World Electric Vehicle Journal

Article

# A Study on the Analysis and Prediction of the Evolution Path of China's Electric Vehicle Industry Policy Based on Text Mining

**Zizheng Liu and Tao Xie ***

School of Economics, Shenyang University, Shenyang 110041, China; 201705190724@smail.xtu.edu.cn
* Correspondence: syu_pdr_xie@syu.edu.cn

**Abstract:** In the 21st century, China's electric vehicle (EV) industry has demonstrated remarkable growth, rapidly catching up with and surpassing other nations in scale and development. Understanding the policy mechanisms behind this rapid ascent is crucial for analyzing the evolution of China's EV sector and making informed decisions for its future development. This study provides a comprehensive analysis of the evolution of China's EV policies from 2009 to 2023, with projections through 2027, using a mixed-method approach that incorporates text mining, co-word network analysis, and BERT-based trajectory models to explore the operational logic of various policy frameworks and predict future policy directions. The study findings reveal distinct phases in the evolution of China's EV policies. Initially, the focus was on building industrial capacity through supply-side measures, laying the foundation for growth. As the industry matured, policies expanded to include demand-side incentives and environmental regulations, reflecting a shift towards a balanced and sustainable approach. Our research shows that early policy decisions significantly influenced later adjustments, highlighting the role of path dependence. By mapping the trajectory of China's EV policies, this study offers a framework for predicting future trends, providing guidance for Chinese policymakers and offering strategies that would allow other countries to effectively compete with China. Ultimately, this research underscores the importance of adaptive and coordinated policy strategies for fostering sustainable growth in strategic industries, providing valuable lessons for China and beyond.

**Keywords:** electric vehicle; policy evolution; path dependence; text mining

check for updates

**Citation:** Liu, Z.; Xie, T. A Study on the Analysis and Prediction of the Evolution Path of China's Electric Vehicle Industry Policy Based on Text Mining. *World Electr. Veh. J.* **2024**, *15*, 572. https://doi.org/10.3390/wevj15120572

Academic Editors: Michael Fowler and Joeri Van Mierlo

Received: 11 October 2024
Revised: 2 November 2024
Accepted: 10 December 2024
Published: 12 December 2024



## 1. Introduction

The rapid development of China's electric vehicle (EV) industry is one of the most remarkable industrial transformations globally. From policy support and technological innovation to the layout of the industrial chain, China has quickly positioned itself as a dominant player in the global EV market through a series of powerful measures [1]. As one of China's seven strategic emerging industries, the EV industry not only offers solutions for addressing environmental crises and enhancing energy security but has also become a key strategy allowing China to overtake global competitors in the automotive industry [2].

The selection of China as the focal point for this study was driven by several key factors. First, despite inherent technological challenges, China has effectively employed strategic policy support, industrial initiatives, and market-driven incentives to achieve the rapid expansion of its electric vehicle (EV) sector [3]. Second, the country's vast population and substantial potential market position its policies such that it can potentially exert a significant influence on the global EV landscape. Third, China's EV industry has developed a relatively comprehensive policy framework, which provides a rich and complete dataset for analysis, thereby enabling more accurate and detailed examination. Moreover, given the strong momentum of China's EV sector, it is crucial to assess how this rapid growth may shape global competition and identify appropriate response strategies [4,5].

China's rise in the electric vehicle (EV) industry is closely linked to concentrated policy support and evolving market mechanisms [6,7]. Since the designation of EVs as the basis of a national strategic emerging industry in 2009, the government has implemented a series of policies, including financial subsidies, technical R&D support, and infrastructure development, forming a coordinated policy framework [8]. This framework's strategic design and adaptability have allowed it to evolve in response to different phases of industrial development. Rather than focusing solely on the number of policies, China's approach has prioritized the creation of responsive policies that address industry needs and support long-term goals. By integrating top-level planning with local implementation, these policies have been effectively adjusted as challenges have emerged, playing a critical role in fostering the sustainable growth of the EV sector [9].

Despite its achievements, China's EV industry still faces significant challenges, including limited control over core technologies, regional disparities in charging infrastructure, and demand-side bottlenecks [10]. These challenges prompt reflection on the deeper policy logic behind China's rapid industrial advancement [11]. China's EV policy evolution is not linear but rather shaped by a unique policy structure driven by the interaction between policy feedback and market practice [12]. Although this structure has enabled rapid growth, it also brings complexities and limitations [13]. Consequently, this study raises several questions: What are the core driving forces within China's policy framework, and can other economies leverage these lessons for their own growth? How can policymakers ensure their designs are forward-looking and responsive to market feedback to support sustainable industry development?

To address these questions, we based this study on path dependency theory and conducted an in-depth analysis of the evolution of China's EV industry policies. We not only evaluate the effectiveness of policies at different stages but also integrate co-word analysis, BERT models, and time series forecasting to make data-driven predictions about future policy directions. By analyzing and processing historical policy texts, this study identifies key trends in policy evolution, quantitatively reveals the dynamic logic behind policy shifts, and provides projections for future policy development. This approach breaks through the limitations of traditional static policy analysis, enabling a more dynamic and systematic understanding of the interaction between policy and industry.

The contribution of this study lies not only in its deep analysis of policy evolution but also in offering a novel methodological framework. By allowing the systematic analysis of historical policy text data, this framework provides quantitative predictions of future policy directions. It also enriches path dependency theory by offering a concrete and practical approach for studying policy evolution, demonstrating how historical policies influence present and future directions within a complex policy ecosystem. While applicable to the EV sector, this approach also serves as a valuable reference for policymakers in other fields. As the global shift towards sustainable and low-emission transportation accelerates, governments worldwide are facing the pressing challenge of guiding industrial upgrading and enhancing international competitiveness through effective policies. Through a systematic examination of China's successful EV policy experience, this study underscores the importance of flexibility and adaptability in policy design, offering valuable lessons for other countries in developing sustainable transportation policies. By understanding China's policy evolution and its potential future development direction, global policymakers can anticipate policy trends and adjust their strategies accordingly to better compete in the global EV industry.

## 2. Research Progress on New-Energy Vehicle Policies and Text Analysis Methods

### 2.1. Current State of Research on EV Industry Policies

Current research on EV industry policies primarily focuses on two aspects: the application effects and the content of these policies. Studies on policy effects are more extensive in the academic community.

Some scholars employ methods such as input–output analysis to investigate the impact of individual policy instruments, such as purchase tax exemptions and quota systems, on dependent variables like EV production and sales volume and technology patents [14,15]. Others examine how industrialization promotion policies influence enterprise innovation performance and the mechanisms of national and local industry policy linkages in driving industry innovation [1,5]. Regarding policy content, most scholars tend to select a single or a series of key policy texts for interpretation, focusing on policy tools, objectives, and overall frameworks. Matschoss et al. [16] analyzed the German electric vehicle subsidy plan, detailing the subsidy targets, standards, and application processes, aiming to provide a reference for EV promotion in other countries. Kumar et al. [17], based on a system dynamics perspective, constructed a causal feedback model for the development of India's electric vehicle industry and combined key policies such as the "National Electric Mobility Mission Plan (NEMMP)" to simulate and analyze industry development paths under different subsidy intensities and charging station construction progress scenarios. Biresselioglu et al. [18] focused on the EU's electric vehicle industry and interpreted a series of directives, such as the "Clean Vehicle Directive", systematically explaining the strategic significance of these documents in promoting electric vehicle development in member states. Additionally, a few scholars have conducted comparative studies, analyzing the differences in EV policies between countries or among provinces, clarifying the advantages and disadvantages [19,20].

The existing research has undertaken relatively objective and beneficial explorations of EV industry policies, but there are still some gaps in certain perspectives. First, current studies on EVs mostly focus on individual policy documents, partial-stage policy documents, or policy documents in specific fields, with few studies comprehensively investigating the evolution of the entire EV industry policy system. Second, current research perspectives on EV industry policies mostly focus on a specific development stage, lacking the longitudinal perspective required to study the changes to and evolution of industry policies over time.

### *2.2. Current State of Quantitative Policy Analysis Methods*

Regarding the quantitative analysis of policies, academic research primarily focuses on two aspects, the first of which is the classification of policy instruments. For example, Rothwell and Zegveld [21] categorized policies into environmental, demand-side, and supply-side based on their application areas. McDonnell [22] and other scholars classified policies into incentive-based, command-based, system-construction-based, and capacity-building-based according to their application methods. The second aspect focused on is research on text mining and policy theme extraction methods. Some scholars have digitally encoded policy texts and conducted quantitative analysis based on the encoded data [23]. For instance, Bromley-Trujillo and Poe [24] employed the LDA topic model to analyze the diffusion effect of climate change policies across the states of the U.S. Other scholars have focused more on the content of the policies themselves. Van der Vooren et al. [25] used co-word analysis to examine the evolutionary characteristics of electric vehicle policy themes in EU countries. Purtle et al. [26] constructed a factor analysis model to determine whether the policies issued by the U.S. Housing Commission between 2009 and 2018 imposed identity restrictions on the target audience, namely, those with criminal justice backgrounds. There is also a third aspect: the quantitative evaluation of policies. Chen et al. [27] used the GMM model to extract themes and quantitatively evaluate China's poverty alleviation policies. Huan et al. [28] constructed a three-dimensional evaluation model to quantitatively assess China's aquaculture policy texts produced over more than a decade.

Considering the current quantitative policy analysis methods, there are clearly some gaps in the following research perspectives. First, in current quantitative analyses of policy texts, whether via policy coding or through constructing policy models, the analyses mostly focus on a series of policy documents or a single policy document. Few studies refine and decompose policy texts one by one to conduct in-depth research on the internal content of policies. Second, the current text analysis methods are mainly semi-quantitative, and many measurement processes still require manual completion, leading to a limited sample size and difficulty in ensuring accuracy.

## 3. Research Design and Data

### *3.1. Research Design*

This study aims to systematically analyze the evolution of China's electric vehicle (EV) industry policies, identify key drivers of policy development, and predict future policy trends. The framework of this research includes three major components, namely, data collection and selection, co-word network analysis, and policy evolution prediction based on machine learning, providing a comprehensive understanding of the policy drivers and development logic while forecasting future policy directions.

1. Data Collection and Selection

The first step involved constructing a systematic and comprehensive policy database for the EV industry, using data sourced from national and local government departments and authoritative information platforms. The collected data span from 2009 to 2023, covering important policy documents relevant to the EV industry. In the data selection process, we focused on policies closely related to the EV industry to ensure the comprehensiveness and representativeness of the analysis sample. After multiple rounds of screening, 142 policy documents were retained, forming a foundation for subsequent analysis.

2. Co-word Network Analysis

Co-word network analysis was employed to reveal the logical structures and thematic evolution of the policy texts. After tokenizing the policy texts and extracting key terms, a co-word matrix was constructed, and relationships between keywords were analyzed to identify core themes within the policies. The degree centrality and other metrics of nodes in the network were calculated to determine the importance of each theme in the policy evolution process. The results of the co-word network analysis provided crucial structural information for the subsequent BERT (Bidirectional Encoder Representations from Transformer) model and served as the basis for initializing the model weights.

3. Policy Evolution Prediction Using BERT

In the BERT-based prediction analysis, we utilized the results of the co-word network analysis as input data to enhance the model's understanding of key aspects of the policy texts. Specifically, quantitative metrics derived from the co-word network, such as degree centrality, were used to initialize the weights of the BERT model. This enabled the model to focus more on core keywords and their evolutionary paths during training. Through this integration, the BERT model effectively captured the semantic features of policy texts, identified temporal changes in policy themes, and predicted future policy trends. This approach improves the model's accuracy and efficiency, allowing policymakers to gain practical insights more effectively.

### *3.2. Theoretical Foundation and Application*

Path dependency theory, a well-established analytical framework, effectively reveals the long-term impacts of policy choices and the resulting "lock-in" effects. This theory posits that early policy decisions continue to influence subsequent choices through cumulative effects, gradually forming a self-reinforcing trajectory that causes future policies to evolve along a predetermined path. This process can be understood as a specific type of "inertia", shaped by factors such as national institutions, the structure of the policy system, and policymakers' habits and practices [29]. Path dependency theory is not only applicable for analyzing the continuity of policies but also offers insights into how current policies shape future developmental trajectories, making it particularly relevant for studying emerging industry policies [30]. In the case of China's electric vehicle (EV) policies, path dependency theory explains the persistence of a supply-side focus in early policy trajectories and the constraints these choices impose on subsequent policy design [31,32].

This study applies path dependency theory to, first, present the current policy trajectory and, second, analyze how this trajectory influences future policy development. These two aspects form the core framework of path dependency theory in this research.

To clearly delineate the current policy trajectory, this study employs co-word analysis to systematically process historical policy texts and reveal thematic shifts over time. Co-word analysis not only helps identify the key policy themes across different stages of development but also quantifies the evolution of these policies using degree centrality metrics. Changes in degree centrality effectively capture the fluctuations in the importance of policy keywords across time, thereby outlining the dynamic shifts in policy focus [32]. This method enables the construction of a logical structure of EV policy evolution in China, identifying critical junctures within the policy trajectory and visually representing the shifts in focus among supply-side, demand-side, and environmental policies. This process not only provides a clear depiction of the cumulative effects within the policy trajectory but also supplies valuable structured data for subsequent BERT model training, allowing the model to capture the historical logic of these policies with greater accuracy in future policy predictions [33].

To further examine the influence of the current policy trajectory on future policy directions, we innovatively incorporated the BERT text analysis model alongside the co-word analysis framework, creating a forward-looking approach for policy prediction. Path dependency theory emphasizes the "lock-in" effect and the continuity of current policy choices regarding future development, yet quantifying this influence has remained a challenging task in academic research [34]. To address this, the BERT model was employed to analyze policy texts, utilizing extensive pre-training on a large corpus of EV policies. This allowed the model to accurately recognize the core structure and logic of EV policies and understand the role of technical terms within the policy context. Through attention mechanisms, BERT conducted deep semantic analysis of policy keywords and grasped their contextual significance. Historical policy texts were then fed into the model as input material, enabling it to predict potential trends and focal points in future policy directions based on the structural patterns it learned from historical data [35].

### *3.3. Construction of the Policy Database and Selection of Analytical Samples*

In 2009, the EV industry was listed as one of China's strategic emerging industries. Since then, relevant industrial policies have emerged, and 2009 has been referred to as the first year of China's EV industrialization [4]. Therefore, this study explores the changes in policy focus and the evolution of regulations since then. The sample was mainly sourced from websites of government departments such as the State Council, the Ministry of Science and Technology, and the Ministry of Finance, as well as information websites such as the China Association of Automobile Manufacturers, the National Legal Database, and the Peking University Legal Information Network. The initial policy pool encompassed a total of 220 central laws and policies, 1394 local laws and policies, 26 policy and legislative materials, 70 legal dynamic information items, one policy contract template, and three legal instruments.

Before forming the policy pool, by referring to the policy quantitative classification method developed by Luo et al. [36], we systematically screened the policy documents. The screening methods are mainly divided into three categories. The first encompasses screening the types of policy documents. The results mainly include programmatic documents, guiding opinions, strategic plans, implementation measures, notices, regulations, announcements, etc. The results do not include industry standards, directories, replies, letters, questionnaires, or conversations. The second encompasses screening the policy content. The results include policy documents that directly mention EVs and related fields as well as documents that do not directly mention but have a significant impact on the development of the EV industry. The third encompasses screening the issuing bodies of the policies. The results include the State Council, the Ministry of Finance, the Ministry of Industry and Information Technology, and other national ministries and commissions. Local legislative bodies, local governments, and industry associations are not included. After multiple rounds of screening, the policy pool contained 142 policy documents related to the EV industry, and the results are shown in Table 1.

**Table 1.** Policy documents on China's electric vehicle industry (excerpts).

| Year | Policy Name | Policy Number |
|---|---|---|
| 2009 | Announcement on the Release of Electric Vehicle Production Enterprises and Product Access Management Rules | Industry [2009] No. 44 |
| 2009 | Notice on the Pilot Work of Demonstration and Promotion of Energy-Saving and Electric Vehicles | Financial Construction [2009] No. 6 |
| …… | …… | …… |
| 2024 | Implementation Opinions on Strengthening the Integration and Interaction of Electric Vehicles and the Power Grid | National Railway Transportation Supervisor (2024) 113 |
| 2024 | Measures for Accelerating the Improvement of Transportation Services and Safety Assurance Capabilities for EV Lithium Batteries | Development and Reform Energy [2024] No. 1721 |

The stages after the completion of assembling the policy pool involved leveraging advanced technical methodologies to transform the documents into formats that are compatible with analytical tools such as Ucinet and BERT. This transformation began with an extensive pre-processing phase, encompassing text normalization, tokenization, and the removal of extraneous content to enhance data quality and reduce analytical noise. Following pre-processing, the documents were formatted to suit specific analytical needs: for Ucinet, data were encoded to represent relational structures conducive to social network analysis, ensuring that policy linkages and network dynamics were clearly delineated. Concurrently, the text was prepared for input into BERT by segmenting it into contextually coherent sequences and encoding it to meet natural-language-processing requirements [37].

## 4. Evolution of China's Electric Vehicle Policy

The evolution of China's electric vehicle (EV) policy reflects a dynamic and adaptive approach adopted by the government to stimulate the industry and respond to emerging challenges. In this section, we provide a comprehensive overview of the evolution of the policies, highlighting the significant phases and major themes that have shaped the EV landscape in China, thereby exploring the underlying policy logic and laying the groundwork for the predictions presented in Section 5.

### *4.1. Methods for Keyword Extraction and Analysis*

We employed degree centrality to examine the evolution of electric vehicle (EV) industry policies. Degree centrality is a core concept in complex network analysis used to quantify the number of direct connections a node has to other nodes. In the context of policy text analysis, each node represents a keyword, and its degree centrality reflects the strength of its associations with other key terms and the extent of its deviation within the overall network structure. Different from traditional word frequency analysis, degree centrality not only considers the occurrence frequency of a keyword but also reveals its relational significance and structural position within the policy network. This enables the identification of both frequently mentioned topics and key concepts that serve as important connectors within the policy system, offering a more comprehensive perspective for understanding the complex relationships and inherent logic within policy texts [38].

The application of degree centrality in policy research is particularly suitable for analyzing policy evolution and understanding the complexity of policy systems. Policy texts typically involve multifaceted content, with different themes and tools interacting to achieve policy goals. Through degree centrality analysis, it is possible to determine which keywords have high importance within a policy network and how they interact with one another, thereby revealing the evolution and focus of policies at different stages. Although degree centrality cannot directly reflect the stringency of policies, it can effectively capture policy tendencies and priorities. Moreover, degree centrality effectively identifies core drivers and key nodes within a policy, providing a scientific basis for understanding policymakers' priorities and the trajectory of policy development.

#### 4.1.1. Sub-Word Extraction and Word Frequency Analysis

For a more precise and effective policy text analysis, this study amalgamated two widely-recognized stop-word lists, namely, the "Baidu Stop-Word List" and "HITC Stop-Word List" [39]. We meticulously eliminated duplicates and redundant entries to construct a comprehensive stop-word list. Upon integrating this list, the Python-based 'jieba' library was utilized for the sub-word segmentation of the selected policy texts. This process entailed sorting the segmented results by their frequency of occurrence to isolate high-frequency terms. Frequency calculations were conducted, as shown in Equations (1) and (2), providing a quantitative measure of word significance within the policy texts.

$$c_N(k_i) = \sum_{j=1}^{N} p_j(k_i),\ \ p_j(k_i) = \begin{cases} 0 & k_i \notin p_i \\ 1 & k_i \in p_i \end{cases} \tag{1}$$

$$c_N(k_q : k_r) = \sum_{j=1}^{N} p_j(k_q : k_r),\ \ p_j(k_q : k_r) = \begin{cases} 0 & (k_q : k_r)_i \notin p_j \\ 1 & (k_q : k_r)_i \in p_j \end{cases} \tag{2}$$

Within the framework of $N$ documents, the probability $c_N(k_i)$ of term $k_i$ not co-occurring with any other term can be calculated as the sum of probabilities $p_j(k_i)$ across all documents, where $p_j(k_i)$ is defined as 1 if term $k_i$ is present in document $p_i$ and 0 otherwise. Similarly, the joint probability $c_N(k_q : k_r)$ of terms $(k_q : k_r)_i$ co-occurring within the same documents is the sum of the product of their individual probabilities $p_j(k_q : k_r)$, which is set to 1 when both terms are present in document $p_j$ and 0 otherwise. The segmentation results were refined by eliminating repetitive, ambiguous, and extraneous terms, thereby forming a high-frequency-word database for EV policy texts.

#### 4.1.2. Co-Word Analysis

Upon completing the segmentation and frequency analysis of words, we conducted a co-word analysis of the processed policy texts, in line with bibliometric methods. Initially treating policy documents as analyzable textual formats, we paired the extracted keywords in combinations. Utilizing the numpy library in Python, a bimodal co-occurrence matrix was computed. This matrix underwent normalization using Ucinet16, transforming it into a correlation matrix. For this process, we adopted the Chiai coefficient method (TANG 2017), as depicted in Equation (3).

$$O_{\text{qr}} = \frac{\dot{c}_N(k_q : k_r)}{\sqrt{\dot{c}_N(k_q)\ \dot{c}_N(k_r)}} \tag{3}$$

Here, $O_{\text{qr}}$ denotes the weighted associative strength, with $\dot{c}_N(k_q)$ and $\dot{c}_N(k_r)$ indicating the weighted occurrence frequencies of terms $k_q$ and $k_r$, respectively, within the corpus. The weighted co-occurrence frequency $\dot{c}_N(k_q : k_r)$ serves to normalize the joint frequency of terms in the corpus. Subsequently, it becomes feasible to compute the degree centrality for each keyword. Degree centrality effectively reflects the influence of keywords within policy documents, wherein greater degree centrality indicates a stronger influence, as demonstrated in Equation (4).

$$C_D(n_i) = \sum_{j=1}^{g} x_{ij}(i \neq j) \tag{4}$$

In this network analysis, the degree centrality $C_D(n_i)$ of node $n_i$ is derived from the frequency of its co-occurrences with other nodes, where $g$ indicates the total node count. The adjacency matrix's $x_{ij}$ elements reflect these co-occurrences. Self-correlations are not considered in the co-word analysis; thus, diagonal entries in the matrix, which represent self-co-occurrences, are omitted by ensuring $i \neq j$.

Finally, Netdraw was used for visualization processing to develop an interactive influence network of high-frequency keywords. Based on the network nodes and connection information, an in-depth analysis was conducted on the evolutionary patterns of EV industry policy paths at different development stages [40,41].

### 4.2. Policy Volume Evolution

Figure 1 shows the changes in China's new-energy vehicle policies over different years. This figure mainly illustrates the evolution of the number of guiding and strategic policy documents, providing an understanding of the overall trend in the policy system.

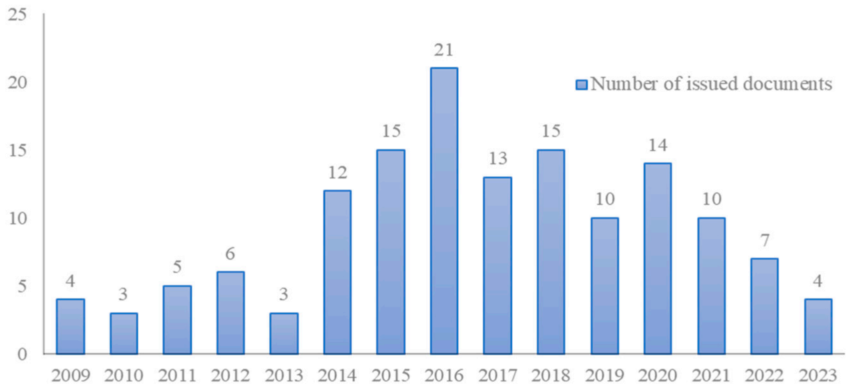


**Figure 1.** Statistics on annual issuance of China's electric vehicle industry policies, 2009–2023.

In 2009, the State Council's decision to include EVs as one of China's seven strategic emerging industries marked the start of EV industrialization, leading to a steady increase in policies. The 2012 "Energy Saving and Electric Vehicle Industry Development Plan" was the first independent strategic planning document. By 2014, the number of policies reached 12, peaking at 21 in 2016. However, as China began to phase out subsidies, policy issuance began to fluctuate and decline. In 2020, the "Electric Vehicle Industry Development Plan (2021–2035)" prompted a temporary rebound. After 2020, as market forces took over, policy issuance slowed, with only four policies issued by the end of 2023.

### 4.3. Evolution of Policy-Issuing Bodies

Figure 2 illustrates the number of policies issued by various departments and agencies in China across different years. The horizontal axis represents the years, while the vertical axis represents different government agencies. The size of the bubbles indicates the number of policies issued by each agency in a given year.

As shown in Figure 2, a total of 17 central government agencies, including the State Council, the MIIT, and the NDRC, have been involved in issuing and implementing EV-related policies. While the State Council only issued four major policies between 2012 and 2020, these were key programmatic or milestone documents. The MIIT issued the most policies, with 62, representing over a third of the total, reflecting China's focus on EV production, manufacturing supervision, and technology development. Notably, joint issuance of policies has increased. Before 2014, policies were mostly issued independently by individual agencies, but as EV industrialization deepened, inter-agency collaboration became more common. Of the 35 policies issued after 2020, 24 (69%) were jointly issued, indicating growing cooperation and improved administrative efficiency [42].


**Figure 2.** Statistics on the number of documents issued regarding China's electric vehicle industry policies from 2009 to 2023.

### *4.4. Policy Focus Evolution*

The EV development trajectory, in line with global technological advancements and pivotal national policies, can be segmented into four phases: demonstration and promotion, steady development, key breakthroughs, and high-quality development [43]. Table 2 illustrates the top three keywords with the highest degree centrality in regard to each phase's policy focus, excluding the term "Electric Vehicles", offering insights into the evolving priorities in these distinct stages.

**Table 2.** Ranking of degree centrality of policy focus points by phase.

| Developmental Stage | Keyword Node | Node Degree Centrality |
|---|---|---|
| Demonstration and Promotion Phase | Enterprise<br>Product<br>Urban Area | 564<br>438<br>468 |
| Steady Development Phase | Core Technology<br>Infrastructure<br>Government | 495<br>411<br>398 |
| Key Breakthrough Phase | Charging<br>Infrastructure<br>Dual-credit | 602<br>546<br>517 |
| High-Quality Development Phase | Market<br>Enterprise<br>Product | 458<br>437<br>424 |

1. Demonstration and Promotion Phase (2009–2011).

From 2009 to 2011, the global electric vehicle industry was in its early stages, with major automakers introducing electric models. The U.S. took the lead through initiatives like the "Cash for Clunkers" program to encourage the adoption of eco-friendly vehicles, while China also rolled out policies to foster industry growth [44].

As shown in Figure 3, the co-word network analysis identified "Electric Vehicle" as the central node, with key terms including "Enterprise", "Product", "City", and "Pure Electric Vehicle". The prominence of "Pure Electric Vehicle" over "Fuel Vehicle" indicated a stronger policy preference for electric vehicles. The appearance of terms like "Fiscal Subsidy", "Subsidy Management", and "Pilot Project" signals the government's gradual introduction of targeted administrative measures, which raised public awareness of EVs. The focus was primarily on urban areas, prioritizing the development of key cities to stimulate regional growth [43]. The high centrality of "Enterprise" highlights that policies at this stage were largely enterprise-driven, leveraging companies to spearhead research, testing, and promotion. Overall, the policies concentrated on promotion and financial subsidies, primarily targeting enterprises, but lacked demand-side incentives and an integrated policy framework for long-term development.

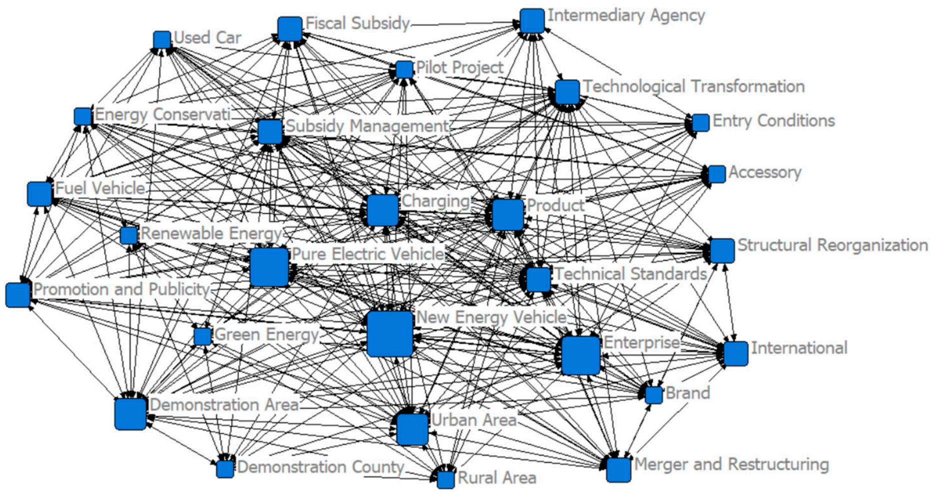


**Figure 3.** China's electric vehicle industry policy focus network, 2009–2011.

2. Steady-Development Phase (2012–2015).

From 2012 to 2015, global EV sales surged significantly, with China's sales up by 238%, making it the largest EV market [45]. Against the backdrop of rapid expansion across major global economies, China's EV industry policy was being fully implemented, with the primary objective of achieving substantial growth in the industry's scale within a short period.

As shown in Figure 4, the co-word network analysis highlighted key terms like "Core Technology", "Infrastructure", and "Sales Volume", with "Government" playing a central role. "Core Technology" is strongly linked to sectors emphasizing the need to reduce technological dependence. The rise of "Infrastructure" reflects China's focus on building foundational support despite regional challenges like land approval and investment. Policies from 2014 and 2015 prioritized infrastructure development. The inclusion of "Taxi" and "Bus" indicates a focus on charging infrastructure for public transportation, further promoting EVs. Meanwhile, keywords like "Renewable Energy" suggest growing attention to clean-fuel vehicles [46]. Government involvement was crucial during this phase, but while fiscal subsidies boosted production, they did little to attract long-term private investment. Demand-side policies remained limited, with relevant actors focusing too heavily on government procurement and pilot projects, constraining broader market growth [47].

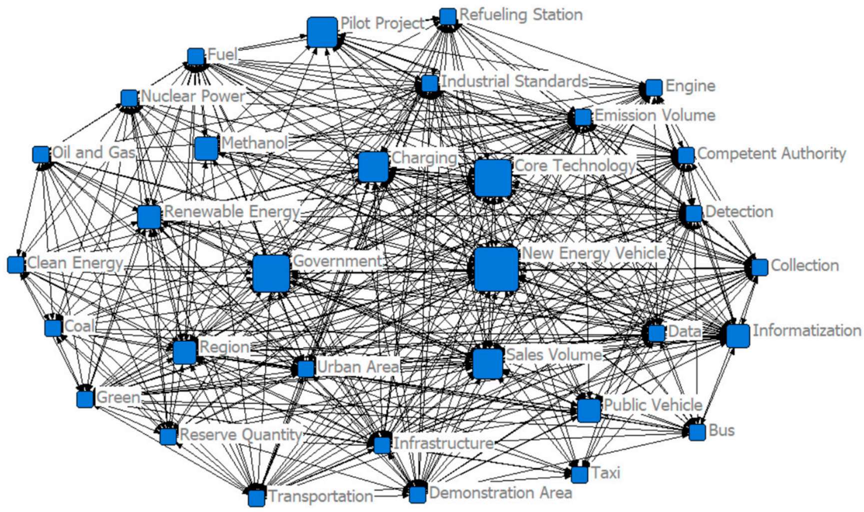


**Figure 4.** China's electric vehicle industry policy focus network, 2012–2015.

3. Key Breakthrough Phase (2016–2019)

From 2016 to 2019, the global development of electric vehicles deepened, with regions like the U.S., Europe, and China creating EV-specific policies suited to their national contexts. As industry competition entered a highly intense phase, each region began to focus on its distinct priorities and sought to establish sustainable competitive advantages through a series of targeted policy measures.

As shown in Figure 5, there was an increase in focus terms and network density, with clear regional divisions. The upper network concentrated on "Infrastructure" and "Charging", while the lower part focused on "Purchase Tax" and "Dual-credit". The centrality of "Charging" grew significantly, reflecting a broader scope. China linked infrastructure progress to financial subsidies, rewarding local governments for meeting targets. Of the key terms identified, many are related to electric vehicle battery management, showing China's focus on this area. "Dual-credit" and "Purchase Tax" remained influential, with the dual-credit policy acting as a market-driven tool for EV manufacturers, influencing supply-side behavior and indirectly stimulating demand. The centrality of "Purchase Tax" reflects continued tax subsidy policies, extending tax deductions for EVs but with increased scrutiny. During this phase, policies had a broader scope and were more comprehensive. The clear division of policy areas indicated a more targeted approach, with the government playing a key role in advancing infrastructure and market oversight. China also promoted marketization through multi-level policy innovations, transitioning industry drivers. However, the policies primarily targeted a few breakthrough areas and lacked a full industry chain perspective, limiting efficiency and ecosystem development. Despite innovations, the imbalance between supply-side "push" and demand-side "pull" factors remained a challenge [42].

4. High-Quality Development Phase (2020–Present)

Since 2020, the global EV industry has navigated both opportunities and challenges. In early 2020, the pandemic and anti-globalization trends led to a 37.4% drop in domestic sales, but by 2022, the industry had rebounded, with over 10 million sales globally [45]. The global competitive landscape has largely taken shape, and policy approaches are becoming more diversified.

As shown in Figure 6, China's policy framework has become more interconnected, with "Market" and "Enterprise" remaining central, reflecting continuity in policy focus. The rise of terms like "Public Service" and "Innovation Platform" indicates a growing emphasis on public support, while the increased presence of "Vehicle Networking" and "Autonomous Driving" highlights the integration of EVs with digital technologies. The introduction of "Rural Promotion" further signals efforts to expand EV adoption in non-urban areas. In this phase of high-quality development, policies addressed most industry segments, with the government taking a more active role as a regulator and market leader, easing financial pressures and promoting growth. While policies such as "dual-credit" and "infrastructure rewards" were implemented, the focus remained on environmental and supply-side measures. As subsidies phase out, stronger demand-side policies are needed to stimulate consumer demand and better align goals like "low-carbon emission reduction" with market strategies for long-term industry growth [48].

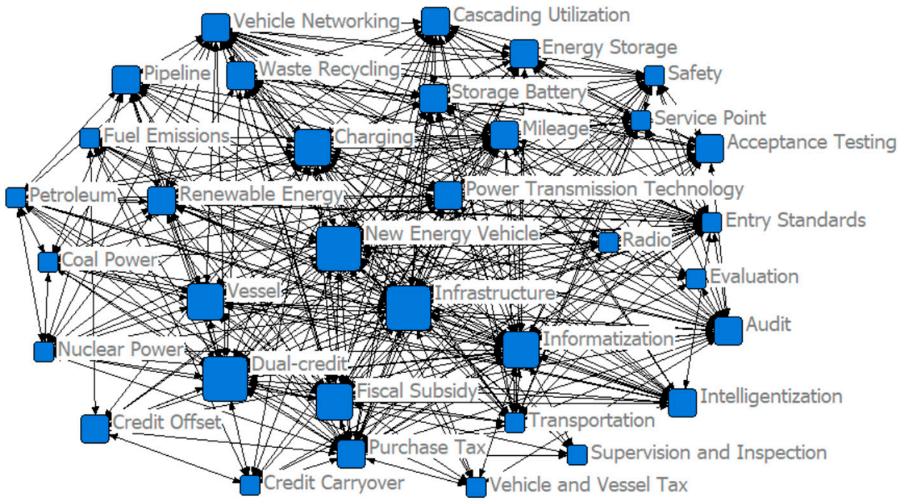


**Figure 5.** China's electric vehicle industry policy focus network, 2016–2019.

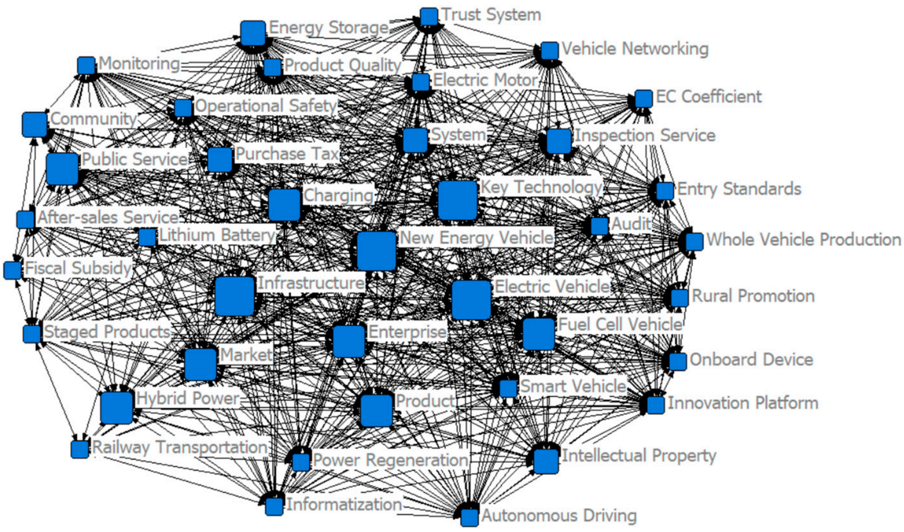


**Figure 6.** China's electric vehicle industry policy focus network, 2020–2023.

## 5. Policy Evolution Path Analysis and Prediction

Co-word network analysis plays a crucial role in examining Chinese electric vehicle (EV) policy texts, revealing the core policy focal terms corresponding to each policy tool and their interconnections, providing detailed information on the evolution of policies across different stages. However, as a qualitative method, co-word network analysis has three main limitations: first, it only reveals static associations within a text and cannot quantify the policy evolution process; second, it focuses primarily on policy changes in different periods, emphasizing local details and failing to capture the long-term trajectories of policies from a holistic perspective; third, co-word network analysis cannot effectively predict future policy developments, thus limiting its ability to analyze policy evolution trends. To address these limitations and enhance the understanding and predictive capability of policy texts, the introduction of the BERT model for quantitative and dynamic analysis is necessary.

### 5.1. Analytical Framework

Based on the analysis of China's EV policy development path, the evolution of policy objectives can be divided into four stages: pilot promotion (2009–2011), steady development (2012–2015), key breakthroughs (2016–2019), and high-quality development (2020–present). Each stage builds upon the outcomes and structures established in the previous one, reflecting a sequential and cumulative approach to policy development. Initially, policies focused on building market awareness and establishing foundational production capabilities; this was followed by efforts to scale production, develop infrastructure, achieve technological breakthroughs, and ultimately optimize the value chain [49]. This trajectory highlights how earlier policy choices set the groundwork for future actions, demonstrating a pattern where each phase relies on the accumulated results of the previous stage, as shown in Figure 7.

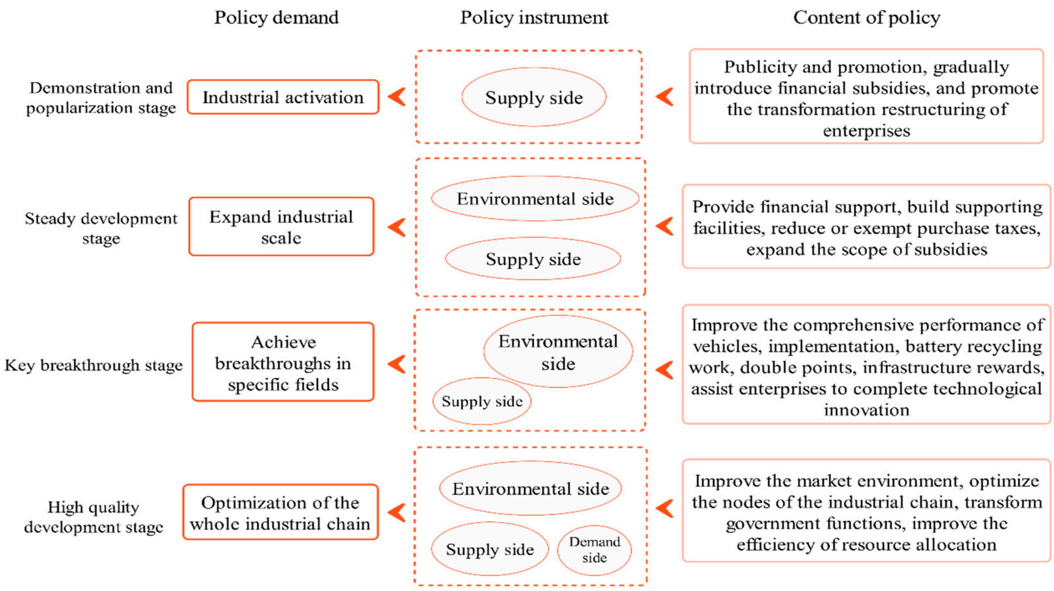


**Figure 7.** Analysis of the policy path of China's electric vehicle industry.

Path dependence theory is particularly suitable for analyzing this policy evolution because it explains how initial choices, or "critical junctures", establish pathways that influence and constrain later development. In the context of China's EV industry, the initial heavy reliance on supply-side measures—aimed at rapidly building technological capacity and production infrastructure—served as such a critical juncture [50]. This early focus shaped the trajectory of the industry's policy development, creating a "lock-in" effect where subsequent policies had to build upon and reinforce this established pathway [21]. As path dependence theory suggests, once a trajectory is set, it becomes self-reinforcing due to increasing returns, making it difficult to deviate from or significantly alter without substantial intervention [4]. The research findings illustrate that while these supply-side policies accelerated industry growth, they also created structural imbalances, such as the lag in developing demand-side measures [51]. These imbalances persist as demand-side policies struggle to match the established momentum of supply-side efforts [14].

Therefore, to fully understand the policy trajectory, quantify its evolution, and explore potential optimizations, quantitative methods are necessary. This approach will help determine the exact nature of the policy path, its future direction, and the strategies required to optimize policies to attain balanced and sustainable growth.

### 5.2. Model Design

The BERT model, leveraging its natural-language-processing and deep learning capabilities, builds a quantitative analysis framework for policy evolution by interpreting the semantics of policy tools and their focal terms [35].

Specifically, the BERT model processes a large corpus of policy texts to extract and quantify the contextual relevance of key policy terms over different time periods, tracking how their significance evolves over time [52]. By employing attention mechanisms and contextual embeddings, BERT captures the semantic relationships and nuances of keywords within policy documents, generating weighted scores that reflect the importance of each keyword in a given period. Through the analysis of these scores, BERT constructs a comprehensive trajectory of policy theme evolution, identifying shifts in the focus of policies across different stages [53]. Integrating path dependence theory, BERT identifies critical junctures where early policy decisions exert self-reinforcing effects, shaping subsequent developments and creating a path-dependent phenomenon [54]. The model analyzes these points to reveal the underlying logic of policy evolution and its constraints on future developments. Using historical data patterns, BERT employs time series analysis and trend models to forecast the direction of future policy themes, detecting long-term patterns and potential shifts in intensity. This quantitative approach provides a precise framework for predicting policy pathways, supporting policymakers in making informed, forward-looking decisions within a dynamic environment [37].

Figure 8 illustrates the architecture of the BERT model, where T1, T2, . . ., TN denote input tokens or sequences. Each of these inputs is processed through multiple Transformer encoder layers (Trm), using self-attention mechanisms to capture contextual relationships. The final output layers (E1, E2, . . ., EN) generate embeddings corresponding to each input, which are subsequently utilized for downstream tasks like prediction or classification.

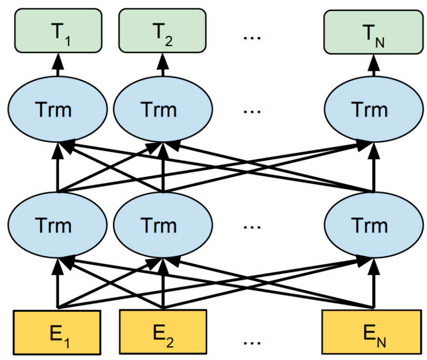


**Figure 8.** BERT model operation mechanism.

To ensure accuracy, the model's classification criteria were defined in accordance with the framework proposed by Rothwell and Zegveld, dividing policy tools into three categories: supply-side, demand-side, and environmental [21]. This approach allows the model to analyze policy texts precisely according to their specific categories. Additionally, the results of the co-word network analysis provide rich input data for the BERT model, enabling it to integrate the focal terms and their evolution patterns for different policy tools during clustering and classification. By combining the data from the co-word network, the BERT model not only identifies the features of policy tools across different periods but also systematically deciphers the evolving trends within policy texts, establishing a foundation for future policy trajectory predictions.

The degree centrality and other quantitative indicators derived from the co-word network provide scientific evidence useful for establishing parameter settings in the BERT model. These indicators guide the model in weighting focal terms across different categories, ensuring that critical policy evolution signals are emphasized during the learning process. In the model design, an adaptive learning rate based on weights is used, with an initial value set at 0.00002. This learning rate dynamically adjusts according to the frequency and distribution of focal terms to accommodate the imbalanced nature of policy text data. The batch size was set to 32 to enhance stability and efficiency when processing large-scale policy data, while the number of training epochs was set to 10, allowing the model sufficient time to learn the underlying patterns within the text. The model also incorporates a focal-term-weight-based regularization strategy, ensuring that the BERT model accurately identifies the evolution characteristics of policy texts during multi-category policy tool classification and clustering.

1. Text Input Processing and Embedding Generation

In the BERT model, each segment of the policy document text is transformed into a structured input representation, referred to as $Input_i$, where $i$ represents the position of each token in the sequence. This input vector combines embeddings that capture semantic, positional, and structural information essential for understanding the content of a policy document. Specifically, each token's input embedding is represented as Equation (5):

$$Input_i = Text\ Embedding_i + Position\ Embedding_i + Segment\ Embedding_i \tag{5}$$

The $Text\ Embedding_i$ component maps each token into a high-dimensional vector space that captures its semantic meaning, enabling BERT to understand each term within the context of the policy document. The $Position\ Embedding_i$ component encodes the position of each token within the sequence, preserving the order of terms, which is essential for capturing the flow and structure of information. The $Segment\ Embedding_i$ component differentiates between segments of the input, such as distinct policy phases or sections, allowing the model to analyze relationships between these parts effectively.

2. Self-Attention Mechanism for Contextual Encoding

After processing the text into embeddings, BERT applies a multi-head self-attention mechanism to dynamically evaluate the relationships and importance of each term within the text. This mechanism allows BERT to capture dependencies between policy terms and understand each term's contribution to the overall policy focus across different time periods.

In the self-attention mechanism, each token's embedding is transformed into three vectors: query ($Q$), key ($K$), and value ($V$). Query represents the active token's "question" in finding relevant information among other tokens, key provides a reference point for evaluating relationships, and value retains the actual information content of the token. Each of these vectors is generated through learned projection matrices, as shown in Equations (6)–(8):

$$Q = W^Q \cdot Input \tag{6}$$

$$K = W^K \cdot Input \tag{7}$$

$$V = W^V \cdot Input \tag{8}$$

$W^Q$, $W^K$, and $W^V$ are trainable matrices specific to each attention head. These transformations allow each token to be represented in three different ways, enabling the model to compute attention scores based on the relationships between queries and keys.

The attention score between tokens is calculated by taking the dot product of the query and key vectors, scaled by the square root of the dimensionality $\sqrt{d_k}$ to stabilize variance. This dot product represents the alignment between tokens, and by applying the softmax function, these scores can be normalized to produce attention weights. These weights reflect each token's relative influence on other tokens within the sequence. In this context, $T$ denotes the transpose operation applied to the key vector, enabling each query to be compared across all keys in the sequence simultaneously. The final attention mechanism can be represented using Equation (9):

$$Attention(Q,K,V) = softmax(\frac{QK^T}{\sqrt{d_k}})V \tag{9}$$

This mechanism allows BERT to assign context-sensitive weights to segments of text, such as sentences describing regulatory guidelines or historical milestones, based on their relevance in relation to other parts of a policy document. The self-attention mechanism is essential for capturing nuanced relationships and shifts in policy focus, as it enables BERT to dynamically focus on the most contextually relevant segments within a document.

3. BERT Output for Relevance Scoring

Following the self-attention layers, BERT generates output embeddings that reflect the contextualized meaning of each token within a policy text. These embeddings are then pooled to derive a single relevance score for each policy term (e.g., "subsidy" or "technology") within a specific time period. This relevance score represents the importance and contextual role of the term in a policy document, as shown in Equation (10):

$$X_t = f(BERT_{output}) \tag{10}$$

$X_t$ denotes the relevance score for a specific policy keyword at time $f(\bullet)$, which represents an aggregation function, such as mean pooling or max pooling, applied to the output embeddings. This function condenses the token-level representations into a single relevance score for each keyword.

These relevance scores provide a quantitative measure of a text's focus across time periods, serving as a foundation for understanding the trajectory of policy evolution and assessing shifts in emphasis within policy documents.

4. Forecasting Policy Trajectories

To forecast future shifts in policy focus, a regression model was applied, using the BERT embeddings generated from historical policy data. This approach leverages the contextual relevance scores to predict the future importance of each keyword. The regression model is formulated as shown in Equation (11):

$$P_{t+1} = W \cdot BERT(X_t) + b \tag{11}$$

$P_{t+1}$ represents the predicted importance score for a policy term at the next time interval $t+1$; $BERT(X_t)$ is the embedding output generated by the BERT model for a keyword at time $t$, capturing the semantic and contextual features of the term within the policy documents; $W$ and $b$ are the weights and biases learned during the training process, calibrated to minimize the prediction error based on historical data.

5. Normalization

To transform these scores into a standardized range between 0 and 1, the following time-sensitive normalization formula was applied:

$$Normalized\ Value_t = \frac{(X_{max,t} - X_{min,t})^{\alpha}}{(X_t - X_{min,t})^{\alpha}},\ 0 < \alpha < 1 \tag{12}$$

$X_t$ is the score assigned by the BERT model for a keyword at time period $t$, indicating its relevance based on the policy context in that time frame. $X_{min,t}$ is the minimum score for the keyword within the specific time window or period under consideration. $X_{max,t}$ is the maximum score for the keyword within the same time window or period. $\alpha$ is a scaling factor greater than 0 that adjusts the sensitivity of the normalization process.

This formula integrates time as a key factor, allowing the intensity of each policy segment to be evaluated not only according to its immediate value but also its variation over time. By effectively capturing temporal changes, this approach enables consistent comparisons of policy themes and highlights shifts in focus. BERT's outputs provide insights that go beyond individual words, classifying them by policy focus areas to analyze trends within specific policy instruments and track their evolving emphasis.

### 5.3. Model Conclusions

The configuration and key results of the BERT-based model, summarized in Table 3, indicate its capacity to accurately capture shifts in the relevance of policy tools. With optimized parameters and an architecture suited to identifying significant contextual patterns, the model demonstrated consistent performance across the training and validation sets, suggesting reliable predictive capability. These findings support the model's applicability in analyzing the directional evolution of policy frameworks, particularly within dynamic regulatory contexts.

**Table 3.** BERT model configuration and performance metrics.

| Parameter/Metric | Value | Description |
|---|---|---|
| Model Type | BERT-based Prediction | Utilizes BERT to predict the evolution of policy tools, capturing key trends |
| Learning Rate | 0.00002 | Initial learning rate, dynamically adjusted |
| Batch Size | 32 | Number of samples per batch during training |
| Epochs | 10 | Number of training epochs, ensuring adequate model learning |
| Training Loss (Final) | 0.158 | Final loss on training data; values closer to 0 reflect a good fit |
| Validation Loss | 0.165 | Loss on validation data; values close to training loss indicate there is no overfitting |
| Embedding Dimensions | 768 | Dimension of embeddings, capturing detailed semantic information |
| Attention Heads | 12 | Number of attention heads for capturing multiple context dimensions |
| Final Training Accuracy | 92.30% | Final accuracy on training data, indicating model's fit |
| Validation Accuracy | 91.80% | Accuracy on validation set; values are close to training performance |
| Attention Weights (Max) | 0.92 | Max attention weight for key policy tools, showing model focus |
| Max Sequence Length | 1024 | Maximum text length handled, suitable for longer policy documents |
| Evaluation Metrics | MSE: 0.013, RMSE: 0.114, R-Squared: 0.89 | Metrics indicating prediction accuracy and stability |
| Prediction Time (Average) | 0.15 s | Average time per prediction, indicating inference efficiency |
| Output Vector Count | 512 | Number of output vectors, representing dimension of relevance scores |

Figure 9 illustrates the evolution of China's electric vehicle (EV) policies from 2009 to 2027 across three dimensions: supply-side, demand-side, and environmental policies. The horizontal axis represents the timeline, divided into semi-annual intervals (e.g., "2009a" indicates the first half of 2009, while "2009b" indicates the second half). The vertical axis lists specific policy focal terms categorized according to policy tools, and these terms were selected based on the results of co-word analysis, highlighting those with higher degree centrality and greater representativeness within each category. The color intensity corresponds to the level of attention policymakers paid to each area during a given period, indicating the importance of that area in the policy content at the time. This visualization provides a clear, quantitative representation of the dynamic changes in policy focus over time. The portion of the heatmap starting from 2024b onward represents predicted data, projecting the future trajectory and evolution of policies to guide decision-making and strategic planning.

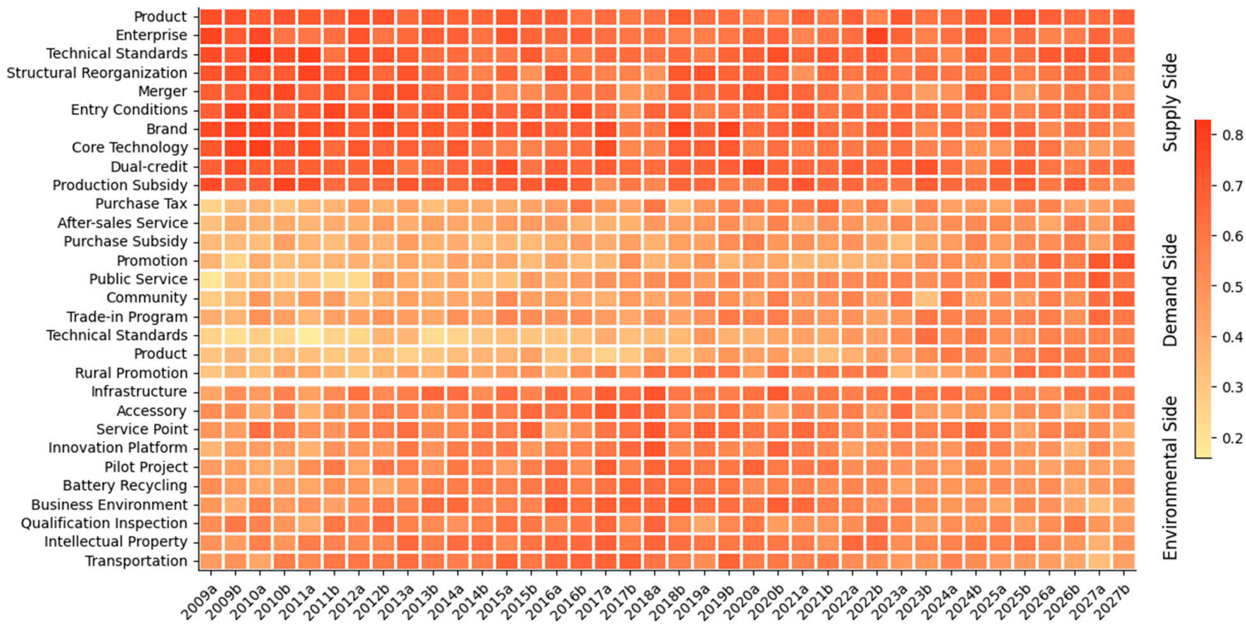


**Figure 9.** Policy path evolution and prediction.

Supply-side policies have generally been stronger than the other two policy tools but show a gradual weakening trend. From 2009 to 2015, supply-side policies received significant government attention, with a focus on establishing the technological and production foundation needed for the electric vehicle (EV) industry. Key terms such as "technical standards", "production subsidy", and "core technology" reflect the government's efforts during this period to build a solid industrial and technological base. After 2015, the emphasis on supply-side policies gradually decreased, although they remained influential. This shift marks a transition from broad-based support to more targeted interventions, focusing on regulating market access and refining technology standards as the industry matures and develops steadily. From the perspective of future projections, supply-side policies are expected to remain a priority in the short term, gradually transitioning to demand-side and environmental policy tools [2].

Demand-side policies show a clear upward trajectory, initially starting with very low levels of government attention, indicating minimal involvement in stimulating market demand. However, from 2015 onward, there has been a significant increase in government focus on promoting EV adoption among consumers. This is highlighted by terms such as "purchase subsidy", "promotion", and "trade-in program", which signify the implementation of various incentives to expand the domestic market. The steady rise in demand-side policies reflects not only a shift towards enhancing market mechanisms and reducing direct governmental intervention but also a strategic response to the global trade environment. Given the impact of international trade tensions and uncertainties, strengthening the domestic market has become increasingly important for ensuring the resilience and sustainability of the EV industry [55].The projected trend beyond 2024b suggests that demand-side policies will remain a focal point, as the government continues to bolster the domestic market to mitigate external risks and sustain EV adoption growth [56].

Environmental policies generally maintained a stable trajectory but experienced a notable phase of fluctuation between 2017 and 2020. During this period, there was a marked increase in the level of attention, with a focus on terms such as "infrastructure", "innovation platform", and "battery recycling". This spike corresponds to the earlier period of intensive supply-side policies, which led to a rapid expansion in EV production capacity. To accommodate this surge in production, the government intensified efforts to build the necessary infrastructure and platforms, ensuring the sustainable growth and operational efficiency of this industry. After this period of adjustment, environmental policies stabilized again, reflecting a realignment as infrastructure development began to catch up with production levels [57]. The forecasted period beyond 2024b indicates that environmental policies will continue to maintain this stability, highlighting a consistent focus on sustaining the established standards and infrastructure needed for the long-term viability of the EV ecosystem [13].

## 6. Discussion

The evolution of China's electric vehicle (EV) policies reflects the government's adaptive strategies for promoting industry growth and addressing emerging challenges. This section focuses on how this study fills theoretical and methodological gaps and highlights its unique contributions to understanding policy evolution.

Previous studies on EV policies have often been limited to static analyses of specific policy measures, failing to fully capture the systemic and dynamic nature of policy development. This has resulted in significant theoretical gaps in understanding the complexities of policy evolution. In particular, the existing research has largely overlooked the dynamic processes of policy evolution and the interactions between different policy instruments. By employing a mixed-methods approach that integrates co-word network analysis with BERT-based trajectory modeling, we systematically analyzed the evolution of China's EV policies from 2009 to 2023, addressing these gaps.

One of the key contributions of this study is the revelation of the interactions between different policy instruments, specifically the synergies between supply-side, demand-side, and environmental measures. Through co-word network analysis, we identified key themes and their interrelationships throughout the evolution of the studied policies, demonstrating how the Chinese government has employed various policy combinations to drive industry growth at different stages. These policy combinations were not implemented in isolation but rather complemented and reinforced each other, forming a cohesive policy framework. This integrated and mutually reinforcing policy framework enabled the rapid development of China's EV industry, ensuring consistency and effectiveness in policy evolution.

The results of the BERT-based trajectory modeling further enhance our understanding of the policy evolution process by providing forward-looking predictions for future policy directions. This study transcends the limitations of traditional policy research, which is often restricted to historical descriptions, by employing machine learning models to gain deep semantic insights into policy texts and perform temporal analyses. The findings reveal trends in policy themes, offering scientific evidence with which policymakers in China can make informed, proactive decisions that align with the rapidly changing landscape of this industry. For policymakers in other countries, anticipating the trajectory of competing policies will provide a strategic advantage in future policy deliberations and enable more favorable decision-making.

This study not only fills theoretical gaps regarding the policy evolution process but also provides new insights for designing and adjusting policies to address the dynamic industrial environment. Our research emphasizes that policy design and implementation must be flexible and forward-looking, particularly in fast-evolving emerging industries, where policy adjustments must align closely with industry development. The effectiveness of policies lies in their dynamic adjustment mechanisms rather than static implementation. This study offers important insights for policymakers: successful policy outcomes are achieved not only through individual measures but also through the strategic combination of these measures and their timely implementation to ensure sustainable industry growth. Given the path-dependent nature of policies, policymakers should establish long-term plans in the early stages of industry development and continuously refine them during their implementation to avoid inefficiencies or imbalances that could negatively impact future development. These insights are valuable not only for China but also other countries with similar developmental goals.

## 7. Conclusions and Policy Recommendations

### 7.1. Conclusions

1. Evolution of China's Electric Vehicle (EV) Industry

China's EV industry policies have evolved through distinct phases since 2009, reflecting the government's strategic adaptation to changing industry needs. The pilot promotion phase (2009–2011) focused on raising market awareness and jumpstarting the industry through pilot projects and subsidies. This was followed by the steady development phase (2012–2015), where policies aimed to expand the industry's scale, emphasizing large-scale production and consumer incentives such as tax breaks and infrastructural enhancements. The period from 2016 to 2019 marked a phase of targeted breakthroughs, with a strong focus on technological advancement and infrastructure improvements, particularly in the expansion of charging networks and advancements in core technologies. The current phase, namely, the high-quality development phase (2020–present), prioritizes optimizing the entire value chain, enhancing market mechanisms, and integrating advanced technologies to support sustainable growth. The co-word analysis results confirm a shift from an initial emphasis on expanding scale to a more refined focus on quality and sustainability, aligning with broader national development goals [58,59].

2. Strengths and Weaknesses of China's EV Industry Policies

China's centralized political system has enabled the rapid and coordinated implementation of EV policies, particularly in the early stages, wherein supply-side measures effectively established the technological and production infrastructure needed for industry growth. These policies have been instrumental in quickly building a robust foundation for the EV sector, showcasing the strength of centralized planning in mobilizing resources. However, our analysis also reveals critical weaknesses and imbalances in the policy structure. The dominance of supply-side policies has led to structural path dependence, with insufficient emphasis on demand-side measures, which lag in supporting market-driven growth [51]. Although recent years have seen an increase in consumer-oriented policies, these efforts have not yet achieved the balance required to create a sustainable and self-sufficient market [60]. Furthermore, environmental policies, while providing necessary regulatory support, tend to be reactive, particularly during periods of rapid production expansion, rather than proactive, i.e., setting the conditions for sustainable industry development. To address these imbalances, it is crucial for policymakers to further integrate the "dual circulation" strategy, ensuring that supply-side, demand-side, and environmental policies are harmonized to foster both domestic market resilience and global competitiveness.

3. Future Directions for China's EV Industry Policies Based on Forecasts

Based on the BERT model's predictive analysis, China's EV policies are expected to stabilize and shift towards a more balanced approach, with increasing emphasis on demand-side measures. The future trajectory suggests a strategic focus on expanding consumer adoption, particularly in less-developed regions, to deepen domestic market penetration and reduce reliance on subsidies as the market matures. Supply-side policies, while expected to decrease in importance, will continue to play a supportive role by maintaining competitive technological standards and enhancing critical infrastructure. Environmental policies are projected to remain consistent, focusing on long-term sustainability initiatives, such as integrating digital innovations, vehicle networking, and advanced battery recycling systems. These adjustments are essential for ensuring the industry's resilience against external risks, as well as for supporting the dual circulation strategy, which emphasizes domestic market strength while maintaining a global presence [61]. The forecast underscores the necessity of the continuous refinement and integration of policies across all dimensions to achieve a sustainable and balanced EV development trajectory.

### 7.2. Policy Recommendations

1. Optimizing China's EV Policy Framework

To further advance the EV industry, China needs to refine its policy framework by creating a more balanced and synergistic approach with respect to supply-side, demand-side, and environmental policies. The historical dominance of supply-side measures has effectively built a technological foundation; however, this has led to structural imbalances that require correction. Enhancing demand-side policies is essential to stimulate sustained consumer interest and adoption. To achieve this, the government should implement long-term consumer incentives beyond initial purchase subsidies, including support for after-sales services, EV maintenance infrastructure, and regional incentives to target rural and less developed markets. Moreover, environmental policies should not merely react to production growth but proactively align with technological and infrastructural advancements to ensure the sustainability of the industry's expansion. Policymakers should establish a dynamic and iterative evaluation mechanism that monitors the effectiveness of these policies in real-time, allowing for timely adjustments. This approach would also involve integrating cross-sectoral strategies that coordinate technological development, market incentives, and environmental goals to fully leverage China's "dual circulation" strategy. The objective should be to create an adaptable policy environment that can evolve with industry demands while maintaining China's competitive edge.

2. Lessons for Other Countries based on China's EV Development

China's EV policy evolution provides a comprehensive blueprint that other countries can adapt based on their specific stages of EV industry development. For early-stage countries, adopting a policy approach that encourages pilot projects and offers subsidies for technological innovation is crucial to stimulate the market and create initial infrastructure. Countries with developing EV industries can benefit from China's dual-credit system, which integrates supply and demand incentives, aligning technological capacity with market growth. Establishing national standards for technological development and infrastructure expansion, as seen in China's targeted-breakthroughs phase, can also help synchronize policy goals [62]. For more mature EV markets, China's high-quality-development phase offers insights into optimizing the value chain and integrating sustainability goals through digital and innovative platforms [63]. However, other nations must recognize the limitations of replicating China's model, particularly regarding centralized planning and rapid policy shifts, which may not be feasible in less centralized or more market-driven systems. Therefore, establishing adaptive policy evaluation mechanisms and fostering public–private partnerships are crucial for maintaining a flexible and responsive policy environment, ensuring that growth is balanced and sustainable across diverse market contexts [51].

3. Policy Strategies for Competing with China's EV Expansion

To effectively counter China's rapidly expanding EV industry, it is crucial for countries to recognize that simple protectionist measures like tariffs are insufficient, as China's government-led, supply-side policies enable it to scale production rapidly and acquire significant cost advantages. Tariffs alone cannot address the underlying issue of China's centralized coordination and investment capabilities, which allow it to dominate global markets. Instead, countries must focus on building their own technological ecosystems through strategic public investments and partnerships, targeting innovation areas like hydrogen fuel cells, high-efficiency electric motors, and smart grid technologies where China's influence is less pronounced. Establishing innovation clusters and R&D hubs with support from both the government and private sector will enable these countries to develop high-value EV products that compete based on technological excellence rather than price, thereby countering China's supply-side advantage. Collaborating with international allies in technology-sharing agreements can further enhance innovation capacities and create a united front against China's supply-side dominance [64].

Meanwhile, to weaken China's expanding demand-side strategies, which are increasingly influencing both domestic and international markets, countries must implement policies that stimulate their own EV demand while strategically limiting China's market penetration. Domestically, this can be realized by expanding consumer incentives, such as long-term purchase subsidies and tax breaks tied specifically to local EV products, along with investments in comprehensive charging and maintenance networks to enhance consumers' confidence and preferences for homegrown vehicles [65]. Internationally, countries should collaborate with allies to set high sustainability and innovation standards that limit Chinese EV entry by requiring compliance with stringent environmental and technological criteria. By creating strategic trade agreements that favor domestic EVs and leveraging international partnerships, countries can build market ecosystems that attract consumers to their own products, thus reducing the impact of China's demand-side policies on their markets [66].

### *7.3. Limitations of This Study*

This study has several limitations that highlight potential directions for future research. Firstly, the analysis focuses predominantly on national-level policies in China, which may overlook the nuances of local policy implementation and regional variations. A deeper understanding of these regional differences could provide more comprehensive insights into policy effectiveness and adaptation across different contexts within China. Future research could address this by including provincial and municipal policies and assessing how central and local policies align and diverge.

Secondly, this study does not include a comparative analysis incorporating other major EV (New Energy Vehicle) markets globally. This limits the understanding of how China's policy evolution compares to the evolutions of other significant players, such as the European Union and the United States. Incorporating such a comparative perspective could offer valuable lessons on best practices and unique approaches in EV policy development across different regions.

Lastly, the current research approach primarily leans towards policy studies, without delving deeply into the economic and political implications of the policies. Future studies could benefit from interdisciplinary analysis, integrating economic, political, and social perspectives to create a more holistic understanding of the factors influencing EV policy evolution and its broader impact.

**Author Contributions:** Data curation, Z.L.; formal analysis, Z.L.; funding acquisition, T.X.; methodology, Z.L.; project administration, T.X.; software, Z.L.; supervision, T.X.; validation, Z.L.; visualization, T.X.; writing—original draft, Z.L.; writing—review and editing, T.X. All authors have read and agreed to the published version of the manuscript.

**Funding:** This research was funded by Liaoning Provincial Social Science Planning Fund Key Project "Analysis on the Focus Change and Path Evolution of Electric Vehicle Industry Policies", grant number "L23AJL001".

**Data Availability Statement:** The original contributions presented in this study are included in the article; further inquiries can be directed toward the corresponding author.

**Conflicts of Interest:** The authors declare no conflicts of interest.

## References

1. Zhang, X.; Liang, Y.; Yu, E.; Rao, R.; Xie, J. Review of Electric Vehicle Policies in China: Content Summary and Effect Analysis. *Renew. Sustain. Energy Rev.* **2017**, *70*, 698–714. [CrossRef]
2. Shang, W.-L.; Zhang, J.; Wang, K.; Yang, H.; Ochieng, W. Can Financial Subsidy Increase Electric Vehicle (EV) Penetration—Evidence from a Quasi-Natural Experiment. *Renew. Sustain. Energy Rev.* **2024**, *190*, 114021. [CrossRef]

3. China Association of Automobile Manufacturers. *Annual Report on the Development of China Automotive Industry*; Social Sciences Academic Press: Beijing, China, 2023.
4. Dong, F.; Liu, Y. Policy Evolution and Effect Evaluation of New-Energy Vehicle Industry in China. *Resour. Policy* **2020**, *67*, 101655. [CrossRef]
5. Du, J.; Ouyang, D. Progress of Chinese Electric Vehicles Industrialization in 2015: A Review. *Appl. Energy* **2017**, *188*, 529–546. [CrossRef]
6. Jiang, Z.; Liu, Z. Policies and Exploitative and Exploratory Innovations of the Wind Power Industry in China: The Role of Technological Path Dependence. *Technol. Forecast. Soc. Change* **2022**, *177*, 121519. [CrossRef]
7. Rosenbloom, D.; Meadowcroft, J.; Cashore, B. Stability and Climate Policy? Harnessing Insights on Path Dependence, Policy Feedback, and Transition Pathways. *Energy Res. Soc. Sci.* **2019**, *50*, 168–178. [CrossRef]
8. Xu, Z.; Li, Y.; Li, F. Electric Vehicle Supply Chain under Dual-Credit and Subsidy Policies: Technology Innovation, Infrastructure Construction and Coordination. *Energy Policy* **2024**, *195*, 114339. [CrossRef]
9. Zhang, L.; Liu, Y. Analysis of New Energy Vehicles Industry Policy in China's Cities from the Perspective of Policy Instruments. *Energy Procedia* **2016**, *104*, 437–442. [CrossRef]
10. Peng, Y.; Bai, X. What EV Users Say about Policy Efficacy: Evidence from Shanghai. *Transp. Policy* **2023**, *132*, 16–26. [CrossRef]
11. Zhang, Q.; Li, H.; Zhu, L.; Campana, P.E.; Lu, H.; Wallin, F.; Sun, Q. Factors Influencing the Economics of Public Charging Infrastructures for EV—A Review. *Renew. Sustain. Energy Rev.* **2018**, *94*, 500–509. [CrossRef]
12. Lazuardy, A.; Nurcahyo, R.; Kristiningrum, E.; Ma'aram, A.; Farizal; Aqmarina, S.N.; Rajabi, M.F. Technological, Environmental, Economic, and Regulation Barriers to Electric Vehicle Adoption: Evidence from Indonesia. *World Electr. Veh. J.* **2024**, *15*, 422. [CrossRef]
13. Murugan, M.; Marisamynathan, S. Policy Analysis for Sustainable EV Charging Facility Adoption Using SEM-ANN Approach. *Transp. Res. Part A Policy Pract.* **2024**, *182*, 104036. [CrossRef]
14. Li, W.; Long, R.; Chen, H.; Geng, J. A Review of Factors Influencing Consumer Intentions to Adopt Battery Electric Vehicles. *Renew. Sustain. Energy Rev.* **2017**, *78*, 318–328. [CrossRef]
15. Wang, N.; Tang, L.; Pan, H. Effectiveness of Policy Incentives on Electric Vehicle Acceptance in China: A Discrete Choice Analysis. *Transp. Res. Part A Policy Pract.* **2017**, *105*, 210–218. [CrossRef]
16. Matschoss, P.; Bayer, B.; Thomas, H.; Marian, A. The German Incentive Regulation and Its Practical Impact on the Grid Integration of Renewable Energy Systems. *Renew. Energy* **2019**, *134*, 727–738. [CrossRef]
17. Kumar, R.R.; Alok, K. Adoption of Electric Vehicle: A Literature Review and Prospects for Sustainability. *J. Clean. Prod.* **2020**, *253*, 119911. [CrossRef]
18. Biresselioglu, M.E.; Demirbag Kaplan, M.; Yilmaz, B.K. Electric Mobility in Europe: A Comprehensive Review of Motivators and Barriers in Decision Making Processes. *Transp. Res. Part A Policy Pract.* **2018**, *109*, 1–13. [CrossRef]
19. Hardman, S.; Chandan, A.; Tal, G.; Turrentine, T. The Effectiveness of Financial Purchase Incentives for Battery Electric Vehicles —A Review of the Evidence. *Renew. Sustain. Energy Rev.* **2017**, *80*, 1100–1111. [CrossRef]
20. Santos, G.; Davies, H. Incentives for Quick Penetration of Electric Vehicles in Five European Countries: Perceptions from Experts and Stakeholders. *Transp. Res. Part A Policy Pract.* **2020**, *137*, 326–342. [CrossRef]
21. Rothwell, R.; Zegveld, W. Reindustrialization and Technology. *Sci. Public Policy* **1985**, *12*, 113–130. [CrossRef]
22. McDonnell, L.M.; Elmore, R.F. Getting the Job Done: Alternative Policy Instruments. *Educ. Eval. Policy Anal.* **1987**, *9*, 133–152. [CrossRef]
23. Wu, Y.A.; Ng, A.W.; Yu, Z.; Huang, J.; Meng, K.; Dong, Z.Y. A Review of Evolutionary Policy Incentives for Sustainable Development of Electric Vehicles in China: Strategic Implications. *Energy Policy* **2021**, *148*, 111983. [CrossRef]
24. Bromley-Trujillo, R.; Poe, J. The Importance of Salience: Public Opinion and State Policy Action on Climate Change. *J. Public Policy* **2020**, *40*, 280–304. [CrossRef]
25. van der Vooren, A.; Alkemade, F.; Hekkert, M.P. Effective Public Resource Allocation to Escape Lock-in: The Case of Infrastructure-Dependent Vehicle Technologies. *Environ. Innov. Soc. Transit.* **2012**, *2*, 98–117. [CrossRef]
26. Purtle, J.; Gebrekristos, L.T.; Keene, D.; Schlesinger, P.; Niccolai, L.; Blankenship, K.M. Quantifying the Restrictiveness of Local Housing Authority Policies Toward People with Criminal Justice Histories: United States, 2009–2018. *Am. J. Public Health* **2020**, *110*, S137–S144. [CrossRef]
27. Chen, X.; Xie, Q.; Cao, X.; Li, Q. Examining the Effectiveness of China's Energy Poverty Alleviation Policies: A Text Analysis on Inter-Provincial Panel Data. *Energy Policy* **2024**, *186*, 113978. [CrossRef]
28. Huan, X.; Shan, J.; Han, L.; Song, H. Research on the Efficacy and Effect Assessment of Deep-Sea Aquaculture Policies in China: Quantitative Analysis of Policy Texts Based on the Period 2004–2022. *Mar. Policy* **2024**, *160*, 105963. [CrossRef]
29. North, D.C. *Institutions, Institutional Change and Economic Performance*; Political Economy of Institutions and Decisions; Cambridge University Press: Cambridge, UK, 1990; ISBN 978-0-521-39416-1.
30. Pierson, P. Increasing Returns, Path Dependence, and the Study of Politics. *Amer. Polit. Sci. Rev.* **2000**, *94*, 251–267. [CrossRef]
31. David, P.A. Clio and the Economics of QWERTY. *Amer. Econ. Rev.* **1985**, *75*, 332–337.
32. Scott, W. *Institutions and Organizations: Ideas and Interests*; Sage: Newcastle upon Tyne, UK, 2008; ISBN 978-1-4129-5090-9.
33. Kleinberg, J.; Oren, S. Mechanisms for (Mis)Allocating Scientific Credit. *Algorithmica* **2022**, *84*, 344–378. [CrossRef]
34. Arthur, W.B. Competing Technologies, Increasing Returns, and Lock-in by Historical Events. *Econ. J.* **1989**, *99*, 116–131. [CrossRef]

35. Devlin, J.; Chang, M.-W.; Lee, K.; Toutanova, K. BERT: Pre-Training of Deep Bidirectional Transformers for Language Understanding. In Proceedings of the 2019 Conference of the North American Chapter of the Association for Computational Linguistics: Human Language Technologies, Volume 1 (Long and Short Papers), Minneapolis, MN, USA, 3–5 June 2019; Burstein, J., Doran, C., Solorio, T., Eds.; Association for Computational Linguistics: Minneapolis, MN, USA, 2019; pp. 4171–4186.
36. Luo, X.; Wang, H.; Kang, Z. Research on the policy changes of China's integrated circuit industry. *Stud. Sci. Sci.* **2023**, *41*, 413.
37. Eang, C.; Lee, S. Improving the Accuracy and Effectiveness of Text Classification Based on the Integration of the Bert Model and a Recurrent Neural Network (RNN_Bert_Based). *Appl. Sci.* **2024**, *14*, 8388. [CrossRef]
38. Krnc, M.; Skrekovski, R. Group Degree Centrality and Centralization in Networks. *Mathematics* **2020**, *8*, 1810. [CrossRef]
39. Oliva, S.Z.; Oliveira-Ciabati, L.; Dezembro, D.G.; Júnior, M.S.A.; de Carvalho Silva, M.; Pessotti, H.C.; Pollettini, J.T. Text Structuring Methods Based on Complex Network: A Systematic Review. *Scientometrics* **2021**, *126*, 1471–1493. [CrossRef]
40. Mangalaraj, G.; Singh, A.; Taneja, A. Probing the Past to Guide the Future IT Regulation Research: Topic Modeling and Co-Word Analysis of SOX-IS Research. *Inf. Syst. Manag.* **2023**, *40*, 302–315. [CrossRef]
41. Obreja, D.M. Mapping the Political Landscape on Social Media Using Bibliometrics: A Longitudinal Co-Word Analysis on Twitter and Facebook Publications Published Between 2012 and 2021. *Soc. Sci. Comput. Rev.* **2023**, *41*, 1712–1728. [CrossRef]
42. Mensi, W.; Reboredo, J.C.; Ugolini, A. Price-Switching Spillovers between Gold, Oil, and Stock Markets: Evidence from the USA and China during the COVID-19 Pandemic. *Resour. Pol.* **2021**, *73*, 102217. [CrossRef]
43. Li, J.; Zhan, J. Policy changes and policy instruments selection of China's new energy vehicle industry. *China Popul. Resour. Environ.* **2017**, *27*, 198–208.
44. Did "Cash-for-Clunkers" Work as Intended? | Whitehouse.Gov. Available online: https://obamawhitehouse.archives.gov/blog/2010/04/05/did-cash-clunkers-work-intended (accessed on 10 March 2024).
45. New Energy Vehicle Data Statistics. Available online: http://www.caam.org.cn/tjsj (accessed on 10 May 2024).
46. Kong, D.; Xia, Q.; Xue, Y.; Zhao, X. Effects of Multi Policies on Electric Vehicle Diffusion under Subsidy Policy Abolishment in China: A Multi-Actor Perspective. *Appl. Energy* **2020**, *266*, 114887. [CrossRef]
47. Wang, Y.; Fan, R.; Du, K.; Bao, X. Exploring Incentives to Promote Electric Vehicles Diffusion under Subsidy Abolition: An Evolutionary Analysis on Multiplex Consumer Social Networks. *Energy* **2023**, *276*, 127587. [CrossRef]
48. Narassimhan, E.; Myslikova, Z.; Gallagher, K.S. Strategies for Green Industrial and Innovation Policy-an Analysis of Policy Alignment, Misalignment, and Realignment around Dominant Designs in the EV Sector. *Environ. Res. Lett.* **2024**, *19*, 014029. [CrossRef]
49. North, D. *The Process of Economic Change*; World Institute for Development Economic Research (UNU-WIDER): Helsinki, Finland, 1997.
50. Carlsson, B.; Jacobsson, S. In Search of Useful Public Policies—Key Lessons and Issues for Policy Makers. In *Technological Systems and Industrial Dynamics*; Springer: Boston, MA, USA, 1997; pp. 299–315. [CrossRef]
51. Ali, I.; Naushad, M. A Study to Investigate What Tempts Consumers to Adopt Electric Vehicles. *World Electr. Veh. J.* **2022**, *13*, 26. [CrossRef]
52. Li, X.; Fu, X.; Xu, G.; Yang, Y.; Wang, J.; Jin, L.; Liu, Q.; Xiang, T. Enhancing BERT Representation with Context-Aware Embedding for Aspect-Based Sentiment Analysis. *IEEE Access* **2020**, *8*, 46868–46876. [CrossRef]
53. Jia, K.; Meng, F.; Liang, J.; Gong, P. Text Sentiment Analysis Based on BERT-CBLBGA. *Comput. Electr. Eng.* **2023**, *112*, 109019. [CrossRef]
54. Bano, S.; Khalid, S.; Tairan, N.M.; Shah, H.; Khattak, H.A. Summarization of Scholarly Articles Using BERT and BiGRU: Deep Learning-Based Extractive Approach. *J. King Saud Univ. Comput. Inf. Sci.* **2023**, *35*, 101739. [CrossRef]
55. Lim, S.; Dolsak, N.; Prakash, A.; Tanaka, S. Distributional Concerns and Public Opinion: EV Subsidies in the US and Japan. *Energy Policy* **2022**, *164*, 112883. [CrossRef]
56. Xue, Y.; Zhang, Y.; Wang, Z.; Tian, S.; Xiong, Q.; Li, L.Q. Effects of Incentive Policies on the Purchase Intention of Electric Vehicles in China: Psychosocial Value and Family Ownership. *Energy Policy* **2023**, *181*, 113732. [CrossRef]
57. Greaker, M. Optimal Regulatory Policies for Charging of Electric Vehicles. *Transp. Res. Part D Transp. Environ.* **2021**, *97*, 102922. [CrossRef]
58. Kafka, K.I.; Kostis, P.C. Unravelling the Innovation Puzzle: The Interplay between Uncertainty, Economic Institutions, and Innovation Performance in Advanced and Developing Economies. *Technol. Forecast. Soc. Change* **2024**, *198*, 123027. [CrossRef]
59. Leng, J.; Ruan, G.; Jiang, P.; Xu, K.; Liu, Q.; Zhou, X.; Liu, C. Blockchain-Empowered Sustainable Manufacturing and Product Lifecycle Management in Industry 4.0: A Survey. *Renew. Sustain. Energy Rev.* **2022**, *132*, 110112, Erratum in *Renew. Sustain. Energy Rev.* **2022**, *167*, 112755. [CrossRef]
60. Liu, Y.; Zhao, X.; Lu, D.; Li, X. Impact of Policy Incentives on the Adoption of Electric Vehicle in China. *Transp. Res. Part A Policy Pract.* **2023**, *176*, 103801. [CrossRef]
61. Veza, I.; Syaifuddin, M.; Idris, M.; Herawan, S.G.; Yusuf, A.A.; Fattah, I.M.R. Electric Vehicle (EV) Review: Bibliometric Analysis of Electric Vehicle Trend, Policy, Lithium-Ion Battery, Battery Management, Charging Infrastructure, Smart Charging, and Electric Vehicle-to-Everything (V2X). *Energies* **2024**, *17*, 3786. [CrossRef]
62. Cao, J.; Ho, M.S.; Ma, R.; Zhang, Y. Transition from Plan to Market: Imperfect Regulations in the Electricity Sector of China. *J. Compar. Econ.* **2024**, *52*, 509–533. [CrossRef]

63. Petrauskiene, K.; Dvarioniene, J.; Kaveckis, G.; Kliaugaite, D.; Chenadec, J.; Hehn, L.; Perez, B.; Bordi, C.; Scavino, G.; Vignoli, A.; et al. Situation Analysis of Policies for Electric Mobility Development: Experience from Five European Regions. *Sustainability* **2020**, *12*, 2935. [CrossRef]
64. Drago, C.; Gatto, A. Policy, Regulation Effectiveness, and Sustainability in the Energy Sector: A Worldwide Interval-Based Composite Indicator. *Energy Policy* **2022**, *167*, 112889. [CrossRef]
65. Gyorffy, D. Liberal and Illiberal Industrial Policy in the EU: The Political Economy of Building the EV Battery Value Chain in Sweden and Hungary. *Comp. Eur. Politics* **2024**, *22*, 574–593. [CrossRef]
66. Li, L.; Wang, Z.; Xie, X. From Government to Market? A Discrete Choice Analysis of Policy Instruments for Electric Vehicle Adoption. *Transp. Res. Part A Policy Pract.* **2022**, *160*, 143–159. [CrossRef]