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Recharging the Future: Unlocking the Potential of Electric Vehicles

The burgeoning new energy electric vehicle (EV) industry is a pivotal force driving sustainable development globally. Amidst the ongoing march of urbanization and technological progress, a myriad of complex factors influence this industry. Hence, the assessment and projection of the EV industry and its impact assume paramount significance.

Primarily, we establish an **Economy-Society-Technology (EST) system** to ascertain the significance of indicators for EV development. This evaluative framework integrates the **Analytic Hierarchy Process (AHP), Entropy Weight Method (EWM)**, and **Coefficient of Variation Method (CMV)** to determine indicator weights. Subsequently, we introduce the **EV Development Index (EDI)** to classify regional development levels into four grades. The EDI for China stands at 0.955 (Grade IV), indicative of significant development in the Chinese EV industry. By ranking the weights, we find that **the number and usage of EV chargers**, **battery capacity**, **population consumption level**, and **policy subsidies** are the five main factors influencing the EV industry.

Secondly, we delve into the dynamics and shifts in the sales of four types of EVs: cars, buses, trucks, and vans, encompassing battery electric vehicles (BEVs) and plug-in hybrid electric vehicles (PHEVs) from 2010 to 2022. Additionally, we analyze the stock share and sales share of EVs to elucidate the evolution of the Chinese EV industry. Given the industry's relative novelty and the limited historical data, we employ the **GM(1,1)** model to forecast stock share and sales share over the next decade, yielding an R^2 of 0.99 and 0.73, respectively.

Thirdly, we categorize the global traditional energy vehicle industry into three stages: upstream (costs), midstream (market), and downstream (price). Through an integrated analysis using the **Spearman Correlation Coefficient** and **Granger Causality Test**, we discern that the EV industry restrains the traditional energy vehicle industry upstream and midstream while exerting a more confined impact downstream.

Subsequently, we scrutinize recent boycott policies in the global EV market. Subsequent adjustments to corresponding values within our EST evaluation system enable us to monitor policy impacts. **Ordinary Least Squares (OLS) Regression** is utilized to analyze the impacts of increased tariff rates. Our findings indicate that with proactive government support, China could mitigate adverse impacts and address challenges.

Next, in an extensive survey covering 196 regions, we gather data on vehicle ownership per capita (V), GDP per capita (G), carbon emissions per capita (E), and market penetration rate (S). Employing k-means++ clustering, we categorize these regions into four classifications—impoverished, developing, emerging, and prosperous, each representing a distinct ecological and electrified context. Subsequently, we introduce the innovative **Vehicle Carbon Impact (VCI) Model**, highlighting reduced carbon emissions percentages of 9.99%, 12.48%, 14.10%, and 3.67% for the respective population categories of 1 million, attributable to EVs.

Ultimately, we have crafted a **compelling advocacy letter** to disseminate the virtues of EVs among global citizens, underlining the transformative potential of EVs in fostering sustainable progress worldwide.

Keywords: Electric Vehicles, EST system, EDI, Granger Causality Test, VCI

Contents

I. Introduction

1.1 Problem Background

Over the past century, internal combustion engines have been dominant in the personal transportation sector, but their negative impact on the environment has been a concern [1]. However, as technology advances, new energy-electric vehicles (EVs) have gained popularity in the auto industry. These vehicles not only reduce dependence on petroleum but also help mitigate pollutant emissions [2]. According to data from the International Energy Agency (IEA) [3], the sales of EVs have surged from 1,500,000 in 2019 to 7,300,000 in 2022. China has emerged as the world leader in both auto production and consumption. However, there is still significant untapped market potential due to the relatively lower number of vehicles per thousand capita [2].

The development of EVs can be influenced by multiple factors, including economy, policy, technology, and so on [4]. Understanding the key factors helps China to make better decisions.

Therefore, this paper aims to investigate the factors that affect EV development, both in China and globally, and to analyze future trends. Additionally, this paper will explore the impact of EVs on various industries and the environment.

1.2 Our Work

First, we establish the Electric Sustainability Index (EST) evaluation system, integrating the Analytic Hierarchy Process (AHP), Entropy Weight Method (EWM), and Contingent Valuation Method (CVM) to compute the weights of the economy, society, and technology. These weights effectively reflect the significance of their influence on the EV industry.

Second, we utilize the Grey Model GM(1,1) to predict the stock and sales share of EVs for the upcoming 10 years. Subsequently, we employ a combination of Spearman correlation analysis and the Granger Causality Test to investigate their impact on the traditional vehicle industry.

Following this, we apply Ordinary Least Squares (OLS) regression to discern the effects of boycott policies on China. Additionally, we develop the Vehicle Carbon Impact (VCI) Model to calculate the reduced carbon emissions of four city types, providing a comprehensive understanding of the environmental impact.

Finally, we craft a meticulously designed letter that encapsulates the findings and insights derived from the aforementioned analyses.

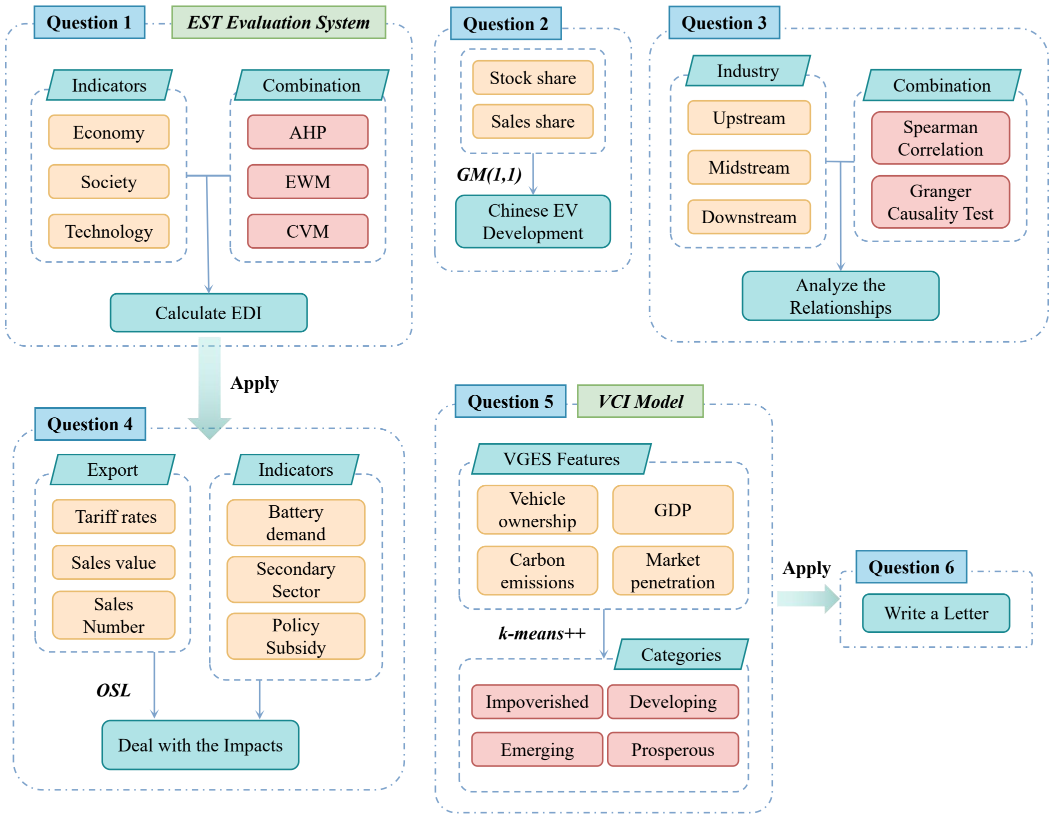


Figure 1 The Flow Chart of the Modeling Process

II. Assumptions and Justifications

• **Assumption 1:** The data sourced from authoritative official reports in this study is presumed to exhibit precision and fidelity in reflecting objective realities.

Justification: The data sourced from authoritative official reports is underpinned by rigorous methodologies and validation processes. Large information errors can affect the final results, so the information collected is assumed to be accurate here.

• **Assumption 2:** The traditional automotive industry is defined herein as encompassing all sectors excluding those related to new energy vehicles.

Justification: The definition of the traditional automotive industry as encompassing all sectors excluding those related to new energy vehicles is based on the need for a clear and delineated scope for analysis.

• **Assumption 3:** It is posited that the development trajectory of new energy electric vehicles remains minimally susceptible to the influence of extreme external conditions.

Justification: The assumption is based on the premise that the industry has demonstrated a degree of resilience to external shocks historically.

• **Assumption 4:** The developmental dynamics of new energy vehicles in diverse cities are conjectured to be contingent upon and influenced by the overall electrification level of new energy vehicles within the national context.

Justification: The development of new energy vehicles in diverse cities is significantly shaped by the comprehensive electrification level of such vehicles at the national level, owing to factors such as national policy directives, domestic market conditions, and infrastructure investments.

III. Notations

The key mathematical notations used in this paper are listed in the table below.

Table 1 Notations used in this paper

Symbol	Description	Unit
E	Value of Economy	-
S	Value of Society	-
T	Value of Technology	-
ρ	Spearman correlation coefficient	-
$p-value$	The evidence against the null hypothesis	-
SSE_r	The sum of squared errors from the restricted model	-
SSE_u	The sum of squared errors from the unrestricted model	-
$P(x)$	The probability of selecting the data point as the next centroid	-
V	Vehicle ownership per capita	-
G	GDP per capita	dollar
E	Carbon emissions per capita	ton
S	Market penetration rate	%
E_{total}	The total carbon emission with EVs	ton
$E_{reduced}$	The reduced amount of carbon emission	ton

*Symbols not listed here will be discussed in the text.

IV. Data Sources and Pre-processing

4.1 Data Sources

Data sources play a crucial role in the modeling process. To ensure accuracy and reliability, we have gathered diverse data from reputable databases, as indicated in the table.

Table 2 Data sources used in this paper

Database Name	Website
National Burea of Statics	https://data.stats.gov.cn/
International Energy Agency	https://www.iea.org/data-and-statistics/
Statista	https://www.statista.com/

Recognizing that the EV industry is relatively new and continually evolving, we have collected available data from various aspects spanning the past 13 years, commencing in 2010. This comprehensive approach enables us to capture the dynamic nature of the EV industry and provide a robust foundation for our analysis and modeling.

4.2 Data Pre-processing

4.2.1 *Missing Value Padding*

• **Mean Padding**

When there is missing data and we have values both before and after the gap, we use mean padding. This involves taking the average of the neighboring values to fill in the missing entry, preserving the overall trend and continuity in the dataset.

• **Proximity Padding**

When there is no data available before or after the missing value, we use proximity padding, which involves filling in the missing value with the value of the nearest neighboring data point.

4.2.2 *Normalization*

By applying these normalization techniques, the data in each column will be transformed to a common scale, facilitating fair comparisons and analysis. We adapted different normalization methods after analyzing the data carefully.

• **Min-Max Normalization (for positive indicators)**

The min-max normalization method is based on the minimum (x_{min}) and maximum (x_{max}) values of that column.

$$\hat{x}_i = \frac{x_i - x_{min}}{x_{max} - x_{min}} \tag{1}$$

In this method, each value in a column is scaled to a range between 0 and 1.

• **Reverse Min-Max Normalization (for negative indicators)**

In reverse min-max normalization, each value (x_i) is subtracted from the maximum value (x_{max}) in the column.

$$\hat{x}_i = \frac{x_{max} - x_i}{x_{max} - x_{min}} \tag{2}$$

In this method, the values in a column are reversed and then scaled to a range between 0 and 1.

V. Models and Solutions

5.1 The Economy-Society-Technology (EST) Evaluation Model

5.1.1 *Establishment of Evaluation System*

After conducting an extensive search of relevant papers, we have identified three key factors that greatly influence the development of EVs: **economy (E), society (S), and technology (T)**. These factors play a critical role in the advancement of EVs and serve as the primary indicators in our evaluation system. Subsequently, we carefully considered these primary indicators and selected 10 secondary indicators to further refine our evaluation framework. The diagram presents the comprehensive framework of the EST system that incorporates these indicators.

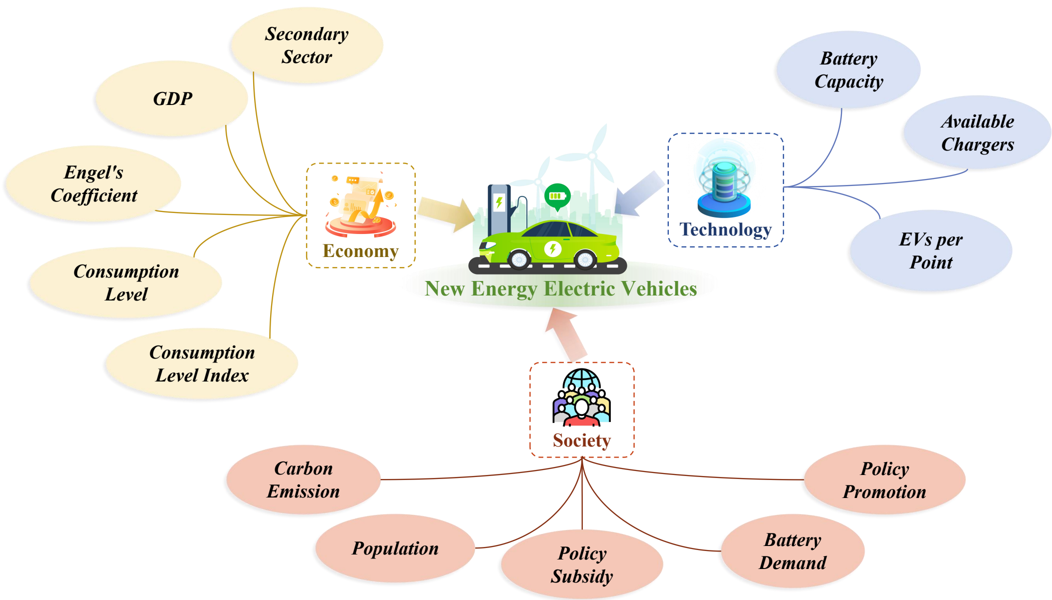


Figure 2 The new energy EVs development system

• **Economy**

The economic factor plays a significant role in Chinese EV development. This is mainly driven by the strong market demand for sustainable transportation solutions and the aim to stimulate industrial growth, create job opportunities, enhance energy security, and pursue technological innovation for global competitiveness. Prioritizing the economic factor ensures that China can reap economic benefits while transitioning to a sustainable and low-carbon transportation system.

E_1. ***GDP***

GDP (Gross Domestic Product) is an indicator that measures the total value of all goods and services produced within a country or region during a specific period. It represents the overall economic activity.

$$GDP = C + I + G + (X - M) \tag{3}$$

where C represents the expenditure by individuals and households on goods and services, I includes private investment and business investment, G represents the expenditure by the government on public goods and services, and $(X - M)$ represents the value of a country's exports minus imports.

E_2. ***Engel's Coefficient***

Engel's coefficient is an economic concept that measures the relationship between household income and household expenditure on a specific good or category of goods.

$$Engel's\ Coefficient = \left(\frac{Expenditure\ on\ a\ Good}{Total\ Household\ Income}\right) \times 100 \tag{4}$$

A higher Engel's coefficient indicates that a larger proportion of household income is devoted to that particular good or category of goods. Engel's coefficient can reflect the development of EVs, which will have an impact on household consumption and expenditure.

E_3. ***Consumption Level***

The consumption level of the population refers to the overall level of spending and consumption by individuals or households within a specific economic unit, such as a country or a region.

$$\text{Consumption Level} = \frac{\text{Total Expenditure}}{\text{Population Size}} \tag{5}$$

The consumption level is an important indicator used to assess the economic well-being and purchasing power of a population. It provides insights into the overall level of consumption and the potential demand for EVs.

E_4. ***Secondary Sector***

Value added in the secondary sector refers to the additional value created during the production process in industries involved in manufacturing and construction.

$$VA = TO - II \tag{6}$$

where both the total output (TO) and intermediate inputs (II) are measured in monetary terms.

The significance of value added in the secondary sector lies in its contribution to economic growth, technological advancement, and energy independence. It helps to shape a cleaner and more sustainable future of transportation.

E_5. ***Consumption Level Index***

The Consumption Level Index (CLI) is an economic indicator used to measure the overall level of consumption in an economy. It provides insights into the purchasing power and spending patterns of consumers.

$$CLI = \left(\frac{C_c}{C_r}\right) \times 100 \tag{7}$$

where C_c represents the current period consumption and C_r represents the reference period consumption.

CLI holds importance for EVs as it reflects consumer interest and market growth within the EV industry.

• **Society**

The societal factor holds significant influence over the development of EVs. The environmental consciousness, public perception, government policies, consumer preferences, and collaborative efforts all interact with and shape the trajectory of EV development. Understanding and addressing societal factors is paramount in fostering a sustainable and successful transition to electric mobility.

S_1. ***Carbon Emission***

Carbon emission refers to the release of carbon dioxide gas into the atmosphere as a byproduct of various human activities, such as the burning of fossil fuels (coal, oil, and natural gas), deforestation, and industrial processes. It is measured by kiloton (kt).

Carbon emissions drive the development of EVs due to the environmental imperative to reduce emissions and mitigate climate change.

S_2. ***Population***

Population refers to the total number of people living within a specific geographic area, whether it be a city, region, or the entire planet. It is a fundamental aspect of society and has wide-ranging implications for various aspects of human life.

Population has a significant influence on EV development as it directly affects the demand for transportation and environmental sustainability.

S_3. ***Policy Subsidy***

The policy subsidy refers to subsidy funds for the promotion and application of EVs measured by $yuan$. It is the financial incentives provided by governments and organizations to encourage the adoption of EVs.

By making EVs more affordable, promoting technological advancements, and addressing infrastructure needs, the subsidy encourages greater adoption of EVs and contributes to the growth of a sustainable transportation ecosystem.

S_4. ***Battery Demand***

Battery demand, measured in gigawatt-hours (GWh) per year, refers to the total amount of energy storage capacity required to meet the growing demand for EVs and other applications.

The level of battery demand directly impacts several aspects of the EV industry, from technological advancements to manufacturing scale.

S_5. ***Policy Promotion***

The policy promotion represents the number of declared promotion vehicles by the government. It reflects the level of government support and incentivizes EV adoption.

The policy promotion showcases the government's commitment to supporting sustainable transportation. It provides the necessary impetus for accelerated EV development in China.

• **Technology**

The technology factor significantly influences EVs' advancement and adoption. Advancements in battery technology and charging infrastructure contribute to the progress and acceptance of EVs. These advancements play a crucial role in accelerating the development of EVs.

T_1. ***Battery Capacity***

Battery capacity, often referred to as the average power accumulator battery capacity of EVs, is a measure of the total amount of energy that can be stored in an EV's battery. It is commonly represented in kilowatt-hours (kWh).

$$E = C \times V \tag{8}$$

where E represents the energy stored in the battery in kilowatt-hours kWh, C represents the battery capacity in kilowatt-hours kWh, V represents the battery voltage in volts V.

The battery capacity is a crucial parameter that determines the driving range and overall performance of an electric vehicle. A higher battery capacity allows for a longer driving range on a single charge, reducing the need for frequent charging and alleviating range anxiety for EV owners.

T_2. ***Available Chargers***

Available chargers refer to the various types of charging infrastructure and equipment that enable the recharging of EV batteries. These chargers provide the necessary electrical power to replenish the energy consumed by EVs during operation.

The availability, accessibility, and diversity of chargers are crucial for supporting the widespread adoption and convenience of EVs.

T_3. ***EVs per Point***

EVs per Point is a metric used to measure the ratio of EVs to charging points or stations available in a specific area or region. It provides insight into the density and availability of charging infrastructure relative to the number of EVs in that particular area.

$$EVs\ per\ Point = \frac{Number\ of\ EVs}{Number\ of\ Charging\ Points} \tag{9}$$

This metric helps gauge the adequacy of charging infrastructure and the ability of EV owners to access convenient charging options.

5.1.2 *Determination of the Weights for Indicators*

In the previous section, we have decided on the EST evaluation system, details of indicators are shown in the table. Then we need to determine the weights of each indicator to reflect the relative importance within the overall evaluation system.

Table 3 The indicators framework of EV development

Primary Indicator	*Secondary Indicator*	*Explanation*	*Unit*
Economy	GDP	Gross domestic product	yuan
	Engel's coefficient	Engel's coefficient of the population	%
	Consumption level	Consumption level of the population	yuan
	Secondary sector	Value added in the secondary sector	billion yuan
	Consumption level index	Previous year = 100	-
Society	Carbon emission	CO2 emission	ton
	Population	The population of the country	-
	Policy subsidy	Subsidy funds for the promotion and application of EVs	yuan
	Battery demand	The demand for EV batteries	GWh/year
	Policy promotion	Number of declared promotions vehicles	-
Technology	Battery capacity	Average power accumulator battery capacity of EVs	kWh
	Available chargers	Amount of publicly available chargers	-
	EVs per point	Average EVs per charging point	-

This section first applies the Analytic Hierarchy Process (AHP) to determine the weights for three primary indicators. Then combines the AHP, Entropy Weight Method (EWM), and Coefficient of Variation Method (CMV) to obtain the weights for secondary indicators.

- **AHP**

The AHP is a decision-making method that helps to prioritize and evaluate alternatives based on multiple criteria.

Step 1: Establish the decision hierarchy. Identify the main goal or objective, criteria, and alternatives involved in the decision.

Step 2: Pairwise comparisons. Compare each criterion or alternative with every other criterion or alternative in terms of their relative importance or preference. A numerical scale is used to derive comparison values.

Step 3: Create the pairwise comparison matrix. Construct a matrix representing the pairwise comparisons. The matrix is usually square and symmetric.

Step 4: Calculate the priority weights. Determine the priority weights of criteria or alternatives by computing the geometric mean or eigenvector method based on the pairwise comparison matrix.

$$\omega_i = \frac{\prod_{j=1}^{n} a_{ij}^{1/n}}{\sum_{i=1}^{n}\left(\prod_{j=1}^{n} a_{ij}^{1/n}\right)} \tag{10}$$

where w_i represents the priority weight of the element, a_{ij} represents the pairwise comparison value between elements i and j, and n represents the total number of elements.

Step 5: Consistency check. Evaluate the consistency of the pairwise comparisons to ensure the reliability of the results. If necessary, adjustments can be made to improve consistency.

$$\begin{cases} CI = \dfrac{\lambda_{\max} - n}{n - 1} \\ CR = \dfrac{CI}{RI} \end{cases} \tag{11}$$

where λ_{max} represents the maximum eigenvalue, RI is a predefined value based on the number of elements being compared. If the CR value is less than 0.10, the consistency is considered acceptable.

Through this method, we obtain the ω_{AHP}.

• **EWM**

The EWM is a multi-criteria decision-making technique used to calculate the weights of different criteria based on their entropy values. It aims to determine the relative importance or significance of each criterion in the decision-making process.

$$\omega_i = \frac{1 - H_i}{k - \sum_{j=1}^{m} H_j} \tag{12}$$

where ω_i represents the weight of the criterion, H_i represents the entropy value of the criterion, m represents the total number of criteria, and k represents the constant value, which is typically set to $ln(m)$.

Through this method, we obtain the ω_{EWM}.

• **CMV**

The CVM is a statistical technique used to assess the relative variability or dispersion of a dataset by comparing it to its mean. It is often employed to compare the variability of different datasets or to evaluate the precision of measurements.

$$\begin{cases} CV_i = \left(\dfrac{\sigma_i}{\mu}\right) \\ \omega_i = \dfrac{CV_i}{\sum_i CV_i} \end{cases} \tag{13}$$

where CV_i represents the Coefficient of Variation, σ_i is the measure of variability or dispersion in the dataset, and μ_i is the average value of the dataset.

Through this method, we obtain the ω_{CVM}.

• **Combined Weight**

We make a combined use of the AHP, EWM, and CVM to calculate the weights of secondary indicators. It offers a comprehensive and objective assessment of alternatives or criteria. This approach considers multiple aspects through AHP, addresses uncertainty and variability with EWM and CVM, and reduces subjective bias.

The formula for the final weights of secondary indicators is shown below. Because AHP is susceptible to subjectivity, the coefficient of AHP is relatively small.

$$\omega = 0.2\omega_{AHP} + 0.4\omega_{EWM} + 0.4\omega_{CVM} \tag{14}$$

The results are shown in the figure.

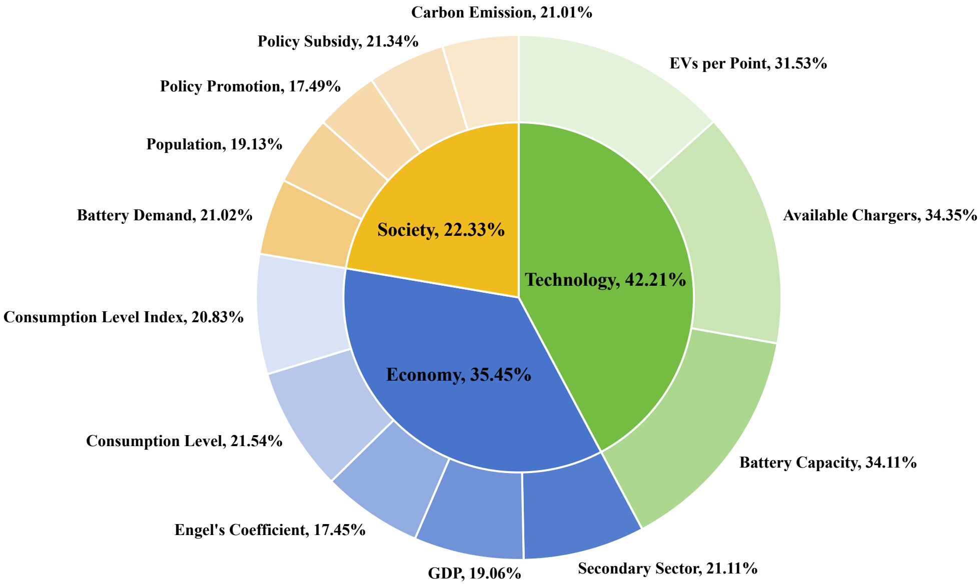


Figure 3 The weights of EST system for Chinese EV development

Technology plays a pivotal role among the three primary indicators, constituting the most significant factor with a weightage of 42.21%. The presence of available chargers holds the largest share, highlighting the crucial role infrastructure plays in driving the development of EVs. Additionally, the economy is of utmost importance, as the consumption level and the strength of the secondary sector serve as the foundation for the EV market. In comparison, the societal aspect has the least weight, encompassing indicators such as battery demand and policy subsidy, which still hold significant importance.

5.1.3 *Determination of EV Development Index (EDI)*

In the previous section, we built up the EST evaluation model to assess the importance of each factor in Chinese EV development. The economy, society, and technology are taken into consideration.

The EDI serves as a measure to gauge the level of development in a particular region.

$$\begin{cases} EDI = \omega_E E + \omega_S S + \omega_T T \\ E = \omega_{E_1} E'_1 + \omega_{E_2} E'_2 + \omega_{E_3} E'_3 + \omega_{E_4} E'_4 + \omega_{E_5} E'_5 \\ S = \omega_{S_1} S'_1 + \omega_{S_2} S'_2 + \omega_{S_3} S'_3 + \omega_{S_4} S'_4 + \omega_{S_5} S'_5 \\ T = \omega_{T_1} T'_1 + \omega_{T_2} T'_2 + \omega_{T_3} T'_3 \end{cases} \tag{15}$$

where the E'_1, E'_2, E'_3, E'_4, E'_5, S'_1, S'_2, S'_3, S'_4, S'_5, T'_1, T'_2, T'_3 represent the data after pre-processing.

Based on the values obtained, the EDI is categorized into four different levels.

In 2022, Chinese EDI stood at 0.955, indicating that Chinese EV development grade is classified as **'Developed'**. This achievement highlights the promising prospects within the Chinese EV industry, emphasizing significant progress.

Table 4 Level of EV development

Grade	I	II	II	IV
EV development level	Underdeveloped	Developing	Advanced	Developed
EDI	> 0.4	0.4-0.6	0.6-0.8	< 0.8

5.1.4 *Rationality Testing for EDI*

We have collected data on the sales, stock, sales share, and stock share of Chinese EVs. Notably, stock share and sales share are widely recognized as the most reliable indicators of the industry's performance [5].

In order to validate the rationale behind our EST model, we conducted a linear regression analysis between the total stock share and the EDI, as well as between the total sales share and the EDI. By incorporating these external metrics, we can evaluate the credibility of the ESI system and ensure its robustness as an assessment tool for the Chinese EV industry.

The mean squared error (MSE) of the linear fit is 0.0015 and 0.030 for stock and sales share, respectively. This exceptionally low value signifies a strong linear relationship between the two variables. Consequently, our EDI score serves as a highly accurate index for evaluating the development of EVs within a particular region.

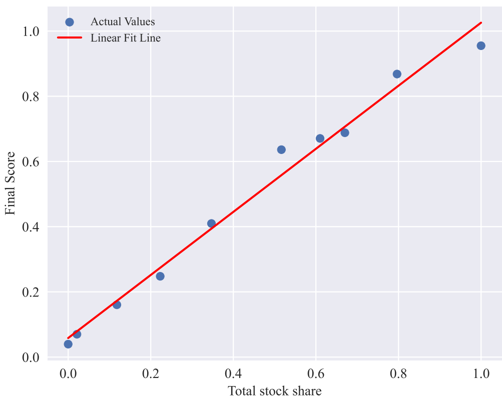


Figure 4 The linear fit diagram of stock share and EDI

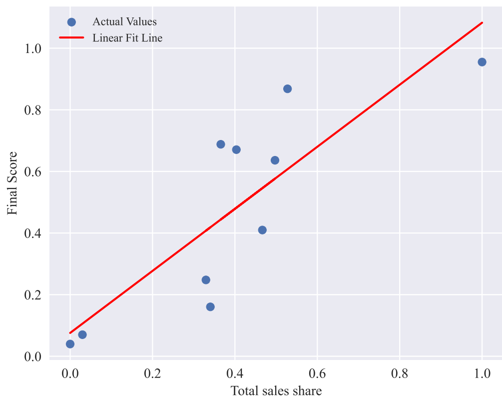


Figure 5 The linear fit diagram of sales share and EDI

5.2 EV Development Prediction

5.2.1 *Overview of Chinese EV Development*

The Sankey diagram illustrates the sales of buses, cars, trucks, and vans in the Chinese market between 2010 and 2022. Within the Chinese EV market, two primary types of vehicles are identified: pure electric vehicles, commonly known as battery electric vehicles (BEVs), and hybrid electric vehicles, also known as plug-in hybrid electric vehicles (PHEVs).

In addition to the Sankey diagram, the accompanying pie chart and line chart provide specific data on the development of the Chinese EV market.

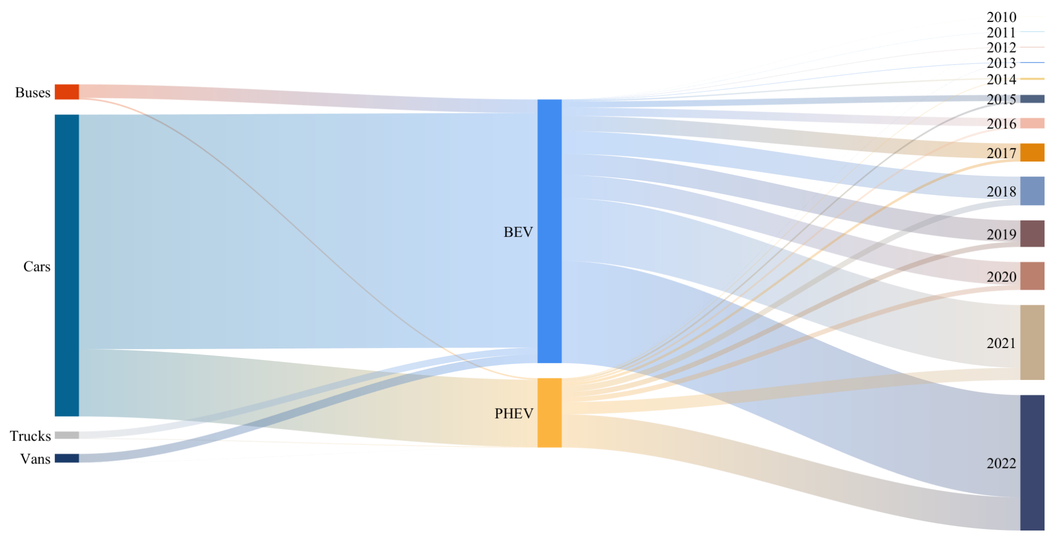


Figure 6 The Sankey diagram of Chinese EV sales

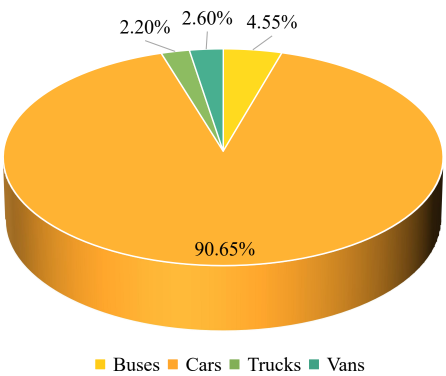


Figure 7 EVs sales distribution

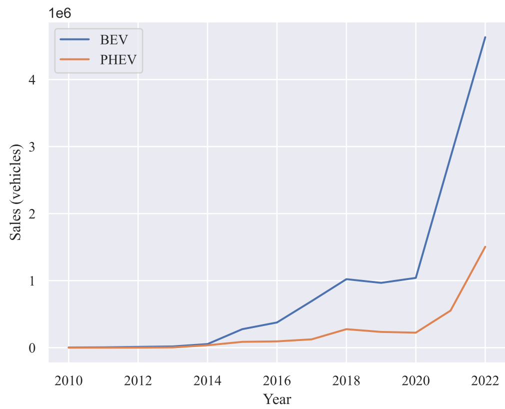


Figure 8 Sales of BEV and PHEV from 2010 to 2022

Based on the figures provided, we can draw critical conclusions about the development of Chinese EVs.

- **The sales of cars account for more than 90% of the four types of EVs.** It indicates that cars are the most popular and active products in the Chinese EV industry. This high demand for electric cars can be attributed to factors such as increasing environmental awareness, government incentives, and improvements in EV technology. Cars are the primary focus for EV manufacturers, as they cater to the needs and preferences of individual car buyers.
- **Buses, trucks, and vans are primarily composed of BEVs.** This trend may be driven by the fact that BEVs offer better performance, meeting the specific requirements of drivers operating these types of vehicles. The advantages of BEVs, such as high torque and extended range capabilities, make them well-suited for commercial and transport purposes. The adoption of BEVs in these segments highlights the potential for reduced emissions and improved efficiency in the transportation sector.
- **The sales trend has significantly changed over time.** Before 2014, the sales of EVs were extremely low, close to zero. Then the sales experienced stable increases

from 2014 to 2020. After that, the sales of BEV surged significantly from 1,041,000 to 4,632,000, while the sales of PHEV from 224,021 to 1,505,300. This growth can be attributed to several factors, including government initiatives, improvements in charging infrastructure, and the introduction of new EV models. The rise in EV sales during this period reflects the increasing acceptance of electric vehicles as a viable alternative to conventional combustion engine vehicles.

- **BEVs outperform PHEVs by nearly four times in the Chinese EV market**. This is primarily due to their earlier market entry and subsequent consumer acceptance. BEVs had a head start, allowing them to establish a stronger foothold and larger market share. Additionally, the advanced technology and zero-emission nature of BEVs aligns well with the rising demand for eco-friendly and sustainable transportation options. These factors combined contribute to the significant sales advantage of BEVs over PHEVs in China's EV market.

5.2.2 *Prediction for the Next 10 Years*

As we have mentioned before, stock share and sales share of EVs play a crucial role in indicating the development of the Chinese EV industry.

On one hand, stock share reflects the market valuation and investor confidence in EV companies, offering insights into their financial performance. On the other hand, sales share provides valuable information about market demand and consumer preferences, allowing us to gauge the popularity and market positioning of different EV manufacturers.

By monitoring these indicators, we can assess industry growth, identify investment opportunities, and understand the impact of government policies and regulations. Together, the two metrics provide a comprehensive picture of the Chinese EV industry's development and potential. So we decided to predict the value of stock share and sales share of the EV industry for the next 10 years.

Due to the new nature of the EV industry, the available data is predominantly limited to the period after 2010. Consequently, conducting extensive research and experimenting with various models such as linear regression, XGBoost, and ARIMA, we encountered challenges due to the scarcity of historical data. This limitation posed a risk of overfitting and resulted in suboptimal performance.

Given these considerations, we have carefully evaluated our options and decided to utilize the **GM(1,1)** model for our prediction purposes. This choice stems from its suitability for handling data with a small historical dataset. By leveraging the capabilities of GM(1,1), we aim to generate more accurate and reliable predictions within the constraints of our available data.

• **GM(1,1)**

GM(1,1), also known as the Grey-Markov Model, is a forecasting method used to analyze and predict the future values of a time series.

$$\hat{x}(k+1) = (x(1) - \frac{b}{a})e^{-ak}(1 - e^{a}) + \frac{b}{a} \tag{16}$$

where $\hat{x}(k+1)$ represents the predicted value of the time series at the time $(k+1)$, $x(1)$ is the initial value of the time series, k is the time index, a is the coefficient of the exponential function, b is the coefficient of the accumulated generating operation (AGO).

The GM(1,1) model utilizes a first-order ordinary differential equation to generate a grey differential equation, which is then solved to obtain the future values of the time series. This model is based on the assumption of exponential data change, and it aims to minimize the accumulated generation error between the predicted and actual values.

• **Prediction Results**

The line charts demonstrate the results of GM(1,1) in terms of total stock share and sales share. We can observe the trend of true value and precited value over time.

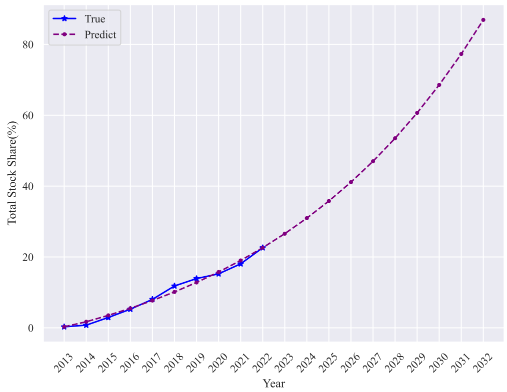


Figure 9 Stock Share Prediction

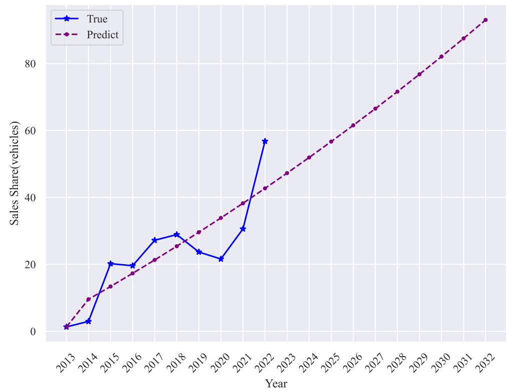


Figure 10 Sales Share Prediction

Table 5 Prediction Results of Stock Share and Sales Share

Year	Stock Share	Sales Share	Year	Stock Share	Sales Share
2023	26.58	47.27	2028	53.49	71.59
2024	30.95	51.92	2029	60.65	76.78
2025	35.78	56.68	2030	68.56	82.08
2026	41.12	61.55	2031	77.28	87.50
2027	47.00	66.52	2032	86.91	93.03

Several conclusions can be drawn from the results:

- **The stock share of the EVs industry has exhibited a stable increase over the past 10 years.** It indicates a growing market presence. From nearly 0% in the initial years, the stock share has steadily risen to 22.60% in 2022. On the other hand, the sales share has shown some fluctuations. It experienced a rise from 2013 to 2018, followed by a slight decline to 19.60% before 2020. However, since then, the sales share has surged significantly, reaching 27.19% in 2022. This suggests that although the market share in terms of sales has varied, the overall trajectory has been positive.
- **The growth patterns of the two shares differ significantly.** In the beginning, the stock share exhibited slower growth compared to the sales share. However, over time, the rate of increase in the stock share began to accelerate. This trend indicates a rising market demand for EVs and an increasing investment in the EV industry.
- **The future of Chinese EV development appears exceedingly promising.** According to the prediction model, the stock share is estimated to grow significantly

and reach an impressive 86.91% by 2032. This signifies a considerable dominance of electric vehicles in the market. Simultaneously, the sales share is projected to surge to 93.03% in the same year. These projections indicate a substantial shift towards EVs, with the majority of vehicles sold and owned being electric.

- **Results Testing and Error Analysis**

To assess the reliability of the GM(1,1) model, it is crucial to calculate and analyze the errors associated with its predictions. By examining these errors, we can gain insights into the model's performance and its level of accuracy.

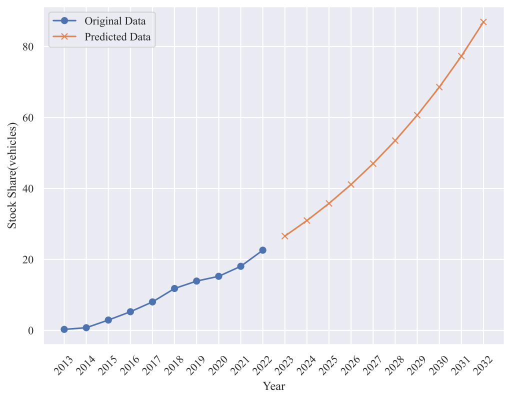


Figure 11 Stock Share Testing

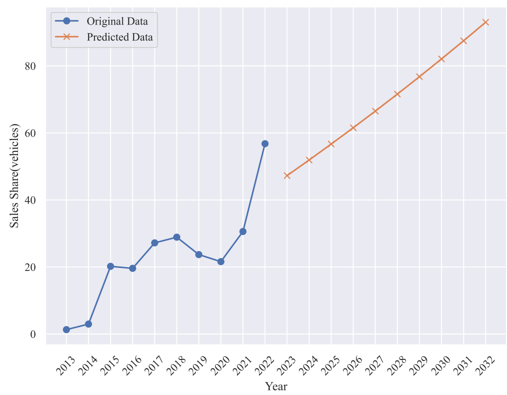


Figure 12 Sales Share Testing

MSE	R^2	$MAPE$	$RMSE$
0.66	0.99	18.57%	0.81

Table 6 Evaluation of stock share

MSE	R^2	$MAPE$	$RMSE$
58.41	0.73	43.25%	7.64

Table 7 Evaluation of sales share

After careful analysis of the data, we have evaluated the GM(1,1) and identified the reasons behind the errors.

- **The GM(1,1) model demonstrates excellent performance in predicting the stock share.** It has a R^2 of 0.99, indicating a perfect fitting. Besides, the MSE and $RMSE$ are relatively low, further indicating the accuracy of the predictions. This suggests that the GM(1,1) model is highly effective in forecasting the stock share of the Chinese EV industry.
- **The GM(1,1) exhibits larger errors in predicting sales share, only a R^2 of 0.73.** This discrepancy can be attributed to the inherent fluctuations present in the original sales data. These fluctuations introduce more uncertainty into the prediction process. Consequently, the GM(1,1) model faces greater challenges in accurately forecasting the sales share.

Overall, the GM(1,1) model demonstrates good robustness and accuracy in predicting both the stock and sales share. Despite the larger errors in predicting the sales share, the model's reliable performance can offer valuable insights into the development of the Chinese EV industry. By leveraging the GM(1,1) model's predictions, stakeholders can make informed decisions based on trustworthy forecasts.

5.3 What is the Global Impact?

5.3.1 *Variable Description*

The global traditional energy vehicle industry can be categorized into three stages [6]: upstream (components costs), midstream (market share), and downstream (sales price). The upstream stage is represented by global fuel engine sales, the midstream stage is represented by the market penetration of conventional fuel vehicles, and the downstream stage is represented by the average gas price.

Sales and stock share are vital indicators of the EV industry, and the price of batteries plays a crucial role in shaping its trajectory.

In this section, the following variables and corresponding symbols are used:

Table 8 The variables for the analysis

Data Type	*Stage*	*Symbol*	*Explanation*	*Unit*
Time	-	F_1	Year	-
Traditional Vehicles	Midstream	F_2	Market penetration of conventional fuel vehicles	%
Traditional Vehicles	Downstream	F_3	Average spot crude price	dollar
Traditional Vehicles	Downstream	F_4	Average gas price	dollar
Traditional Vehicles	Downstream	F_5	Average energy price	dollar
Traditional Vehicles	Upstream	F_6	Global fuel engine sales	-
Electric Vehicles	Upstream	F_7	Battery price	dollar
Electric Vehicles	Midstream	F_8	Average EV sales share in the world	%
Electric Vehicles	Midstream	F_9	Average EV stock share in the world	%
Electric Vehicles	Midstream	F_{10}	Average EV share performance in the world	%

The variables provide insights into both the traditional and new energy vehicles industry. The categorization framework provides a structured and systematic approach to understanding the industry.

5.3.2 *Model Principles*

• Spearman Correlation Coefficient

The Spearman correlation coefficient is a measure of the strength and direction of the monotonic relationship between two variables.

By utilizing the Spearman correlation coefficient in this analysis, we can assess the impact of EVs on the global traditional energy vehicle industry while considering potential non-linear relationships and ranking-based data.

$$\rho = 1 - \frac{6 \sum d_i^2}{n(n^2 - 1)} \tag{17}$$

where ρ represents the Spearman correlation coefficient, $\sum d_i^2$ denotes the sum of the squared differences between the ranks of the two variables, n represents the number of data points.

The Spearman correlation coefficient ranges between -1 and 1. A positive value indicates a positive monotonic relationship, where higher values of one variable correspond to higher values of the other variable. Conversely, a negative value indicates a negative monotonic relationship. A value of 0 indicates no monotonic relationship.

• Granger Causality Test

The Granger causality test is a statistical hypothesis test. It helps assess the causal relationship between two variables based on their past values.

By utilizing the Granger causality test in this analysis, we can explore the causal links between EVs and the global traditional energy vehicle industry.

Step 1: Conduct the Augmented Dickey-Fuller (ADF) test. The ADF test is performed to check the stationarity of the time series variables. It ensures that each variable is free from unit roots, which is a prerequisite for the Granger causality test.

Step 2: Formulate the null and alternative hypotheses. The null hypothesis states that variable X does not Granger-cause variable Y, while the alternative hypothesis suggests that variable X does have Granger-causal influence on variable Y.

Step 3: Collect time series data for the variables of interest. Gather the necessary time series data for both variables X and Y.

Step 4: Fit autoregressive (AR) models to each variable individually. The AR model for variable Y is denoted as $Y_t = \alpha_Y + \sum_{i=1}^{p} \beta_{Y_i} Y_{t-i} + \epsilon_Y$, where p represents the lag order included.

Step 5: Fit the joint autoregressive model that includes both variables. The joint model for variables Y and X is denoted as $Y_t = \alpha_Y + \sum_{i=1}^{p} \beta_{Y_i} Y_{t-i} + \sum_{i=1}^{q} \beta_{X_i} X_{t-i} + \epsilon_Y$, where q represents the lag order included for variable X.

Step 6: Compare the 'restricted' model (individual AR models) with the 'unrestricted' model (joint AR model) using the F-statistic.

$$F = \frac{(SSE_r - SSE_u)/q}{SSE_u/n - q - p - 1} \sim F(q, n - q - p - 1) \tag{18}$$

where SSE_r represents the sum of squared errors from the restricted model, SSE_u denotes the sum of squared errors from the unrestricted model, q represents the difference in the number of parameters between the models, n represents the total number of observations, and p represents the number of lagged terms for variable Y.

By comparing the calculated F-statistic with the critical value from the F-distribution, we can determine the statistical significance of the Granger causality relationship between the variables.

5.3.3 *Result Analysis*

- **Results of Spearman Correlation Analysis**

The results of Spearman's Correlation Coefficient analysis show that **the EV industry affects the market share of the traditional energy vehicle industry.** Specifically, fuel engine sales, which represent the raw materials component, have a strong negative correlation with EV variables. This means that as EVs gain more market share, the sales of fuel engines in the traditional automobile industry decrease.

However, the correlation between EV variables and energy prices in the traditional automobile industry is low. This suggests that changes in the market share of new energy vehicles have little impact on energy prices.

These findings highlight the disruptive impact of the EV industry on the traditional industry. As the market share of new energy vehicles increases, consumer preferences shift towards more sustainable transportation options, leading to a decline in demand for fuel engines.

However, it is important to note that energy pricing dynamics in the traditional automobile industry are influenced by factors other than the market share of EVs. Global

Figure 13 The heatmap of Spearman Coefficient

energy market dynamics and government policies play significant roles in shaping energy prices.

Stakeholders in both the new energy vehicle and traditional energy vehicle industries should closely monitor and adapt to the changing market dynamics. The transition to new energy vehicles presents both challenges and opportunities, necessitating strategic planning and adaptation to ensure competitiveness and sustainability in the evolving automotive industry.

• **Results of Granger Causality Test**

To delve deeper into the relationship between variables, we conducted the Granger Causality Test as an additional step in our correlation analysis.

All the variables have passed the ADF test with a p-value less than 0.05, so the next step of the Granger causality test can be carried out.

Table 9 Results of Granger Causality Test

Lag Order	EV Variable	EV Stage	Traditional Vehicle Variable	Traditional Stage	p-value
3	Average EV share performance in the world	Midstream	Global fuel engine sales	Upstream	0.028**
1	Battery price	Upstream	Market penetration of conventional fuel vehicles	Midstream	0.007***
1	Average EV share performance in the world	Midstream	Average gas price	Downstream	0.006***

Note: ***, **, * represent 1%, 5%, and 10% significance levels, respectively.

Several conclusions can be drawn based on the p-values of each pair:

- **The pricing of the EV industry strongly influences and has a causal relationship with the market sales of the traditional automobile industry.** A reduction in the cost pricing of the EV industry can, to some extent, impede the development of the traditional automobile industry.
- **The relationship between the traditional automobile industry and the market share of new energy vehicles is mutually influential.** There is no explicit causal link, but a strong correlation exists. Therefore, by implementing market policies that expand the new energy industry, it is possible to significantly influence and limit the development of the traditional automobile industry.
- **The expansion of the new energy market will cause the upstream industry of traditional automobile production and sales to contract.** There exists a causal and sequential relationship between the two. The cost pricing of the EV industry (specifically new energy battery prices) indirectly affects the upstream industry by influencing the sales of the traditional automobile industry in the midstream. Additionally, the expansion of the traditional automobile upstream industry also impacts the development of the EV upstream industry (battery manufacturing), leading to mutual influences and constraints between the two.
- **The market development of new energy vehicles will exert a decreasing effect on the price of traditional automobiles in the downstream industry.** However, the relationship between the midstream market of new energy vehicles and the downstream industry of traditional automobiles is weakly causal.
- **There are multiple factors that influence gas prices, resulting in a weak and negative correlation between the development of the new energy vehicle market and gas prices.** Consequently, the increase in market share of new energy vehicles will lead to a less pronounced decrease in gas prices within the traditional automobile market.

• Overview of the Impacts on Traditional Vehicle Industry

In summary, the EV industry inhibits the upstream (fuel engine manufacturing) and midstream (market share) sectors of the traditional vehicle industry. However, its impact on the downstream industry, such as gas and oil prices, is limited.

Firstly, the development of the new energy vehicle industry's upstream sector (battery manufacturing) strongly influences the midstream sector of traditional vehicles. There is a significant bidirectional relationship between the traditional automobile industry and the market share of new energy vehicles.

Secondly, there is a negative causal relationship between the midstream sector (market share) of new energy vehicles and the upstream sector of traditional vehicles. The development of the new energy vehicle industry indirectly affects the upstream sector of traditional vehicles in a negative manner.

Finally, compared to other sectors in the new energy vehicle industry, the development of the EV upstream sector leads to a decline in energy prices in the downstream industry of traditional vehicles. The midstream sector of EVs has a causal relationship and a minor negative impact on the prices of the downstream industry.

5.4 The Impacts of Boycott Policies on EVs

5.4.1 *Policy Review and Data Collection*

The recent actions in the global EV market have noticeably shaped the industry landscape. Notably, former US President Donald Trump initiated a 25% tariff on Chinese auto imports, as reported by The Wall Street Journal [7]. Moreover, electric vehicles meeting specified criteria are entitled to receive up to $7,500 in tax credits in the US, as outlined in a report by the Center for Strategic and International Studies [8]. Concurrently, the European Commission's investigation into potential subsidies for Chinese electric vehicles has instilled significant uncertainty within this burgeoning sector, a development highlighted in a Reuters article [9]. These events collectively underscore the intricate interplay of policy, trade, and competition that are shaping the future of electric vehicles on a global scale.

In this section, we gather data on Chinese export tariff rates, the number of EVs exported from China, and the sales value of exported EVs from China for regression analysis.

5.4.2 *Model Principles*

• Ordinary Least Squares (OLS) Regression

The Ordinary Least Squares (OLS) Regression is a statistical method used to estimate the relationship between independent and dependent variables.

In its simplest form, it aims to find the line (in the case of simple linear regression) or hyperplane (in the case of multiple linear regression) that best fits the observed data points by minimizing the sum of the squares of the vertical differences (residuals) between the observed and predicted values.

$$Y = \beta_0 + \beta_1 X + \varepsilon \tag{19}$$

For multiple linear regression with p independent variables, the equation becomes:

$$Y = \beta_0 + \beta_1 X_1 + \beta_2 X_2 + \ldots + \beta_p X_p + \varepsilon \tag{20}$$

The least squares estimates for the coefficients $\beta_0, \beta_1, \beta_2, \ldots, \beta_p$ involve matrix operations and can be represented in a compact matrix form as:

$$\hat{\beta} = (X^T X)^{-1} X^T Y \tag{21}$$

where X denotes the design matrix of independent variables, Y represents the vector of dependent variable values, and $\hat{\beta}$ represents the vector of least squares estimates for the coefficients.

5.4.3 *The Results of Chinese EV Development under Boycott*

• OSL Results

The least squares (OLS) regression model, with an R^2 of 0.86, explains approximately 86% of the variance in the dependent variable. This indicates that the model provides a good fit to the data and suggests that 86% of the variability in the dependent variable can be attributed to the independent variables included in the model.

Additionally, the high F-statistic of 55.61 and the low probability value (2.82e-18) indicate that the overall model is statistically significant.

Table 10 The Results of OSL for Chinese Export Tariff Rates

Variable	Coefficient	p-value	Standard Error	t
Number of EVs exported from China	0.0111	0.002	0.003	3.204
Sales value of exported EVs from China	-0.0109	0.046	0.005	-2.036

There is a positive relationship between the number of EVs exported from China and Chinese export tariff rates. This indicates that as Chinese export tariff rates increase, the number of EVs exported from China tends to increase as well. It implies that higher export tariff rates may serve as an incentive for an increased number of EV exports, potentially due to factors such as import restrictions or trade agreements.

Conversely, there is a negative relationship between the value of Chinese exported EV sales and Chinese export tariff rates. This suggests that as Chinese export tariff rates increase, the sales value of exported EVs from China tends to decrease. Higher export tariff rates may result in elevated costs for imported EVs in other countries, making them less appealing to consumers and leading to lower sales values.

• **Strategies Analysis on EDI**

Competing countries like the US have enacted boycott policies specifically targeting Chinese EVs due to concerns over national security and intellectual property. For example, the US provides a substantial tax credit of $7,500 exclusively for EVs that do not incorporate Chinese components.

This incentive has led to a significant shift in consumer behavior, prompting more individuals to favor EVs from other countries to capitalize on the available tax credits. Consequently, this trend is anticipated to drive a gradual decline in the export of Chinese EVs.

As a direct consequence, there will be a corresponding decrease in the demand for batteries used in these vehicles. Simultaneously, the decreased export and production of Chinese EVs will inevitably lead to a reduction in value-added activities within the secondary sector, impacting various segments of the economy that are closely tied to EV manufacturing and components.

In this particular examination, we have adjusted the battery demand and secondary sector factors from a -5% impact to a more substantial -15% impact within our EST evaluation system. By doing so, we aim to closely monitor the overall resistance and susceptibility that foreign policies may have on the industry. The EDI demonstrates a modest decrease, while still maintaining a relatively high level. This suggests that the influence of the boycott policies is limited and indicates that China is capable of sustaining stable growth within the EV industry.

Nevertheless, China can proactively address these challenges by implementing positive strategies. For instance, the introduction of policy subsidies can serve as an encouraging factor in both the production and consumption of EVs. Therefore, we have also adjusted the subsidy factor from 0% to 10% in order to examine the corresponding impact on the EDI. The results reveal that with a 10% increase in the subsidy, the EDI

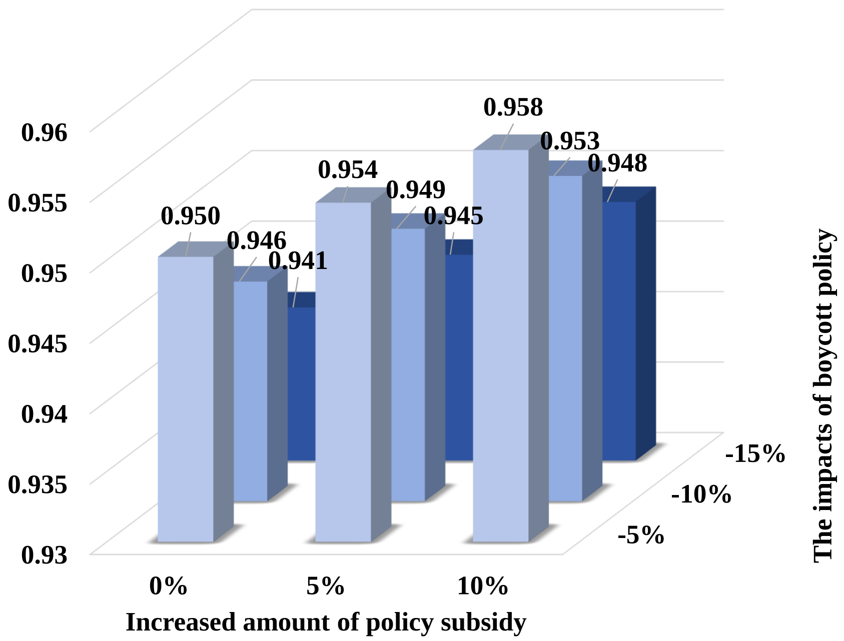


Figure 14 Results of the Impacts of Policy

reaches 0.958, which effectively offsets the negative repercussions of these policies. This demonstrates the potential of offsetting the adverse effects through proactive measures.

5.5 The Impacts on Ecological Environment

5.5.1 *Data Collection*

The impact of EVs on the ecological environment may vary across different cities worldwide, primarily due to market distinctions. To better understand these variances, we have collected data on several key factors from 196 regions, including **vehicle ownership per capita** (V), **GDP per capita** (G), **carbon emissions per capita** (E), **and market penetration rate** (S). It is worth noting that the GDP data is adjusted using Purchasing Power Parity (PPP), which provides a more accurate reflection of the regions' purchasing power. At the same time, **carbon emissions** are a key indicator of ecology, reflecting the impact of human activity on the environment [10]. Therefore, this paper uses carbon dioxide emissions to measure the ecological impact of electrification of automobiles.

To analyze and represent the ecological environment of specific cities in greater detail, we have categorized the regions into four classes: **impoverished, developing, emerging, and prosperous.** Each of these classes serves as a representation of a particular ecological environment category. Based on these categorizations, we then calculate the corresponding effect values associated with EVs.

By considering these factors and classifying regions accordingly, we aim to gain a comprehensive understanding of the diverse impacts of EVs on the ecological environment across different cities worldwide.

5.5.2 *Model Principles*

- **K-means++**

The k-means++ algorithm is an enhancement over the standard k-means clustering algorithm. It is designed to intelligently select the initial cluster centers to improve clustering performance.

Step 1: Initialization. The first centroid is chosen randomly from the data points.

Step 2: Selecting Subsequent Centroids. For each data point, the algorithm calculates the distance to the nearest centroid that has already been chosen.

The probability of selecting each data point as the next centroid is directly proportional to the square of its distance from the nearest chosen centroid.

$$P(x) = \frac{D(x)^2}{\sum_{x' \in X} D(x')^2} \tag{22}$$

where $D(x)$ is the distance from data point x to the nearest centroid that has already been chosen, $\sum_{x' \in X} D(x')^2$ computes the sum of the squared distances of all data points to their nearest centroids. This acts as a normalization factor.

The next centroid is then chosen from the data points, with the probability of selection being determined by the calculated probabilities.

Step 3: Step 2 is repeated until k initial centroids are chosen.

• Vehicle Carbon Impact (VCI) Model

We propose a groundbreaking model called the VCI model, specifically designed to quantify carbon emissions and evaluate the reduction achieved through the incorporation of EVs.

To calculate the total carbon emissions with the presence of EVs, we employ the following formula:

$$E_{total} = P \cdot V \cdot S \cdot e_{EV} + P \cdot V \cdot (1 - S) \cdot e_{TV} \tag{23}$$

where E_{total} represents the total carbon emission with EVs, P represents the population, P is the population, V is the vehicle ownership per capita, S is the market penetration rate, e_{EV} is the emission of EV, e_{TV} is the emission of traditional vehicles.

Furthermore, we can quantify the reduction in carbon emissions resulting from the influence of EVs using the following calculation:

$$E_{reduced} = P \cdot V \cdot e_{TV} - E_{total} \tag{24}$$

where $E_{reduced}$ represents the reduced amount (ton) of carbon emission.

The VCI model offers several advantages. Firstly, it provides a comprehensive framework to estimate the total carbon emissions considering the presence of EVs, taking into account factors such as population, vehicle ownership, market penetration rate, and emissions from both EVs and traditional vehicles. This allows for a holistic assessment of carbon footprints.

Additionally, the model allows for the calculation of the actual reduction in carbon emissions specifically attributable to the effects of EVs. This enables policymakers and stakeholders to quantify the environmental benefits achieved through the adoption of EVs and evaluate the effectiveness of EV integration in reducing carbon emissions.

By utilizing the VCI model, researchers and policymakers gain a robust tool to analyze and compare the carbon impacts of different scenarios, facilitating evidence-based decision-making for sustainable transportation strategies and policies.

5.5.3 *Results Analysis*

The scatter plot and clustering centers are as follows.

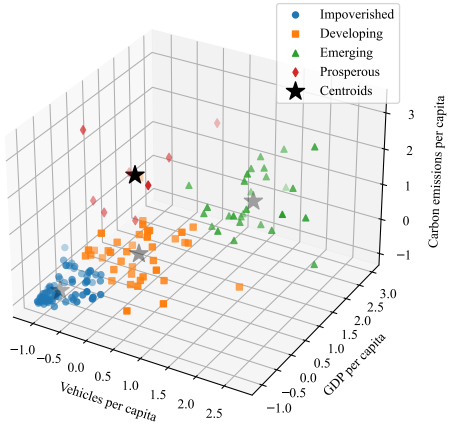


Figure 15 Scatter Plot of Clustering Result

Category	V	G	E	S
Impoverished	0.073	5650.37	0.94	13.60%
Developing	0.30	22033.12	10.88	5%
Emerging	0.31	21704.7	3.76	17%
Prosperous	0.65	47491.71	7.31	19.20%

Table 11 Clustering Centers

The features of each category are as follows:

- The Impoverished category represents cities characterized by low vehicle ownership, relatively low GDP per capita, lower carbon emissions per capita, and a moderate market penetration rate. These cities likely have limited access to vehicles and lower economic conditions, resulting in lower carbon emissions. The market penetration rate suggests a moderate adoption of EVs, indicating a potential for reducing carbon emissions in the future.
- The Developing category represents cities with moderate vehicle ownership, higher GDP per capita, significantly higher carbon emissions per capita, and a low market penetration rate. These cities are in the process of economic development, with increasing vehicle ownership and higher carbon emissions. However, the low market penetration rate indicates limited adoption of EVs, resulting in higher overall carbon emissions in this category.
- The Emerging category represents cities with moderate vehicle ownership, relatively high GDP per capita, and moderate carbon emissions per capita. These cities are experiencing growth and development, with a moderate adoption of vehicles and carbon emissions. The market penetration rate suggests a substantial potential for electric vehicle adoption and reduction in carbon emissions in this category.
- The Prosperous category represents cities with higher vehicle ownership, significantly higher GDP per capita, relatively higher carbon emissions per capita, and a high market penetration rate. These cities have higher affluence and vehicle ownership, resulting in higher carbon emissions. The high market penetration rate suggests a strong adoption of EVs and the potential for further reductions in carbon emissions in this category.

Having conducted an analysis using the VCI Model, the following conclusions have been derived:

- The impact of electrification on carbon emissions is more pronounced in cities with better economic conditions and higher levels of electrification. On the contrary, in countries with average economic conditions (with fewer vehicles per capita) or poor electrification, the environmental effects of electrification changes are minimal.

Table 12 The Total and Reduced Carbon Emissions by Categories

Category	Actual Carbon Emission	Reduced Carbon Emission	Reduced Percentage
Impoverished	3555.46	394.47	9.99%
Developing	15656.47	596.75	3.67%
Emerging	14922.73	2128.58	12.48%
Prosperous	30051.77	4932.38	14.10%

- This observation suggests that the benefits of transitioning to EVs and reducing carbon emissions are more significant in economically prosperous areas and cities with an advanced electrification infrastructure. These cities typically have the resources and infrastructure necessary to support the widespread adoption of EVs and make a substantial reduction in carbon emissions. The presence of a robust electrification network ensures the availability of charging stations and promotes the feasibility of EV usage.
- In contrast, cities with average economic conditions, where vehicle ownership per capita is relatively low, may have fewer incentives or resources to prioritize electrification initiatives. Similarly, cities with poor electrification infrastructure face challenges in providing reliable and accessible charging facilities for EVs. As a result, the ecological impact of electrification in these areas is relatively low.

To maximize the environmental benefits of electrification, it is important to focus on improving economic conditions, expanding electrification networks, and supporting the transition to EVs. This way, the potential for reducing carbon emissions through electrification can be harnessed effectively across different cities and economic contexts.

5.5.4 *Sensitivity Analysis*

In this section, we enhance the market penetration rate from -5% to 50% to closely track the progress in electrification and to observe the resulting changes in reduced carbon emissions for each category.

We notice that the prosperous category exhibits the highest sensitivity to alterations in the market penetration rate. Conversely, the impoverished category shows the least sensitivity. Additionally, the developing and emerging categories demonstrate similar patterns, both experiencing moderate increases as the market penetration rate grows.

Potential reasons for the varying sensitivities could include differing financial capacities to adopt new technologies, infrastructure availability, and varying levels of government support and incentives. These factors often play a significant role in shaping the responsiveness of different ecological categories to changes in market dynamics.

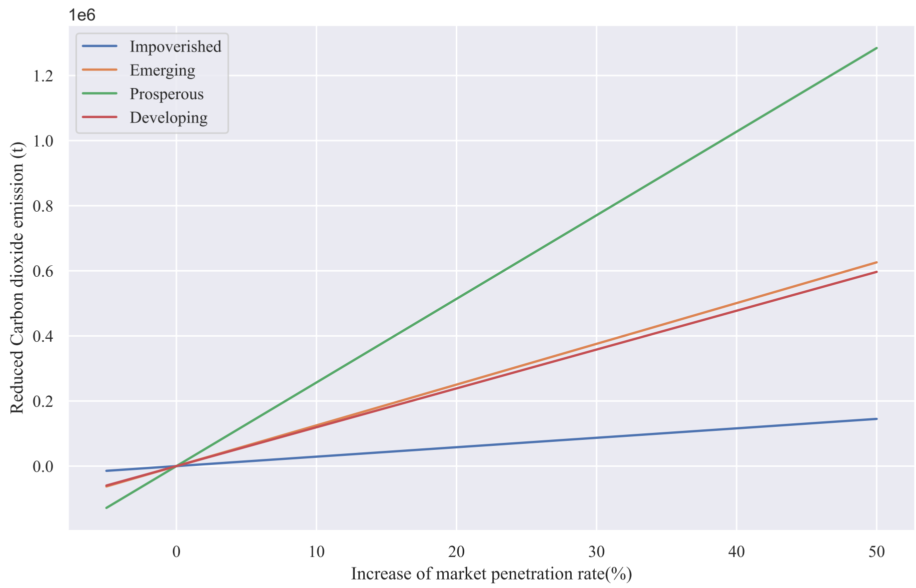


Figure 16 The Results of Reduced Carbon Emission

VI. Model Evaluation and Further Discussion

6.1 Strength

- The EST system considers the economy, society, and technology of EV development. It incorporates multiple indicators that provide a comprehensive analysis of the industry.
- The GM(1,1) forecasting model is advantageous for the EV industry due to its simplicity, ease of implementation, and ability to work with limited data. Besides, its adaptability makes it suitable for forecasting in dynamic and changing environments.
- The combination of Spearman correlation and Granger Causality test offers a comprehensive evaluation of the relationships between the EV industry and the traditional vehicles industry. This approach provides insights into the interactions and influence between these sectors.
- The VCI model offers a comprehensive framework to calculate the specific reduction in carbon emissions. It provides a robust tool for decision-making in sustainable transportation policies.

6.2 Weakness

- Due to the novelty of the EV industry, the availability of data is limited, and the analysis and prediction models may be subject to bias.
- Due to the diverse sources of data, the information utilized in the model may be incomplete. It is not always possible to obtain all the required indicators, leading to unavoidable gaps and missing values in the data. Despite efforts to address these missing values, the accuracy of the model fit may be somewhat affected.

6.3 Further Discussion

As the EV industry continues to evolve, it will eventually reach a stable phase, and more data will be available. This presents an opportunity to refine our models and obtain more accurate and meaningful results for evaluating and predicting the effects of EV development.

VII. Conclusion

This paper proposed a novel Economy-Society-Technology (EST) evaluation system and EV Development Index (EDI) to identify the development level of the EV industry. The system categorized the development level into four grades: Grade I (Underdeveloped), Grade II (Developing), Grade III (Advanced), and Grade IV (Developed). Based on the system, the EDI of the Chinese EV industry is 0.955, indicating a bright prospect.

Besides, we applied GM(1,1) to predict the developing trend of the Chinese EV market for the next 10 years.

The combination of the Spearman Correlation Coefficient and Granger Causality Test proved that the EV industry has a negative impact on the upstream and midstream of the global traditional vehicles industry, with insignificant impacts on the downstream.

Meanwhile, we employed k-means++ to classify the ecological environment into four typical categories. Then we introduced a novel Vehicle Carbon Impact (VCI) Model to calculate the reduced carbon emissions in terms of different categories.

Based on the above model, we have written a letter to present our key findings to the public in order to promote the popularization of EVs.

SUSTAINABLE FEATURE

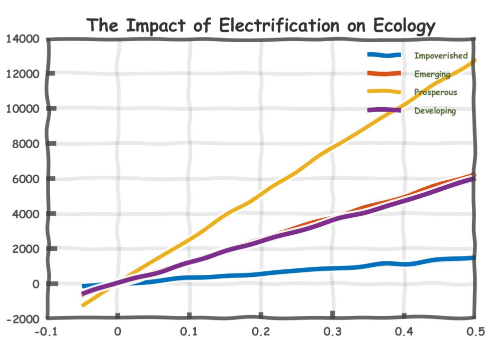
Harnessing the Power of New Energy Electric Vehicles

Dear Citizens,

Welcome to a world where the wheels of progress turn towards a greener future. Today, we want to take a moment to share with you the profound positive ecological impacts of the electrification of new energy vehicles. Beyond the cold facts and figures, let us delve into the emotional essence of this transformation and understand why it is a cause worth championing.

In our current reality, high carbon dioxide emissions have cast a shadow over the health of our planet. The burning of fossil fuels, like gasoline, has led to a surge in greenhouse gases, exacerbating climate change and its devastating consequences. Rising global temperatures, extreme weather events, and disappearing ecosystems are but a few of the unfortunate outcomes we face.

But amidst this crisis, a ray of hope emerges. The electrification of new energy vehicles offers a glimmer of possibility, a chance to turn the tide on our carbon footprint. By transitioning from conventional combustion engines to electric power, we can significantly reduce carbon dioxide emissions. This shift presents a golden opportunity to mitigate climate change, protect our fragile ecosystems, and safeguard the well-being of future generations.



In our analysis, we divided the cities into four categories. It is interesting to note that among these categories, increased EV adoption presents an avenue for substantial future reductions in carbon emissions. To maximize the environmental benefits of electrification, we must focus on improving economic conditions, expanding electrification networks, and supporting the transition to EVs. By doing so, we can effectively harness the potential for reducing carbon emissions through electrification.

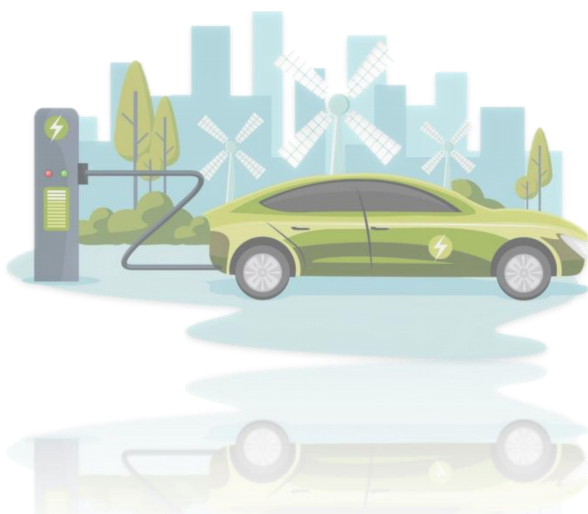
But it doesn't stop there. The positive contribution of the new energy vehicle industry extends far beyond the reduction of carbon emissions. Embracing this revolution means embracing a future of innovation, job creation, and economic growth. **As we invest in the development and production of electric vehicles, we foster a thriving industry that offers employment opportunities, drives technological advancements, and positions us as global leaders in sustainable transportation.**

Now, my dear public, we implore you to join me on this transformative journey. Let us take positive initiatives that propel us towards a cleaner, greener world. Support the development of new energy vehicles by advocating for policies that incentivize their adoption. Consider replacing your current vehicles with electric alternatives, reducing your carbon footprint while enjoying the many advantages they offer. Together, we can forge a path towards a future where sustainability and progress go hand in hand.

The power to make a difference lies in your hands. Choose to be a force for change, an advocate for a greener tomorrow. Embrace the electrification of new energy vehicles and let us write a story of hope, resilience, and environmental stewardship. Together, we can create a world that future generations will thank us for.

With warm regards,

Team # apmcm2305793



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IX. Appendix

Listing 1: The Python source code of Linear fitting

```
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
from sklearn.linear_model import LinearRegression
from sklearn.metrics import mean_squared_error

file_path = 'Normalized_S+_Score.xlsx'
df = pd.read_excel(file_path)

# Select feature and target columns
X = df['Total stock shares'].values.reshape(-1, 1)
y = df['score'].values

# Create a linear regression model
model = LinearRegression()

# Fit the model
model.fit(X, y)

# Make predictions
y_pred = model.predict(X)

# Calculate mean squared error
mse = mean_squared_error(y, y_pred)

# Set the font family to 'Times New Roman'
plt.rcParams['font.family'] = 'Times New Roman'

# Plot scatter plot and linear fit line
plt.style.use('seaborn') # Choose 'seaborn' style

plt.scatter(X, y, label='Actual Values')
plt.plot(X, y_pred, color='red', label='Linear Fit Line')


# Set font properties for the tick labels
font_properties = {'family': 'Times New Roman', 'size': 12}

# Set tick labels font for x-axis
plt.xticks(fontproperties=font_properties)

# Set tick labels font for y-axis
plt.yticks(fontproperties=font_properties)
plt.rcParams['font.family'] = 'Times New Roman'
plt.xlabel('Total stock share',font_properties=font_properties)
plt.ylabel('Final Score',font_properties=font_properties)
print(mse)
```

```
plt.legend()
plt.show()
```

Listing 2: The Python source code of EWM and CVM

```
import pandas as pd
import numpy as np

# Calculate entropy for each indicator
def calculate_entropy(series):
    p_i = series / series.sum()
    entropy_i = -np.sum(p_i * np.log2(p_i))
    return entropy_i

# Calculate entropy values
entropy_values = df1.apply(calculate_entropy)

# Calculate weights
total_entropy = entropy_values.sum()
weights = [(1 - entropy_i / total_entropy) for entropy_i in
    entropy_values]

# Normalize weights
normalized_weights = weights / sum(weights)

print("Entropy values for each indicator:")
print(entropy_values)
print("Weights for each indicator:")
print(weights)
print("Normalized weights:")
print(normalized_weights)


# Calculate coefficient of variation for each indicator
def calculate_coefficient_of_variation(series):
    mean_value = series.mean()
    std_dev = series.std()
    coefficient_of_variation = std_dev / mean_value
    return coefficient_of_variation

# Calculate coefficients of variation
coefficients_of_variation =
    df1.apply(calculate_coefficient_of_variation)

# Calculate weights
total_coefficient_of_variation = coefficients_of_variation.sum()
weights_coefficient = [(1 - cv_i / total_coefficient_of_variation) for
    cv_i in coefficients_of_variation]

# Normalize weights
normalized_weights_coefficient = weights_coefficient /
```

```
    sum(weights_coefficient)

print("Coefficients of variation for each indicator:")
print(coefficients_of_variation)
print("Weights for each indicator (coefficient of variation method):")
print(weights_coefficient)
print("Normalized weights (coefficient of variation method):")
print(normalized_weights_coefficient)

ahp_weights1 = [0.19854706, 0.45455929, 0.34689366]

# Convert the list to a NumPy array
ahp_weights_array = np.array(ahp_weights1)

# Perform the weighted average
weights_combined1 = 0.4 * np.array(normalized_weights) + 0.4 *
    np.array(normalized_weights_coefficient) + 0.2 * ahp_weights_array

print("Weighted average weights:")
print(weights_combined1)
```

Listing 3: The Python source code of cointegration test

```
import pandas as pd
from statsmodels.tsa.stattools import coint
from statsmodels.tsa.stattools import grangercausalitytests
import matplotlib.pyplot as plt

result = coint(df['Battery price ($)'], df['Market penetration of
    conventional fuel vehicles (%)'])

# Output test results
print(f'Cointegration test statistic: {result[0]}')
print(f'P-value: {result[1]}')
print(f'Critical values: {result[2]}')

# Determine cointegration based on P-value
if result[1] < 0.05:
    print('Cointegration exists')
else:
    print('No cointegration exists')
```

Listing 4: The Python source code of K-means++

```
import pandas as pd
from sklearn.cluster import KMeans
import matplotlib.pyplot as plt
from mpl_toolkits.mplot3d import Axes3D
import seaborn as sns

X = result_df2_standardized[['Vehicles per capita', 'GDP per capita',
```

```
    'Carbon emissions per capita']]

# Set the number of clusters
K = 4

# Initialize K-means with K-means++ initialization
kmeans = KMeans(n_clusters=K, init='k-means++', random_state=42)

# Fit the K-means model to the data
result = kmeans.fit_predict(X)

result_df2_standardized['Cluster'] = result

# Visualize the clustering results in 3D
fig = plt.figure(figsize=(10, 8))
ax = fig.add_subplot(111, projection='3d')

markers = ['o', 's', '^', 'd']
for i in range(K):
    cluster_data =
        result_df2_standardized[result_df2_standardized['Cluster'] == i]
    ax.scatter(cluster_data['Vehicles per capita'], cluster_data['GDP
        per capita'], cluster_data['Carbon emissions per capita'],
              label=f'Cluster {i + 1}', marker=markers[i])

ax.set_xlabel('Vehicles per capita')
ax.set_ylabel('GDP per capita')
ax.set_zlabel('Carbon emissions per capita')
ax.set_title('K-means Clustering Results in 3D')

# Plot the cluster centers as well
ax.scatter(kmeans.cluster_centers_[:, 0], kmeans.cluster_centers_[:,
    1], kmeans.cluster_centers_[:, 2],
          s=200, c='black', label='Centroids', marker='*')

plt.legend()
plt.show()
```

Listing 5: The Python source code of calculation of carbon emissions

```
import matplotlib.pyplot as plt
import numpy as np

# The values
V_values = [0.072877,0.3146, 0.645464, 0.299875]
GDP_values = [5650.37037,21704.7, 47491.71429, 22033.125]
carbon_emission_values = [0.939506,3.755, 7.307143, 10.875]
market_penetration_values = [0.136,0.17, 0.192, 0.05]
Car_total=[3555.464774, 14922.7364, 30051.7711, 15656.47375]
Totalc=[939506, 3755000, 7307143, 10875000]
```

```
# Range of X
X_range = np.linspace(-0.05, 0.5, 100)

# Plot
plt.figure(figsize=(10, 6),dpi=1000)

for i in range(len(V_values)):
    # Calculate y_values
    y_values = [1000000 * V_values[i] * (market_penetration_values[i] +
        X) * 0.0144 +
               1000000 * V_values[i] * (1 - market_penetration_values[i]
                   - X) * 0.0542 for X in X_range]
    normalized_values = Car_total[i]-np.array(y_values)
    # Draw the diagram
    labels = ["Impoverished", "Emerging", "Prosperous", "Developing"]
    plt.style.use('ggplot')
    plt.plot(X_range, normalized_values, label=labels[i])

plt.rc('font',family='Times New Roman')
plt.xlabel('Increase of automotive electrification')
plt.ylabel('Reduced Carbon dioxide emission (t)')
plt.legend()
plt.grid(True)
plt.show()
```