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Evaluating the Factors Affecting Electric Vehicles Adoption Considering the Sustainable Development Level

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Abstract: Electric vehicles are an important part of governments' environmental policies, and therefore understanding the factors affecting their market share is very important. So, this research is designed to investigate the factors affecting electric vehicle adoption, considering the effects of the COVID-19 pandemic and sustainable development level. Effective factors have been investigated in three categories. One is the characteristics of electric vehicles; the other is the impact of the COVID-19 pandemic on demand for these vehicles; and finally, the impact of the level of sustainable development of countries on adopting electric vehicles. Our analysis method is based on grey econometric and grey regression methods. The results show that vehicle dimensions, battery warranty conditions, battery life, and charging facilities are effective factors in the field of vehicle characteristics that can increase the adoption of electric vehicles. Also, the analysis shows that the COVID-19 pandemic has reduced the adoption of electric vehicles. Finally, we have shown that the market share of electric vehicles is higher in countries with a higher sustainable development level because of better economic, social, and cultural infrastructures.

Keywords: electric vehicles; sustainable development goals; grey econometrics; regression; SDG; COVID-19

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1. Introduction

Using statistical methods and data analysis based on grey systems theory, this research examines some factors affecting the adoption of electric vehicles (EVs), including vehicle characteristics, the level of sustainable development, and the impact of the COVID-19 pandemic on them. Today, most governments of developed countries promote using electric vehicles to reduce the concentration of pollutants, CO_2, and other greenhouse gases [1]. They promote sustainable and efficient mobility, in particular through a variety of initiatives, mainly through tax subsidies, consumer shopping guides, or other specific measures, such as free public parking or free use of highways [2]. Since EVs are thought to reduce the problem of air pollution, consumers' perception of this benefit could lead to greater adoption of EVs. Governments in auto-producing countries are eager to make their local manufacturers more competitive, as the auto industry has a major impact on employment and exports in these countries [3]. On the other hand, humanity is currently facing the challenge of a major transition from the current fossil fuel-based economy to a sustainable society within planetary boundaries [4].

One of the most important aspects of this development is the reduction of CO_2 emissions to reduce climate change, which requires major changes in many areas. One of the important contributions to these goals is undoubtedly the change from combustion engine vehicles to alternative fuel vehicles, including electric vehicles. Sustainability is a very urgent and global concern, and in this electric way, they believe electric vehicles can be a suitable option to solve this concern [5]. However, governments need a systematic view and a thorough understanding of the interrelationships between EVs adoptions and other aspects of sustainable development, including the economy, culture, environment, and public health, to formulate effective EVs policies [6]. As a result, discovering and understanding the factors affecting the demand for EVs and their interrelationships with different aspects of sustainable development is one of the first steps and the basic policy principles in this field. Through cross-national and systematic studies, we may be able to uncover certain generalizable principles as well as country-specific findings, which may then lead to different managerial and policy implications [7].

Many researchers have shown that the adoption of electric vehicles and the development of such vehicles can have positive effects on various aspects of sustainable development, especially in the field of the environment [8]. However, there are many differences in this area, and many researchers believe that using electric vehicles will not help much in sustainable development [9]. On the other hand, Electric vehicle development is crucial for achieving sustainable development objectives, but the COVID-19 outbreak has impacted the market and posed hurdles for the entire sector. Quarantined laborers, extensive firm closures, disturbed global supply routes, and declining demand have all harmed the automotive industry's viability [10]. Hence, it is critical to understand the factors driving the demand for electric vehicles, which is the primary driver of this sector. The impact of the pandemic on this demand, in particular, can aid in better understanding future patterns [1].

According to the description, many questions are raised about the different dimensions of EVs usage. The most important and main one is the relationship between sustainable development and EVs adoption rate. This research aims to investigate the interaction of electric vehicle adoption and sustainable development by considering its various aspects as a system and with a holistic view using grey econometric approaches. Therefore, the basic questions are what is the impact of sustainable development in different sectors on the adoption of electric vehicles? Will development, especially sustainable development, lead to growth in adoption? In a circular cause-and-effect mechanism, what sustainability changes will this growth lead to? Therefore, this study first tries to investigate the relationship between the adoption of electric vehicles and countries' sustainable development levels. For this purpose, we will use the number of sales of electric vehicles and the ranking of countries in the Sustainable Development Goals (SDG) provided by the United Nations.

Most of the previous studies about EVs adoption have focused on either the antecedents or consequences with less focus on mediating or moderating variables. In addition, less research has examined the adoption of EVs with a systematic and holistic view. Considering different aspects of sustainable development and its interrelationship with the adoption of EVs from a systematic perspective has also received less attention from researchers. Most past research has dealt with the problem discretely, and linearly. The academic emphasis is typically focused on the battery and vehicle technology breakthroughs, specific other critical drivers are equally critical for EVs growth in the world. While several of the crucial drivers have been examined extensively over time, they have not been adequately assessed in the context of purchase behavior and the widespread pandemic. So, another purpose of this article is to evaluate Factors Affecting Electric Vehicles Adoption Considering the Effects of COVID-19, as an epidemic has heightened awareness of global environmental problems and the consequent beneficial impact on electric vehicle demand as a result of these elevated environmental concerns and various other factors.

This research uses grey econometric methods and analyzes the secondary data to identify the factors affecting the demand for electric vehicles. This research will use best-subset grey regression, best-fit regression methods, and ANOVA analyses. The lack of fit test will validate the models, Durbin Watson statistics for remnant independence test, and Variance Inflation Factor (VIF). MINITAB software will be used for data analysis. The findings will significantly impact researchers, manufacturers, and legislators modifying their policies to support electric mobility.

The paper is organized as follows. Section 2 provides an extensive literature review on the characteristics of EVs adopters and the research aim. Section 3 describes the variable and methods used to collect data and the sources. Section 4 discusses the outcomes of our study based on the approach mentioned in Section 3. Section 5 describes explanations and interpretations of the findings in Section 5. Section 6 provides some concluding remarks.

2. Literature Review

Various researchers have been investigating the impact of various factors on the adoption of electric vehicles in recent years. Especially in India and China, which are among the largest and fastest-growing markets for electric vehicles, more attention has been paid to this issue. Qian and Yin (2017) provide a conceptual model that hypothesizes the importance of Chinese cultural values in understanding Chinese consumers' intentions to adopt electric vehicles by analyzing the influence of the human-nature interaction, long-term perspective, face awareness, and risk attitude on the decision-making process [10]. Feng et al. (2019) investigated the adoption of electric vehicles as a credible alternative to internal combustion engine vehicles and their emergence as a mobile intelligent terminal for social commerce. They used a fuzzy logic-integrated system dynamics (SD) model to mimic the adoption process. Their findings indicate that the advantage of incorporating social commerce in EVs is an alternative push to drive EVs adoption [11].

Chu et al. (2019) compared the psychological and behavioral elements that influence EVs adoption and satisfaction in China and Korea. They Used samples from reasonably mature EVs users in four major Chinese cities (early Chinese majority) and members of the young EVs community in Korea (early Korean adopters). They discovered that the early Chinese majority had a higher level of environmental concern. Consequently, environmental concerns were recognized as the key motive for the early Chinese majority to purchase an EV. But for early adopters in Korea, the most compelling reasons to purchase an EVs were economic, i.e., reduced expenditure and government subsidies [4].

Okada et al. (2019) conducted a state-wide online survey to ascertain consumers' intentions to purchase and post-purchase satisfaction with electric vehicles in Japan. They established the relationship by the use of SEM. Additionally, they developed and analyzed two models that depicted non-EVs owners' purchase intentions (Model I) and EVs owners' post-buy satisfaction (Model II) [12].

In 2020 Mukherjee and Ryan also examined the factors that influence the uptake of battery electric vehicles (EVs) among early adopters in Ireland. Consecutively they used the results of the focus groups to identify the variables for the econometric analysis. Their results suggest that Irish EVs owners are concentrated in and around the country's largest urban areas with the highest population densities [13].

The elements influencing a consumer's intention to adopt an EVs were studied by Patyal et al. (2021). A total of 211 peer-reviewed research articles published between 2009 and 2019 were chosen, with topics including consumer intents, adoption intentions, purchase intentions, behavioral intentions, and usage intentions. Influential elements are divided into four categories in this study: demographic, situational, contextual, and psychological. A complete overview of theoretical viewpoints was established to better understand adoption behavior and consumer intentions toward EVs. Their findings show how to evaluate, analyze, and compare the relationships among EVs variables using the most standard study approach [6].

Zhou et al. (2021) used a survey to investigate the factors affecting Chinese taxi drivers' adoption of electric vehicles for everyday usage and broaden it to study the influence of taxi drivers' contentment with the government's invectives on their adoption of electric vehicles for personal use. The empirical studies suggest that the most significant factors are satisfaction with incentive policies, performance expectancy, effort expectancy, facilitating conditions, hedonic motivation, price value, and habit, all contribute significantly to behavioral intention; satisfaction with incentive policies, facilitating conditions, and behavioral intention all contribute significantly to user behavior. Additionally, the findings demonstrate the mediating effect of behavioral purpose on user behavior, in addition to the moderating influence of demographic factors, including gender, education level, and driving experience [14].

Dua et al. (2021) studied the potential for EVs adoption in India, the obstacles that stand in the way of the country's ambitions, and possible solutions. They used the survey approach to ask 51 Indian light-duty vehicle specialists [15]. Huang et al. (2021) questionnaires to investigate the psychological factors that contribute to and influence consumer adoption of EVs across various business formats [8].

Tarei et al. (2021) also investigated the Indian electric vehicle market, with a particular emphasis on technological, infrastructural, financial, behavioral, and external hurdles. They employed a hybrid two-phased multi-criteria decision-making (MCDM) technique. Their research indicates that EVs constraints such as performance and range, the total cost of ownership, a lack of charging infrastructure, and a lack of customer awareness about EVs technology all have a significant impact on EVs adoption [16]. Haustein et al. (2021) also examined changes between 2018 and 2019 in the acceptance and use of EVs in Denmark and Sweden and identified factors influencing acceptance with the data collected from the online survey. Their results suggest that there has been a slight rise in cross-border journeys made in EVs, as well as a slight increase in purchase intent [17].

Chhikara et al. (2021) explored the factors that contribute to, hinder, and promote the mass adoption of battery electric vehicles in a developing country such as India, using qualitative research methodology. The finding identified that the government's proclivity for R&D investment and the provision of financial and non-financial incentives were cited as important drivers [2].

Natalia et al. (2020), also investigated the Indonesian electric car market. They pointed to the low level of adoption of EVs and argued that accelerating the adoption of electric vehicles through better policies and regulations is necessary to help meet the Indonesian government's commitment to reduce greenhouse gas (GHG) emissions by 29 percent by 2030. Their model consists of six reinforcing loops and three balancing loops, which are categorized into five fundamental aspects of EV adoption: vehicle repurchase, technological change, infrastructure development, and commercial-induced purchase for first-time consumers and repeat purchases. Their results show that pricing, infrastructure development, and perceived social desirability are the most determining factors for increasing the willingness to adopt EVs. Aspects of innovation and education also emphasize a particular role in accelerating higher adoption rates [18]. Cao et al. (2021), also claimed that electric vehicles are emerging as a possible strategy for decarbonization and green transportation due to social demand. Their study analyzes the relevant research in the industry, thereby examining the development trends of the electric vehicle industry with a data evaluation system based on scientometrics, in which three key issues are identified: "Vehicle Exhaust Emissions", "Climate Change", and "Integration" [19]. Jin et al. (2020) investigated car sharing and pointed out that car sharing as a sustainable mode faces many problems, such as low market share and adoption rate in developing and developed countries. They provide insights into the effects of key factors, including customer attitudes, service levels, and vehicle restriction policies, on battery electric vehicle sharing service adoption. Their choice of model framework was mixed with quantifying unobserved attitudinal variables and their effects. They showed that attitudes such as environmental awareness, social benefits, satisfaction with the transportation system, and reliability significantly affect the adoption of battery-electric vehicle sharing [20]. Wu and Kontou (2022), design and allocate charging infrastructure investments, rebates, and investments to induce electric vehicle adoption and achieve emission reduction targets. They propose a nonlinear mixed integer mathematical model for optimizing investment allocation in a planning horizon. Their analysis suggests that rebates should come earlier than chargers because of the neighborhood effects of EVs adoption and cost minimization. The availability of home charging affects the choice of consumers and the electric mileage of drivers. Discounts are more effective for regular drivers, while charging stations should be prioritized for frequent drivers [21]. Muratori (2018) has used highly resolved models of residential electricity demand to assess the effect of asynchronous charging of EVs at home on residential electricity demand. He showed that while the increase in aggregate demand may be minimal even for high levels of adoption of EVs, uncoordinated charging of EVs can significantly change the shape of aggregate residential demand, with impacts on electricity infrastructure, even at low levels of adoption [22]. In another article, Hossain et al. (2022) discussed the concept of an electric vehicle as a sustainable development and evaluated the feasibility of developing electric vehicles. Their study expands the conventional definition of sustainable development by combining and prioritizing the critical areas of technology, environment, and policy performance [23].

To maximize the environmental advantages of EVs, it is critical to understand the factors that influence customers' readiness or unwillingness to use EVs during a pandemic. The existing research on EVs adoption has concentrated on the effects of product-related factors (such as purchase and operating costs, vehicle performance, and emission level), service-related factors (such as charging infrastructure), policy-related factors (such as government incentives and regulations), and individual-level factors (such as environmental and technological awareness). Moreover, available data are sparse, indicating that subsequent patterns in EVs development in different regions following the COVID-19 outbreak must be observed, and in-depth research should be conducted in the future to determine the impact of COVID-19 on the EVs industry.

3. Methodology

The method used in this research is a data analysis method based on grey systems theory. We use grey econometric methods and analyze secondary data to identify factors affecting the demand for electric vehicles. Also, this research used best-subset grey regression, best-fit regression, and ANOVA analysis. The models are validated with the lack of fit test, Durbin-Watson statistic for residual independence test, and variance inflation factor (VIF). MINITAB software will be used for data analysis.

In econometrics, there are different types of models, such as linear regression models in one or more variables, non-linear models, systems of equations, etc. When estimating the parameters of these models, we often encounter phenomena that are difficult to explain [24]. For example, the coefficients of the main visual variables are almost zero. The signs of some of the estimated values of the parameters do not correspond to reality or contradict the theoretical economic analysis. Small fluctuations in a few individual observations cause large changes in many other estimated parameter values. Grey econometric methods can help reduce some of these problems [25]. The grey econometric hybrid model obtained in this way can reflect the relationship between system variables more accurately. At the same time, the prediction results made on the endogenous variables of the grey econometric model system have a stronger scientific basis. In addition, by comparing the results of grey forecasts of endogenous variables with the results of econometric models, the reliability of forecasts can be further improved [26].

The steps to create and use grey econometric models are as follows:

Step 1: Designing the theoretical model: In this step, we will select the variables of the model. According to research purposes, we have chosen the variables that can potentially affect the adoption of electric vehicles. Table 1 shows the investigated variables and their symbols. The dependent variable in our model is the total sale of EVs. Independent variables include price, car type, battery range, Maximum power, Vehicle Warranty policy, Battery pack warranty, charging capability, charging method, number of seats, COVID-19, and sustainable development rank.

Table 1. Variable definitions and symbol.

Variable	Symbol	Definition
Sale	SALE	Represents the customer purchasing volume of pure electric vehicles measured in units
Price (RMB)	PRICE	The amount of money required per the manufacturer's quotation in payment for the vehicle and value
Number of seats	NOS	Refers to the maximum number of people a vehicle can transport, including the driver
COVID-19	COV19	COVID variable represents the sales of EVs during the period after 2020, from January 2020 onward till February 2022
Minicar	MINS	A minicar is a small, battery-powered electric vehicle designed for use in low-speed urban situations
Subcompact car	SMLS	Cars that feature three, four, or five doors and are intended to accommodate four people comfortably. It is smaller than a compact car but bigger than a Minicar
compact car	COMS	They have a total capacity of 100–109 cubic feet between their passenger and freight compartments
MPV	MPVS	It is a Multi-purpose vehicle intended to transport travellers on a regular journey
Suv	SUVS	They are capable of driving through rugged terrain and in adverse situations
Sedan	SEDS	A sedan is a three-box passenger vehicle having distinct compartments for the engine, passengers, and freight
Battery range (KM)	BTRKM	Battery range is the maximum distance a pure electric vehicle can go before recharging
Maximum power (kW)	MRPKW	Refers to the electric motor's maximum output. Similar to a standard internal combustion engine, this is measured in kilowatts. The greater the kW value, the more oomph you will receive at the cost of increased energy usage
Battery pack warranty (km)	BWRKM	Indicates the vehicle battery warranty for a discrete mileage that it may be fixed and replaced free of charge in the case of its own quality concerns by the manufacturer
Battery pack warranty (years)	BWRY	The vehicle battery warranty is for a discrete duration in years after the purchasing date, that it may be fixed and replaced free of charge in the case of its own quality concerns by the manufacturer
Vehicle Warranty Policy (km)	WRPKM	It is a vehicle service contract for a limited mileage in which the provider guarantees to repair items that fail due to design or installation flaws by the manufacturer
Vehicle Warranty Policy (years)	WRPY	It is a vehicle service contract for a limited number of years in which the provider guarantees to repair items that fail due to design or installation flaws by the manufacturer
Public charging pile	PCP	A car can only be charged using public charging pile
Dedicated charging pile & Public charging pile	PCPB	A car can only be charged using public charging pile and by Dedicated charging pile
Fast charge method	FCM	A vehicle that can be charged by fast charging
Both type charge	BCM	Vehicles that can be charged by fast charging and slow charging
Sustainable Development Rank	SDG	The United Nations' sustainable development goals (SDG) tracker rank

We will use sustainable development indicators of the United Nations to examine the relationship between sustainable development and the adoption rate of electric vehicles. The United Nations Sustainable Development Goals (SDG) Tracker presents data across all available indicators, using official statistics from the UN and other international organizations [27]. This indicator defines the 17 Sustainable Development Goals in a list of 169 SDG Targets. Progress towards these Targets is agreed to be tracked by 232 unique Indicators. The SDGs are no poverty; zero hunger; good health and well-being; quality education; gender equality; clean water and sanitation; affordable and clean energy; decent work and economic growth; industry, innovation, and infrastructure; reduced inequalities; sustainable cities and communities; responsible consumption and production; climate action; life below water; life on land; peace, justice, and strong institutions; and partnerships for the goals. The SDGs emphasize sustainable development's interconnected environmental, social and economic aspects by putting sustainability at their center [28]. The online publication SDG-Tracker was launched in June 2018 and presented data across all available indicators. It relies on the "Our World in Data" database and is also based at the University of Oxford. We also consider six car types. They discussed in this empirical analysis include Minicars, Subcompact cars, compact cars, MPV, SUVs, and sedans.

Our basic assumption is that the sales variable is a function of other variables as follows:

$$\begin{aligned}\text{SALE} = f\,(&\text{PRICE, NOS, COV19, MINS, SMLS, COMS, MPVS, SUVS, SEDS, BTRKM,}\\ &\text{MRPKW, BWRKM, BWRY, WRPKM, WRPY, PCP, PCPB, FCM, BCM, SDG})\end{aligned} \tag{1}$$

We confined our analysis to the three years preceding and following the COVID-19 epidemic. We classified the factors into six categories: Basic parameters, Car Type/size, Battery specification, Warranty policy, Charging capability, and Charging method. We investigated a total of 20 independent factors in relation to the dependent variable of sales. Several datasets are combined to form the final dataset for analysis, including sales data from the Shenzhen Cheyou Alliance Auto Service Co and car specification from websites that stores all specification information about each car model, such as Auto Service Co maintains a database of electric vehicle sales in China for each month from 2017 onwards.

Using the published stats from this website, we distinctively collected 2175 sales data and manufacturer selling prices for only pure electric vehicles from 2017–2022 February in an Excel sheet. Since there are various specification options for each pure electric vehicle model for customers to select, as a result, in this paper, we selected only one specification, which is the most popular specification as per the Auto Service Co-published data. Furthermore, we use a website like Sohu.com Limited and many more for vehicle specification information to collect data about a variable related to car specification, such as Sina Corporation, PCAUTO, Netease auto, and Autohome. Sales of the electric vehicle, manufacturer, selling price, and car type were collected from the Auto Service Co. The vehicle power, battery range, charging method, charging capability, warranty policy, and battery were searched online in various car specification databases to ascertain data for the variable of our model. Electric vehicle sales were obtained from the Auto Service Co website in the Electric vehicle's sales section, where all the sales data and vehicle parameters are available for all types of electric vehicle models available in the Chinese market.

Moreover, the database not only consists of monthly sales of each vehicle model but also shows the popularity of each version of that distinctive model in the model-related parameter section. In addition, in the parameter section manufacturer's guide price and car type are mentioned. Data about the specification of the electric vehicle, such as battery range, maximum power, battery capacity, and warranty policy regarding the battery and the vehicle, were collected mainly from Sohu.com and other related websites. We also obtained information related to the sustainable development indicator from the Sustainable Development Report, published annually by the United Nations.

Step 2: We create GM (1, 1) models in order to remove the random effect or error noise in the observed values of the individual variables of the model for the observed sequences individually. Model GM (1, 1) is the basic model of grey prediction theory and has been used widely since its development in the early 1980s [29]. The grey mean GM(1,1) modelling process is as follows:

Let the original data $Y^{(0)}$ be the demand sequence of electric vehicles.

$$Y^{(0)} = \left[y^{(0)}(1), y^{(0)}(2), \ldots y^{(0)}(n)\right] \tag{2}$$

Cumulatively sum the original data to get $Y^{(1)}$

$$Y^{(1)} = \left[y^{(1)}(1), y^{(1)}(2), \ldots y^{(1)}(n)\right] \tag{3}$$

And the summation formula is obtained by $Y^{(1)}(k)$

$$Y^{(1)}(k) = \sum_{i=1}^{k} y^{(0)}(i) k = 1, 2, 3 \ldots\ldots n \tag{4}$$

First, the generation sequence of the nearest mean value with $H^{(1)}$ as $Y^{(1)}$ is defined, then,

$$H^{(1)} = \left[h^{(1)}(2), h^{(1)}(3), \ldots h^{(1)}(n)\right] \tag{5}$$

In which Formula (6) is the form of mean GM (1, 1) model:

$$\begin{cases} h^{(1)}(k) = 1/2\left(y^{(1)}(k) + y^{(1)}(k-1)\right) \\ y^{(0)}(k) + ah^{(1)}(k) = b \end{cases} \tag{6}$$

Set the parameter vector $\hat{u} = (a, b)^T$, according to the least square method, the estimated values of a and b can be obtained, there are $\hat{u} = \left(B^T B\right)^{-} B^T X$. In which,

$$B = \begin{pmatrix} -h^{(1)}(2) & 1 \\ -h^{(1)}(3) & 1 \\ \vdots & \vdots \\ -h^{(1)}(n) & 1 \end{pmatrix} X = \begin{pmatrix} y^{(0)}(2) & 1 \\ y^{(0)}(3) & 1 \\ \vdots & \vdots \\ y^{(0)}(n) & 1 \end{pmatrix} \tag{7}$$

The whitening differential equation in the form of mean GM (1, 1) model is,

$$\frac{dy^{(1)}}{dt} + ay^{(1)} = b \tag{8}$$

The time response function of the mean GM (1,1) model for solving the whitening differential equation is

$$\hat{y}^{(1)}(t) = \left\{y^{(0)}(1) - \frac{b}{a}\right\} e^{-a(t-1)} + \frac{b}{a} k = 1, 2, 3 \ldots\ldots n \tag{9}$$

The discrete form of the time response sequence is,

$$\hat{y}^{(1)}(k) = \left\{y^{(0)}(1) - \frac{b}{a}\right\} e^{-a(k-1)} + \frac{b}{a} \tag{10}$$

For (9), the Formula of one reduction is,

$$\hat{y}^{(0)}(k) = (1 - e^a)\left(y^{(0)}(1) - \frac{b}{a}\right) e^{-a(k-1)} \tag{11}$$

where $Y^{(1)}(k)$ is the forecasted value of the demand of EVs [25].

Step 3: We estimate the parameters and try to get the best model using step-by-step regression methods. After the model form is established based on the GM (1, 1) model, the simulated sequences are solved for the estimated values of the parameters using an appropriate method, such as least squares estimation. Once the parameters are clearly defined, the relationships between the variables in the model can be defined and the model can be specified.

Step 4: Model validation will be done using ANOVA, Pearson correlation coefficients, Durbin Watson statistics, Lack-of-fit Test, and Variance Inflation Factor.

4. Results

A total of 3142 data were collected in this research. Data analysis related to the characteristics of cars from the Chinese market and the relationship between the level of sustainable development and the adoption of EVs has been collected from 169 countries. In the first step, using the grey econometric method, the two-by-two relationship between the variables was identified. This is a correlation analysis with a scatter plot showing the relationship between variable pairs. The correlation coefficient values range from −1 to 1. Positive correlation coefficient values show that one variable tends to increase or decrease in tandem with another variable. Table 2 shows the analytical Pearson correlation coefficient for 20 problem variables. Using the Pearson Correlation Coefficient found the relationship between the BTRKM and BTCKWH was statistically significant, as the r-value is nearly equivalent to 1 ($r = 0.843$), making it a strong correlation. In addition, variables MRPKW and BTCKWH also have a strong positive linear relationship between these two variables, as the Pearson r value is 0.761. BWRKM and BWRY variables have a Pearson r-value of 0.75; as a result, there is a strong positive correlation between these variables. A robust positive linear relationship between the variables is also seen between PRICE and MRPKW with a Pearson r-value of 0.83. There is a strong negative relationship between MINS and BTCKWH, as the r-value is nearly equivalent to −1 ($r = -0.75$).

Not to mention, MINS and NOS also have a strong negative correlation. MINS and BTRKM also have a strong negative correlation, since the r-value is −0.563. However, it is worth noting that the SALE and PCPB variables nearly do not correlate as the r-value is −0.001, which is very close to 0. A similar trend was seen between SEDS and NOS, as the Pearson r value is 0.002. At the same time, the majority of the viable has a weak or moderate degree of correlation. On the contrary, it is worth noting that we omitted a few variables for our regression analysis due to the strong intercorrelation between the variable and nominal distribution size. Such as, BTCKM, MRPKW, SMLS and MPVS. Since the data for BTCKM and MRPKW have the same meaning as BTCKWH data. As BTCKWH means Battery Capacity of a vehicle, which explains the Battery range (BTRKM) of the vehicle as higher BTCKWH means the car will also have a more extended battery range; thus, the data for BTRKM will also be higher. In addition, the Maximum power of the vehicle (MRPKW) is also interrelated to the Battery Capacity (BTCKWH). Maximum (MRPKW) power refers to the electric motor's maximum output, and higher output can only be provided if the Battery Capacity is higher and vice versa. Due to multicollinearity and the meaning of the variable having the same meaning, these variables will be omitted in the regression analysis.

In the next step, using the best subsets regression method, we selected the subsets of independent variables that best predict the sales of pure electric vehicles. After selecting the subsets of variables, we performed our final regression analysis using the fitted regression model. The obtained regression equation is as follows:

$$\begin{aligned}\text{Sale} =& 1286 + 0.006286\text{PRICE} + 633\text{MINS} - 568\text{SUVS} + 9081\text{SEDS} - 26.43\text{BTCKWH} \\ &+116.5\text{BWRY} - 0.005768\text{WRPKM} - 700\text{PCP} + 415\text{PCPB} + 509\text{FCM} - 360\text{COV19}\end{aligned} \tag{12}$$

Table 2. Analysis of correlation coefficient and mutual relationship of variables.

Variables	SALE	PRICE	SMLS	MINS	MPVS	COMS	SUVS	SEDS	BTRKM	MRPKW	BTCKWH	BWRKM	BWRY	WRPKM	WRPY	PCP	PCPB	FCM	BCM	NOS
PRICE	0.034																			
SMLS	0.047	−0.05																		
MINS	0.087	−0.431	−0.036																	
MPVS	−0.08	0.013	−0.015	−0.092																
COMS	0.006	−0.091	−0.043	−0.26	−0.109															
SUVS	−0.231	0.38	−0.08	−0.483	−0.202	−0.571														
SEDS	0.565	0.099	−0.013	−0.078	−0.033	−0.092	−0.17													
BTRKM	−0.002	0.442	0.004	−0.563	−0.026	0.071	0.326	0.175												
MRPKW	0.07	0.83	0.065	−0.467	−0.054	−0.049	0.371	0.122	0.551											
BTCKWH	−0.036	0.71	−0.026	−0.657	0.032	0.051	0.409	0.138	0.843	0.761										
BWRKM	0.117	0.095	0.15	−0.25	0.012	−0.006	0.108	0.185	0.258	0.243	0.261									
BWRY	0.156	0.08	0.175	−0.165	−0.209	−0.065	0.191	0.131	0.282	0.297	0.261	0.75								
WRPKM	−0.074	0.341	0.028	−0.223	0.021	−0.046	0.183	0.053	0.231	0.202	0.335	0.327	0.122							
WRPY	0.023	0.082	0.028	−0.131	0.248	0.161	−0.169	0.102	0.108	0.107	0.152	0.007	0.087	0.294						
PCP	0.076	−0.167	0.024	0.142	0.06	0.121	−0.241	0.009	−0.265	−0.15	−0.206	−0.088	−0.012	−0.301	0.004					
PCPB	−0.001	−0.12	0.04	−0.138	0.1	0.027	0.022	0.056	0.139	−0.106	0.071	0.099	0.104	0.043	−0.001	0.508				
FCM	0.064	0.077	0.032	−0.206	0.081	0.206	−0.064	0.036	0.065	0.054	0.146	0.039	0.051	0.041	0.051	0.554	0.446			
BCM	−0.029	0.094	0.017	−0.219	−0.129	0.14	0.132	−0.11	0.029	0.108	0.127	−0.021	0.019	−0.019	−0.152	0.448	0.299	0.717		
NOS	−0.085	0.46	0.013	−0.655	0.277	0.104	0.308	0.002	0.42	0.453	0.568	0.272	0.044	0.212	0.11	−0.15	0.17	0.191	0.115	
COV19	−0.046	0.065	0.047	−0.158	0.033	−0.098	0.152	0.101	0.375	0.143	0.278	0.181	0.166	0.083	−0.066	−0.099	0.27	−0.042	−0.057	0.16

Table 3 displays the fit regression analysis performed on the secondary data obtained for the sales of pure electric vehicles in the Chinese automobile industry to determine the influence of the other independent variable mentioned previously. The *p*-value of the best-fit regression model was found to be statistically significant at the 0.05 level. This indicates a statistically significant association between Sales and the model's independent variables. Since the *p*-value is less than 5%, we may assert with 95% confidence that our data is substantial. In addition, with an adjusted R^2 of 42.27%, it was concluded that the model's prediction accuracy was reasonably good. In addition, because the VIF value is less than 5, we may assert that our analysis is precise and the regression coefficient is reliably estimated due to negligible multicollinearity in the model. The link between Sales and Price, MINS, SEDS, BTCKWH, BWRY, WRPKM, PCP, PCPB, FCM, and COVID-19 was supported by substantial evidence.

Table 3. Best fit regression model analysis.

Term	Coef	SE Coef	T-Value	*p*-Value	VIF
Constant	1286	306	4.20	0.000	
PRICE	0.006286	0.000695	9.05	0.000	2.46
MINS	633	169	3.75	0.000	2.18
SUVS	−568	111	−5.14	0.000	1.57
SEDS	9081	283	32.12	0.000	1.13
BTCKWH	−26.43	4.77	−5.55	0.000	3.33
BWRY	116.5	15.6	7.48	0.000	1.19
WRPKM	−0.005768	0.000865	−6.67	0.000	1.24
PCP	−700	255	−2.75	0.006	2.55
PCPB	415	162	2.56	0.011	2.05
FCM	509	171	2.98	0.003	1.84
COV19	−360	114	−3.16	0.002	1.27

Consequently, Price was statistically significant, given that the *p*-value was 0. The regression equation revealed that sales of electric vehicles rose by six units when the Price of the vehicle was raised by 1000 RMB, while all other model variables remained the same. It was discovered that three-car size-related parameters had a statistically significant influence on the sales of pure electric vehicles. At the 0.05 level, MINS, SUVS, and SEDS were statistically significant. The regression equation indicated that electric vehicle sales rose by 633 units per MINS and 9081 units per SEDS for every SEDS. However, when SUVs became the primary vehicle type, sales of electric vehicles plummeted by 568 units per SUV. In addition to vehicle specifications, the BTCKWH factor was shown to have a statistically significant influence on sales, as indicated by the *p*-value of 0.

The regression research indicates that when the BTCKWH value of a car is increased by one unit, sales of pure electric vehicles decline by 26 units. However, variables related to battery warranties have a statistically significant influence on sales. Since both BTCKWH and BWRY have a *p*-Value of zero, the regression equation indicates that sales of pure electric vehicles grew by 116 units for each unit rise in BWRY. However, BTCKWH has a detrimental impact on the sales of pure electric vehicles, since a one-unit rise in BTCKWH results in an average 26-unit decline in sales. Likewise, WRPKM has a negative coefficient value of −0.005, indicating that a one-unit increase in WRPKM value will have a minor effect on sales volume. Two factors linked to charging capabilities were shown to have a statistically significant influence on the sales of pure electric vehicles. As the *p*-values for PCP and PCPB terms were very low, the regression equation indicated that sales of electric vehicles grew by 415 units when charging capacity was PCPB and decreased by 700 units on average for each unit increase in PCP charging capability. The fast-charging process parameters significantly impacted the sale variable. The FCM was statistically significant since the p-value was below 0.05. The regression equation indicated that sales of pure electric vehicles with FCM charging rose by 509 units. Lastly, one of the essential factors in our research is COVID-19, which has a p-value of only 0.002 and statistically significantly influences the sales of pure electric vehicles. The regression equation suggested that sales of pure electric vehicles decreased by 360 units during the COVID-19 pandemic since the value of the COVID-19 variable may only rise by 1 when sales were reported during the epidemic. The outcomes offered significant evidence for the connection between Sales and the aforementioned independent variable.

In summary, Table 4 shows this data model accounts for around 43% of the response variance, and the R2 value indicates that the model fits the data adequately. In addition, it is possible to declare that the predictor's coefficient is not equal to zero and that not all level means are equal. In conclusion, the relationship between a predictor and a response is dependent on the other predictors in the term.

Table 4. Best fit regression model summary.

S	R-sq	R-sq(adj)	R-sq(pred)
1993.34	42.58%	42.27%	40.99%

In ANOVA, the null hypothesis is that there is no difference between group means. If any group differs greatly from the overall group mean, then the ANOVA will provide a statistically significant result. The highest p-value, according to analysis in Table 5, is 0.011, which is less than the significance level of 0.05, we can reject the null hypothesis and conclude that each group has different means. This indicates that the variable of our regression analysis accounts for a significant amount of variation in the Sales variable of the pure electric vehicle. Therefore, there is very strong evidence to suggest that the means are not all equal. It is worth noting that there is no evidence that the model does not fit the data, as the p-value for the lack of fit test is greater than 0.05 ($p > 0.05$). The confidence interval in ANOVA was considered to be 95%. Durbin-Watson statistic is utilized to test for autocorrelation in the regression model's mistakes. Autocorrelation refers to the correlation between the errors of nearby data. The Durbin-Watson statistics of our analysis is 2.1, which is nearly equivalent to the value 2 in the Durbin-Watson statistics to suggest there was no autocorrelation in our analysis sample.

Table 5. ANOVA analysis.

Source	DF	Adj SS	Adj MS	F-Value	*p*-Value
Regression	11	5996595115	545145010	137.20	0.000
PRICE	1	325404218	325404218	81.90	0.000
MINS	1	55942444	55942444	14.08	0.000
SUVS	1	105007080	105007080	26.43	0.000
SEDS	1	4099823141	4099823141	1031.82	0.000
BTCKWH	1	122188276	122188276	30.75	0.000
BWRY	1	222127831	222127831	55.90	0.000
WRPKM	1	176767560	176767560	44.49	0.000
PCP	1	29946151	29946151	7.54	0.006
PCPB	1	25951091	25951091	6.53	0.011
FCM	1	35298789	35298789	8.88	0.003
COV19	1	39785989	39785989	10.01	0.002
Error	2035	8085852179	3973392		
Lack-of-Fit	204	5858658054	28718912	23.61	0.191
Pure Error	1831	2227194126	1216381		
Total	2046	14082447294			
Durbin-Watson statistics	2.1				

In the next step, we examined the relationship between the adoption of electric vehicles and the level of sustainable development. For this purpose, we used The Sustainable Development Reports that are published annually by the United Nations. In these reports, the ranking and index of the Sustainable Development Goals (SDGs) are presented. For this purpose, we collected data from 2016 to 2021 and analyzed the SDG Index Scores with the market share of EVs in different countries. For this purpose, we reviewed the data of 37 countries. The selected countries were those where EVs had a share of the total vehicle market during the study period. The results of the survey using the *t*-test show that the countries where EVs had a market share had an average of 14 points higher in the SDG index. The results of the *t* test are shown in Table 6. In this table, SDG Index Scores (Selected) are related to the countries in which electric vehicles have been sold, and SDG Index Scores (All) are related to all countries in the world. According to this table, it seems that there is a significant difference between the SDG index scores of countries with EVs markets and other countries. Countries with EVs market are more developed countries with higher SDG index scores.

Table 6. One-Sample T: to check the impact of the SDG index score on EVs market.

Sample	N	Mean	StDev	SE Mean	95% CI for μ
SDG Index Scores (Selected)	169	78.309	4.004	0.308	(77.701, 78.917)
SDG Index Scores (All)	967	64.710	11.229	0.361	(64.002, 65.419)

Also, for more certainty, we used the Two-Sample *t*-Test to compare the average score of the SDG index of the countries that own the electric vehicle market and other countries. The null hypothesis in this test is the equality of the average SDG index score of both samples. As Table 7 shows, due to the *p*-value being zero, the averages are not equal, and as a result, the average score of the SDG index for the countries with an electric vehicle market is about 13.599 points higher. This means that the countries with the electric vehicle market are more developed. As a result, it can be concluded that the development and higher level of SDG index score can effectively accept electric vehicles.

Table 7. Two-Sample *t*-Test: to check the impact of SDG index score on EVs market.

Sample	N	Mean	StDev	SE Mean
SDG Index Scores (Selected)	169	78.31	4.00	0.31
SDG Index Scores (All)	967	64.7	11.2	0.36
Estimation for Difference				
Difference		95% CI for Difference		
13.599		(12.667, 14.531)		
Test				
Null hypothesis		H_0: $\mu_1 - \mu_2 = 0$		
Alternative hypothesis		H_1: $\mu_1 - \mu_2 \neq 0$		
T-Value	**DF**	***p*-Value**		
28.65	712	0.000		

In addition, the correlation between the SDG index score and the market share of EVs shows that there is a positive and direct relationship between these two variables. In other words, a higher level of development and a higher score on the SDG index leads to a higher market share of EVs. In other words, this means that EVs have a higher market share in countries with a higher SDG index. That is, the acceptance of electric vehicles is higher in countries with a higher sustainable development rating. You can see the results of the correlation test and regression analysis in Table 8.

Table 8. Regression analysis of the relationship between EVs market share and the SDG index score.

Regression Equation					
EV Market Share =	**−0.814 + 0.01140 SDG Index Scores (Selected)**				
Coefficients					
Term	**Coef**	**SE Coef**	**T-Value**	***p*-Value**	**VIF**
Constant	−0.814	0.197	−4.13	0.000	
SDG Index Scores (Selected)	0.01140	0.00251	4.54	0.000	1.00
Model Summary					
S	**R-sq**	**R-sq(adj)**		**R-sq(pred)**	
0.130256	10.99%	10.46%		8.58%	
Analysis of Variance					
Source	**DF**	**Adj SS**	**Adj MS**	**F-Value**	***p*-Value**
Regression	1	0.3499	0.34992	20.62	0.000
SDG Index Scores (Selected)	1	0.3499	0.34992	20.62	0.000
Error	167	2.8334	0.01697		
Lack-of-Fit	147	2.2883	0.01557	0.57	0.969
Pure Error	20	0.5452	0.02726		
Total	168	3.1833			

5. Discussions

This research was designed to achieve three major goals. First, what factors of a vehicle's characteristics affect the adoption of EVs? Second, what has been the impact of COVID-19 on the market of EVs and their acceptance? And the third objective is to investigate the relationship between the level of sustainable development and the market share of EVs. For these purposes, we used grey econometric methods. Our research used two sets of data. We used data from the Chinese market for the first and second purposes. But for the third purpose, we used the data published by the United Nations and the SDG indicators.

The secondary data collected gave deep insights into an influential factor in adopting pure electric vehicles and an ideal vehicle specification for higher sales in the market. A few independent variables from the secondary data were not utilized for the regression analysis, such as BTRKM, MRPKW, SMLS, and MPVS. As it is not only insignificant in terms of other variables but also has very high intercorrelation. Moreover, our analysis has a fascinating insight into the sales distribution of Sedan's car size and the ratio of car models based on car size. Sedans have the fourth-highest sales distribution according to the car size, but the car size in market-based on ratio, Sedans are the 2nd lowest. Thus, it shows that though the sales of Sedans are high, the majority of manufacturer released more SUV models in the market than Sedans. This shows that Chinese consumers are not interested in a large vehicle with higher mileage, higher power, or more than five seats in the car. Instead, the majority of consumers want to drive a car with small battery electric vehicle models. A vehicle that is easier to park for all types of people takes less time to charge (as SUVS require a longer time to charge) and is well-suited for daily use, which is also supported by Ma et al. (2019) [30]. Thus, it illustrates that our model is precise and our interpretation is authentic.

In addition, the stats show that over 70% of the data retrieved was during the COVID-19 pandemic. As a result, the impact on monthly sales volume due to COVID-19 can be observed. In our regression analysis, Sedan's car size had the highest coefficient impact on the sales variable compared to the other car size in the market. Our regression analysis instantiates that COVID-19 decrease the sale of EVs in the market significantly. Since the coefficient is −360, which mean for each month, due to COVID-19, the sale of EVs is lower by 360 unit. Hence, it can be said that a pandemic like COVID-19 causes an overall reduction in sales of EVs in the Chinese market, which could be due to the strict nationwide lockdown. As people could not go and visit EVs showroom nor receive monthly wages during the initial phase of COVID-19 to spend on EVs purchase. Moreover, social distancing due to the pandemic is causing the problem of selling EVs in the traditional manner, leading the firm to change its strategy to sell online. However, this finding conflicts with the research conducted by Wen et al. (2021), where they found that EVs adoption increased in COVID-19 [1]. It is worth noting that their analyses are based on twelve months of COVID-19 and not for 26 months, as in our analysis. Since the pandemic has caused uncertainty in the market, such a difference due to the data set used in finding is logical.

Also, the fast-charging method and dedicated charging pile, and public charging pile variable had a significant favorable influence on sales. The finding is further supported in a published article by Mukherjee and Ryan (2020) [13]. Where there finding a state that EVs sold in the market will rise if the vehicle can be charged at home and if a car has a dedicated charging pile and public charging pile capability, then the vehicle can be charged at home using the dedicated charging pile given by the vehicle manufacturer. Thus, it can be said that our analysis illustrates validity in the real-world scenario and are coherent with previous finding to support the validity of our finding. Thus, it indicates that in order for EVs producers to alleviate customers' range anxiety, it is more effective to decrease the charging time by increasing the battery charging rate and ability to use the public and dedicated charging port rather than blindly increasing battery capacity and the driving range of EVs for Chinese EVs owners.

Also, the price variable shows a high standard deviation and range, due to the dynamic automobile market in China. As there are over 50 manufacturers in the market who sell the pure electric vehicle to serve customers in China and succeed in the market, the manufacturer varies the price of the car to grab the customer's attention and have a competitive advantage over the competitors. Such price difference is due to the manufacturer's vehicle specification, quality, and facilities. It is noteworthy that the price variable is not considered the most crucial variable in our regression analysis. As there is negligible impact on the sales due to the price variable. Since price is the most important variable for the Chinese consumer. So, it can be suggested that the manufacturer may develop good-looking vehicle designs, because in our secondary data collected, it had the highest volume of sales in a month even though the price was higher than similar cars manufactured by Chinese automobile firms. This is further strengthened by Chu et al. (2019), who compared the psychological and behavioral elements influencing EVs adoption and satisfaction in China and Korea [4]. The finding shows that the economic variable is not essential for Chinese consumers; instead, it is the environmental concern and consumer willing to pay higher for good-looking EVs. Hence, it goes without saying that our results are compatible with previous research findings and are precise.

The analysis in the context of battery warranty illustrates few meaningful insights. BWRY variable represents the battery warranty period in the number of years, whereas the WRPKM variable shows the vehicle warranty period in car mileage. The regression analysis instantiates that the battery warranty period variable positively influenced the sale of EVs, but the vehicle warranty period in car mileage variable had a negligible negative influence on the sale of EVs. Since a large portion of EVs purchasers in China are taxi drivers and people who travel short distances, the obvious choice of car for such a purchaser would be a car with a battery warranty for more years. The major drawback or concern for EVs customers is the battery of the vehicle and not any other component of the car. In addition, taxi drivers will often need to drive larger mileage and ensure battery life. But suppose the car has a battery warranty for several years. In that case, they can be assured about battery life for specific years and be encouraged to buy the car over an Internal combustion engine vehicle. On the contrary, people who travel short daily distances might not even dive to the mileage limit of a battery warranty. Hence, a higher number of years for the battery warranty will assure the purchaser for a specific time frame that they will not have anxiety about battery issues, which is one of the significant barriers to EVs purchase.

Finally, the analysis showed that the SDG index score and the market share of EVs have a positive and direct relationship. This means that a higher level of sustainable development can lead to a higher market share of EVs. The reason can be related to the need for infrastructure. It is clear that the development of EVs requires some infrastructure, and naturally, more developed countries have more opportunities to develop the necessary infrastructure. In addition, SDG depends on different dimensions. A higher score in the SDG index means more development of education, equality, and clean water, air, and environment, and naturally, the market share of EVs is also dependent on these things.

In addition, we are keen to point out the research of Omahne et al. (2021), who specifically addressed the social aspects of the adoption of EVs, and their results are interestingly similar to our research results [31]. As understood from the analysis of the published literature, it can be argued that there is a lack of articles evaluating the impact of electric vehicles on social welfare and user experience, and this is an important challenge to be addressed. In addition, articles that evaluate social impacts often study economic and environmental aspects in addition to the social aspect, which shows great progress in sustainability assessment and the trend of evaluating all three dimensions of sustainability. Finally, both their research and our research prove that sustainable development, in various social, economic and environmental dimensions, will eventually lead to the development of the use and acceptance of EVs as an infrastructure.

6. Conclusions

This research aims to investigate some factors affecting the adoption of EVs, including vehicle characteristics, the COVID-19 pandemic, and the level of sustainable development of countries. Grey econometric methods have been used for analysis. As a developing product, the demand and desires of customers for EVs have not yet been stabilized, and several researchers have attempted to determine these demand factors. This study examined customers' EVs preferences by collecting secondary data based on the monthly sales record of each EVs model and vehicle specifications in the Chinese market, considering the effects of COVID-19. We also used the United Nations-published data for the SDG index score to investigate its impact on the market share of EVs. The results mostly corroborate the broader literature and provide some intriguing insights that may be applied to other similar EVs markets that are present in the early adoption stage. We anticipate the model's precision to increase as data quality increases. Our econometric model identifies several significant factors influencing the adoption of pure electric vehicles.

The regression analysis which was used to study revealed that the COVID-19 pandemic had reduced the sales volume of pure electric vehicles. Moreover, the smaller overall volume of EVs like Sedans and Mini cars causes the sale volume to rise, unlike SUVs, which affects sale volume negatively. Although price and battery capacity variables were not considered the most important factor by Chinese consumers, the fast charging method with the dedicated charging pile and the public charging pile significantly positively affected sales. Hence, it is evident that customers who want to buy EVs with quick-charging batteries and flexibility to charge are more popular among consumers than those who cannot be charged quickly and cannot charge at the public station or at home. Not to mention, battery warranty in years (BWRY) is more crucial for the chinses consumer than vehicle warranty in km (WRPKM), when purchasing EVs in China. The results also showed that a higher SDG index score means a greater share of electric vehicles in the market.

The contribution of this research can be mentioned in several aspects. The first aspect relates to the dynamic approach of problem and uncertainty analysis. Considering the uncertain dynamic analysis method in this research leads to the results having a clearer view of the external reality. Since the problem is essentially uncertain and dynamic, the research results can be presented with better accuracy than other past research. The second essential contribution of this research is to consider conflicts outside the market, including the impact of a global pandemic on businesses, and especially the electric vehicles market as a growing innovation. Finally, the last contribution of the research is to consider the dynamic relationship of sustainable development infrastructures on the acceptance of electric vehicles and the opposite effect of these two factors. This approach can lead to an understanding of how different countries offer different adoption rates.

Although this study provides some novel insights for ongoing research, certain limitations remain. This study's analysis is based on mainland China. Consequently, the conclusion may not apply to all global market scenarios. Our data collection does not contain all the present vehicle models available and upcoming EVs. In order to increase the validity of the future study, larger data sets with a greater number of vehicle models may be used. Our regression study indicates that the independent variable COVID-19 has a negative effect on the dependent variable sale. There may be Spillover effects between sales and supply chain interruption resulting from COVID-19, a nationwide lockdown, socio-demographic characteristics, and promotion for which we have no data and are therefore unable to analyze. Each automobile model has many variants with varying specifications and prices. In our study, however, we utilized the specification of the most popular variation automobile and assumed that all sales of that model happened in the following month is based on the most popular model. In addition, we assumed that only the most recent model variation of a vehicle issued to the market is sold, and not older model variants. We require microdata to study sales depending on each variant's specifications for a particular model data.

To the best of our knowledge, this is one of the first studies to use secondary data to analyze the impact of the COVID-19 pandemic on EVs adoption in a country with the biggest number of EVs and the first COVID-19 outbreak. Although prior studies have extensively explored the factors that influence EV adoption, they have not specifically included pandemic situations such as COVID-19. In addition, the preponderance of the study employed the survey approach to determine the components rather than secondary data that is not affected by survey bias. Thus, our study offers new perspectives on EVs literature and enhances our understanding of the variables that impact the adoption of EVs in the Chinese electric vehicle market. Another thing that can be considered as an approach for future studies is the impact of the adoption of EVs on the power system at the macro level. The adoption of EVs will undoubtedly lead to the growth of demand and load on the electricity distribution system. Production capabilities, the impact of electrical energy production methods and electrical distribution systems and their relationship with sustainable development, and the level of acceptance of EVs can be a very important axis of research in the future. In addition, it is clear that the situation of COVID-19 is now far behind us. But it was important to understand its impact on the markets, and that's why we considered it. But as another suggestion for future research, it can be interesting to examine some speculations about the increase in demand for electric cars after quarantine, and social distancing, as well as supply and demand challenges for raw materials, semiconductors, the struggle to supply materials, and issues like that.

Supplementary Materials: The following supporting information can be downloaded at: https://www.mdpi.com/article/10.3390/wevj14050120/s1.

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