levels in the field of NEVs and reveal the policy shortcomings of local governments. Based on the key concerns of the central government, corresponding local policies can be formulated to help local governments adjust and coordinate policies effectively, thereby optimizing resource allocation and improving the consistency and effectiveness of central-local government policies in the field of NEVs.

5.2.2 Assisting NEVs enterprises grasping policy dynamics in timely.

Policy coordination analysis aids NEVs enterprises in gaining a more comprehensive understanding of the policy orientations and support intensities emphasized by various government at all levels, providing essential references for the future development direction and strategic planning of enterprises. Furthermore, the richness analysis encompasses the domains and objectives involved in policies, offering NEVs enterprises references for layout and production strategies, enabling them to better grasp the differences in policies across regions, which is conducive to flexible adjustment of production layouts and sales strategies, enhancing competitiveness and market share in different regions.

5.2.3 Providing decision support for the public to purchase NEVs.

The thematic structure extracted by the multi-LDA model reveals the preferences and priorities of different governments in the field of NEVs, helping the public better understand the policy support and preferential measures of various government levels in the field of NEVs, providing more convenience and choices for purchasing and using NEVs. On one hand, this research can help the public understand the policy preferences of various governments, maximizing the enjoyment of policy dividends and preferential policies. Secondly, by analyzing policy objectives, the public can choose a more suitable time to purchase vehicles based on the differences in policies across regions, thus providing more choices and convenience for purchasing and using new energy vehicles in environments with improved infrastructure.

5.3 Limitations and Future Work

This paper has certain limitations and warrants further investigation. In future policy coordination studies, it is imperative to incorporate a wider array of machine learning models coupled with natural language processing techniques to explore more fitting collaborative patterns and delve deeper into latent patterns and correlations within textual data, thus providing more accurate structural insights into textual topics. Furthermore, machine learning models often present themselves as black boxes, whereas decision-making in the policy domain necessitates models with high credibility and reliability, necessitating the attribution mechanisms of interpretable artificial intelligence methods. Attribution models such as SHAP can be applied to explain the results, thereby enhancing the interpretability of the outcomes by identifying the primary factors influencing the coordination of central and local policy objectives.

6. Conclusion

Policy coordination plays a crucial role in the successful implementation of public policies by the government. However, in the context of multiple organizational actors, it presents new challenges in identifying semantic information from different actors and enhancing result interpretability. This study focuses on improving the precision of semantic information in coordination measurement and introduces a framework-based naming approach to enhance interpretability. Topic modeling and natural language processing techniques are well-suited for addressing these issues. By incorporating these methods, we have developed a three-tier policy coordination measurement model to complete the measurement task. The multi-LDA topic modeling effectively identifies thematic patterns across actors, preserving the richness of distinctive topics for subsequent research. At this stage, a seven-dimensional policy objective framework for NEVs was constructed to associate topics, and LDA topics were named based on policy objectives, overcoming the issue of poor interpretability in topic models. The Word2Vec word embedding model further extracted semantic similarities from LDA topics, achieving a multi-level policy objective coordination measurement model through the “word-topic-document” hierarchy. Finally, the model was utilized to measure the coordination of central and local policy objectives in the context of the NEVs policy. The research results on policy coordination indicate a moderate level of coordination between central and local NEVs policy objectives, with Shanghai exhibiting the highest level of actor coordination, followed by Zhejiang and Jiangsu, while Anhui displays the lowest coordination. For Shanghai and Zhejiang, local governments should continue to closely align with central policies, maintaining high policy coordination and continuously introducing policies to promote the research and management of NEVs. Conversely, Jiangsu and Anhui need to enhance the interpretation of policy texts continually, optimizing the coordination of central and local policy objectives.

Declarations

Ethics approval and consent to participate Not applicable.

Consent for publication Not applicable.

Availability of data and material The data that support the findings of this study are available from the corresponding author upon reasonable request.

Competing interests The authors declare that they have no competing interests.

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Authors’ contributions All the named authors have contributed substantially to conducting the underlying research and preparing the manuscript.

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References

[1] Åhman, M. (2006). Government policy and the development of electric vehicles in Japan. *Energy Policy, 34*(4), 433-443. https://doi.org/10.1016/j.enpol.2004.06.011

[2] Alshalan, R., Al-Khalifa, H. S., AlSaeed, D., Al-Baity, H. H., & Alshalan, S. (2020). Detection of hate speech in COVID-19-Related tweets in the Arab Region: Deep learning and topic modeling approach. *Journal of Medical Internet Research, 22*(12), e22609. https://doi.org/10.2196/22609

[3] Altarturi, H. H., Saadoon, M., & Anuar, N. B. (2023). Web content topic modeling using LDA and HTML tags. *PeerJ Computer Science, 9*, e1459.

[4] Belford, M., & Greene, D. (2020). Ensemble topic modeling using weighted term co-associations. *Expert Systems With Applications, 161*, 113709. https://doi.org/10.1016/j.eswa.2020.113709

[5] Biesbroek, R., Badloe, S., & Athanasiadis, I.N. (2020). Machine learning for research on climate change adaptation policy integration: an exploratory UK case study. *Regional Environmental Change, 20*(3), 1-13. https://doi.org/10.1007/s10113-020-01677-8

[6] Blei, D. M., Ng, A. Y., & Jordan, M. I. (2003). Latent dirichlet allocation. *Journal of Machine Learning Research, 3*, 993-1022. https://doi.org/10.5555/944919.944937

[7] Borrás, S., & Edquist, C. (2013). The choice of innovation policy instruments. *Technological Forecasting and Social Change, 80*(8), 1513-1522. https://doi.org/10.1016/j.techfore.2013.03.002

[8] Careja, R. (2011). Paths to policy coherence to create market economies in Central and Eastern Europe. *International Political Science Review, 32*(3), 345-366. https://doi.org/10.1177/0192512110388316

[9] Cejudo, G. M., & Michel, C. L. (2017). Addressing fragmented government action: coordination, coherence, and integration. *Policy Sciences, 50*(4), 745-767. https://doi.org/10.1007/s11077-017-9281-5

[10] China Automotive Technology & Research Center (CATARC), Nissan (China) Investment Co., Ltd. (NCIC) & Dongfeng Motor Co., Ltd. (DFL). (2015). *China New Energy Vehicle Industry Development Report (2015)*. Beijing: Social Sciences Academic Press.

[11] Christensen, T., Lægreid, O. M., & Lægreid, P. (2019). Administrative coordination capacity; does the wickedness of policy areas matter? *Policy and Society, 38*(2), 237-254. https://doi.org/10.1080/14494035.2019.1584147

[12] Chudnovsky, M., & Trujillo, N. E. (2019). Conflict between Formal and Informal Rules in Policy Coordination: The Case of Child Homelessness in Mexico City. *Latin American Policy, 10*(1), 120-143. https://doi.org/10.1111/lamp.12158

[13] Fang, J., & Partovi, F. Y. (2021). Criteria determination of analytic hierarchy process using a topic model. *Expert Systems with Applications, 169*, 114306. https://doi.org/10.1016/j.eswa.2020.114306

[14] Griffiths, T. L., & Steyvers, M. (2004). Finding scientific topics. *Proceedings of the National Academy of Sciences of the United States of America, 101*(suppl_1), 5228-5235. https://doi.org/10.1073/pnas.0307752101

[15] Jungblut, J., & Rexe, D. (2017). Higher education policy in Canada and Germany: Assessing multi-level and multi-actor coordination bodies for policy-making in federal systems. *Policy and Society, 36*(1), 49-66. https://doi.org/10.1080/14494035.2017.1278864

[16] Lee, M., & He, G. (2017, July). Why Is Korea Lagging behind in Electric Vehicle Technology Innovation? Analysis of Korea's Electric Vehicle Technology Innovation Policy through the Lens of Systems of Innovation Approach. In 2017 *Portland International Conference on Management of Engineering and Technology (PICMET)* (pp. 1-14). IEEE. https://doi.org/10.23919/picmet.2017.8125254

[17] Li, C., Liu, J., & Wang, L. (2024). Research on the influence mechanism of public green behavior guiding policy effect: from the perspective of policy synergy system. *Environment, Development and Sustainability*, 1-42. https://doi.org/10.1007/s10668-023-04397-1

[18] Li, J., Jiao, J., Xu, Y., & Chen, C. (2021). Impact of the latent topics of policy documents on the promotion of new energy vehicles: empirical evidence from Chinese cities. Sustainable *Production and Consumption, 28*, 637-647. https://doi.org/10.1016/j.spc.2021.06.023

[19] Li, W., Long, R., & Chen, H. (2016). Consumers' evaluation of national new energy vehicle policy in China: An analysis based on a four paradigm model. *Energy Policy, 99*, 33-41. https://doi.org/10.1016/j.enpol.2016.09.050

[20] Li, W., Yang, M., & Sandu, S. (2018). Electric vehicles in China: A review of current policies. *Energy & Environment, 29*(8), 1512-1524. https://doi.org/10.1177/0958305x18781898

[21] Li, X., Zhao, X., Xue, D., & Tian, Q. (2023). Impact of regional temperature on the adoption of electric vehicles: an empirical study based on 20 provinces in China. *Environmental Science and Pollution Research, 30*(5), 11443–11457. https://doi.org/10.1007/s11356-022-22797-0

[22] Liu, D., & Wang, D. (2022). Evaluation of the synergy degree of industrial de-capacity policies based on text mining: A case study of China's coal industry. *Resources Policy, 76*, 102547. https://doi.org/10.1016/j.resourpol.2021.102547

[23] Ma, Y., Shi, T., Zhang, W., Hao, Y., Huang, J., & Lin, Y. (2019). Comprehensive policy evaluation of NEV development in China, Japan, the United States, and Germany based on the AHP-EW model. *Journal of Cleaner Production, 214*, 389-402. https://doi.org/10.1016/j.jclepro.2018.12.119

[24] Meijers, E., & Stead, D. (2004). Policy integration: what does it mean and how can it be achieved? A multi-disciplinary review. *In 2004 Berlin Conference on the Human Dimensions of Global Environmental Change: Greening of Policies - Interlinkages and Policy Integration* (pp. 1-15). Freie Universität Berlin. http://userpage.fu-berlin.de/ffu/akumwelt/bc2004/download/meijers_stead_f.pdf

[25] Metz, F., Angst, M., & Fischer, M. (2020). Policy integration: Do laws or actors integrate issues relevant to flood risk management in Switzerland? *Global Environmental Change, 61*, 101945. https://doi.org/10.1016/j.gloenvcha.2019.101945

[26] Mimno, D., Wallach, H., Talley, E., Leenders, M., & McCallum, A. (2011, July). Optimizing semantic coherence in topic models. *In Proceedings of the 2011 conference on empirical methods in natural language processing* (pp. 262-272). http://dirichlet.net/pdf/mimno11optimizing.pdf

[27] Nie, Y., Zhang, G., Duan, H., Su, B., Feng, Y., Zhang, K., & Gao, X. (2022). Trends in energy policy coordination research on supporting low-carbon energy development. *Environmental Impact Assessment Review, 97*, 106903. https://doi.org/10.1016/j.eiar.2022.106903

[28] Prince-Tritto, P., & Ponce, H. (2023, November). Exploring the Challenges and Limitations of Unsupervised Machine Learning Approaches in Legal Concepts Discovery. *In Mexican International Conference on Artificial Intelligence* (pp. 52-67). Cham: Springer Nature Switzerland.

[29] Schmitz, L., & Eimer, T. R. (2019). From coherence to coheritization: explaining the rise of policy coherence in EU external policy. *Globalizations, 17*(4), 629-647. https://doi.org/10.1080/14747731.2019.1676103

[30] Shirota, Y., Hashimoto, T., & Sakura, T. (2014, October). Extraction of the financial policy topics by latent dirichlet allocation. In *TENCON 2014-2014 IEEE Region 10 Conference* (pp. 1-5). IEEE. https://doi.org/10.1109/tencon.2014.7022493

[31] Song, C., Guo, J., Gholizadeh, F., & Zhuang, J. (2022). Quantitative Analysis of Food Safety Policy—Based on text mining Methods. *Foods, 11*(21), 3421. https://doi.org/10.3390/foods11213421

[32] Tanner, S. (2014). QCA is of questionable value for policy research. *Policy and Society, 33*(3), 287-298. https://doi.org/10.1016/j.polsoc.2014.08.003

[33] Valdez, D., Thij, M. T., Bathina, K. C., Rutter, L. A., & Bollen, J. (2020). Social media insights into US mental health during the COVID-19 pandemic: Longitudinal analysis of Twitter data. *Journal of Medical Internet Research, 22*(12), e21418. https://doi.org/10.2196/21418

[34] Van Den Bergh, J. C., Castro, J., Drews, S., Exadaktylos, F., Foramitti, J., Klein, F., Konc, T., & Savin, I. (2021). Designing an effective climate-policy mix: accounting for instrument synergy. *Climate Policy, 21*(6), 745-764. https://doi.org/10.1080/14693062.2021.1907276

[35] Van Geet, M. T., Verweij, S., Busscher, T., & Arts, J. (2021). The importance of policy design fit for effectiveness: a qualitative comparative analysis of policy integration in regional transport planning. *Policy Sciences, 54*(3), 629–662. https://doi.org/10.1007/s11077-021-09429-z

[36] Wang, J., Zhou, Y., Wei, Z., Evans, R., & Zhu, C. (2020). Concerns expressed by Chinese social media users during the COVID-19 pandemic: Content analysis of Sina Weibo microblogging data. *Journal of Medical Internet Research, 22*(11), e22152. https://doi.org/10.2196/22152

[37] Xu, Z., Chang, X., & Zhang, N. (2024). An analysis of China's power battery industry policy for new energy vehicles from a product life cycle perspective. Environment, *Development and Sustainability*, 1-23. https://doi.org/10.1007/s10668-023-04405-4

[38] Yan, X., Hui, S. C., & Xin, L. (2023). "Harmonization" or "Fragmentation": The impact of Low-Carbon policy synergy on inclusive Low-Carbon development. *Sustainability, 15*(8), 7009. https://doi.org/10.3390/su15087009

[39] Yao, C., Sun, M., & Liu, L. (2023). Evaluation of policy synergy in coastal ocean pollution prevention and control: The case from China. *Frontiers in Marine Science, 10*, 1131590. https://doi.org/10.3389/fmars.2023.1131590

[40] Ye, R., Gao, Z., Fang, K., Liu, K., & Chen, J. (2021). Moving from subsidy stimulation to endogenous development: A system dynamics analysis of China's NEVs in the post-subsidy era. *Technological Forecasting and Social Change, 168*, 120757. https://doi.org/10.1016/j.techfore.2021.120757

[41] Yuan, X., Liu, X., & Zuo, J. (2015). The development of new energy vehicles for a sustainable future: A review. *Renewable & Sustainable Energy Reviews, 42*, 298-305. https://doi.org/10.1016/j.rser.2014.10.016

[42] Zhang, X., Rao, R., Xie, J., & Liang, Y. (2014). The Current Dilemma and Future Path of China's Electric Vehicles. *Sustainability, 6*, 1-27. https://doi.org/10.3390/SU6031567.

[43] Zhu, B., Zheng, X., Liu, H., Li, J., & Wang, P. (2020). Analysis of spatiotemporal characteristics of big data on social media sentiment with COVID-19 epidemic topics. *Chaos, Solitons & Fractals, 140*, 110123. https://doi.org/10.1016/j.chaos.2020.110123