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Study on the impact of new energy vehicles on urban air quality

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Graphical abstract

Figure 1. Framework diagram of the research concept

Abstract

This study aims to assess the impact of the new energy vehicle industry on urban air quality in China, focusing on the spatial and temporal variation of $PM_{2.5}$ concentrations. Based on panel data from 286 prefecture-level cities in China from 2013 to 2022, an analytical framework is constructed, covering the development level of new energy vehicles, $PM_{2.5}$ concentrations, and seven control variables (population size, the number of traditional fuel vehicles, etc.). A Spatial Durbin Model (SDM) and instrumental variable method are used to test for spatial spillover effects. The research confirms the spatial autocorrelation of $PM_{2.5}$ through Moran's I index (0.3457) and verifies the robustness of the core conclusions. The results show that the development of new energy vehicles significantly reduces $PM_{2.5}$ concentrations (total effect -2.980), with environmental regulation, industrial structure upgrading, and technological innovation being the key mediating pathways, contributing to emission reductions of -0.219, -0.236, and -0.394, respectively. Heterogeneity analysis indicates that the emission reduction advantages are more pronounced in economically developed cities and resource-based cities. The conclusion suggests strengthening differentiated policy support, improving charging infrastructure and battery recycling systems, to collaboratively promote air quality improvement and low-carbon transformation.

Keywords: New energy vehicles; urban air quality; $pm_{2.5}$ index; spatial durbin model

1. Introduction

The intensification of the global energy crisis and the growing demand for environmental protection are key factors driving the development of the new energy vehicle industry (Arpaci *et al*. 2024) As the primary direction for the transformation and development of the automobile industry, new energy vehicles have achieved significant promotion and progress due to their substantial advantages in alleviating energy and environmental pressures. They are considered the best alternative to traditional fuel vehicles to realize environmental protection. According to the "*Regulations on the Access Management of New Energy Vehicle Manufacturers and Products*" issued by the Ministry of Industry and Information Technology of China, new energy vehicles refer to vehicles that use unconventional fuel as the source of power (or conventional fuel but with a new type of on-board power system). These vehicles primarily include Battery Electric Vehicles (BEVs), Plug-in Hybrid Electric Vehicles (PHEVs) and Fuel Cell Vehicles (FCVs) (Ministry of Industry and Information Technology of China, 2009). The International Energy Agency (IEA) released "*the World Energy Outlook 2023*", which states that under the established policy scenario, the consumption of coal, oil, and natural gas will peak between now and 2030. The excessive reliance on and consumption of traditional fossil fuels will not only lead to instability in energy supply, but also exacerbate issues of environmental pollution and climate change. Air pollution is a major challenge in the process of urbanization and industrialization, posing serious threats to human health and accelerating the rate of climate warming and the frequency of extreme weather events (Zhao and Sun. 2022). In response to the potential threats of air pollution to climate change and economic growth, the Chinese government has formulated a series of proactive policies to encourage the development of new energy vehicles. As early as 2009, the Ministry of Finance issued the "*Notice on Launching Pilot Programs for the Demonstration and Promotion of Energy-Saving and New Energy Vehicles*", initiating generous subsidies for new energy vehicles in various regions. Moreover, in 2011, the Ministry of

Finance, the Ministry of Science and Technology, the Ministry of Industry and Information Technology, and the National Development and Reform Commission jointly issued the "*Notice on Further Improving the Demonstration and Promotion of Energy-Saving and New Energy Vehicles"*, mandating the exemption of new energy vehicles from restrictions such as license plate number-based driving restrictions and lottery-based license plate issuance. On August 29, 2024, the State Council released the white paper "*China's Energy Transition"*, which comprehensively introduces China's efforts to promote a new model of green energy consumption, build a new energy system, and develop new energy productivity. The paper calls on the international community to pursue extensive energy cooperation, jointly address global climate change, promote harmonious coexistence between humans and nature, and jointly build a clean and beautiful planet. With strong support of the policy, data from the National Bureau of Statistics shows that in 2023, the production and sales of new energy vehicles in China reached 9.495 million units, with a year-on-year growth of 37.9%. In order to realize the government's goal of "carbon peak" by 2030 and "carbon neutrality" by 2060, the development of the new energy vehicle industry is regarded as an effective way to alleviate the energy crisis and improve the urban air quality. Evaluating its effectiveness in mitigating air pollution is a critical issue that urgently needs to be addressed (Su *et al*. 2021; Bigerna *et al*. 2021).

The rapid development of new energy vehicles has brought multiple benefits, including energy security, urban air quality improvement, noise mitigation, and greenhouse gas emission reduction (Rao. 2021; Henderson. 2020; Zhang and Qin. 2018). The development of new energy vehicles is considered an important means to combat climate change and air pollution. Several European countries, California in the United States, Japan, and numerous vehicle manufacturers have announced plans to phase out fuel vehicles (Dua *et al*. 2024; Nigam *et al*. 2024). As the world's largest automobile market, The development of the new energy vehicle market in China is particularly notable. In recent years, China has not only led globally in electric vehicle sales but also made remarkable achievements in policy support, technological innovation, and infrastructure construction. Government subsidy policies (Muehlegger and Rapson. 2022), large-scale construction of charging facilities, and increased consumer acceptance of new energy vehicles have collectively driven the rapid growth of China's new energy vehicle market. This paper primarily studies the impact of new energy vehicles on environmental pollution from the impact of $PM_{2.5}$ on air quality perspectives of exhaust emissions, technological progress and innovation, policy support, and public acceptance.

First, the impact of $PM_{2.5}$ on air quality. $PM_{2.5}$ (particulate matter with an aerodynamic diameter ≤ 2.5 μm) is a core component of urban air pollution, and its sources and toxic effects change significantly with the transition of the energy structure. $PM_{2.5}$ is one of the primary causes of hazy weather, and its increased concentration significantly reduces air visibility, affecting transportation and people's daily lives (Zhang *et al*. 2024. New energy vehicles such as electric vehicles) are powered by electricity and do not produce tailpipe emissions, including harmful pollutants such as particulate matter and carbon monoxide (Li and Zhang. 2024). A source apportionment study by Zhang *et al*. (2023) showed that the contribution of fuel vehicle exhaust to Beijing's $PM_{2.5}$ decreased from 15.7% in 2018 to 8.3% in 2022, directly related to the growth of NEV penetration rates. Therefore, studying the sources of $PM_{2.5}$, its influencing factors, and its impact on air quality is of great significance.

Second, the promotion of new energy vehicles plays an important role in reducing air pollutant emissions (Hawkins *et al*. 2013; Ke *et al*. 2017; Fang *et al*. 2019; Qiao *et al*. 2019). Focusing on GHG emission reduction, for example, using the Well-to-Wheels (WTW) life cycle analysis model to calculate the energy consumption and GHG emissions of a certain type of electric vehicle, studies have shown that the adoption of electric vehicles has a positive effect on reducing NO_X emissions. Song *et al*. (2023) found that pure electric vehicles can reduce fossil energy consumption and CO_2 emissions at the use end, but energy consumption is higher in the raw material processing and manufacturing assembly phases, suggesting that optimization of the power structure and improvement of the battery recycling can effectively reduce the economic cost of pollution control. Adila *et al*. (2020) in Shanghai case study proposed the promotion of new energy vehicles in the reduction of CO_2 and air pollutant emissions has synergistic benefits, especially pure electric buses show the best synergistic benefits in carbon emission reduction and air pollution control.

Third, the promotion and application of the innovation and development of new energy vehicle technology has a significant effect on improving air quality. Liang *et al*. (2019) proposed that the development of solid-state battery technology is expected to further improve the performance and safety of electric vehicles, while the application of autonomous driving technology will optimize traffic flow and reduce emissions caused by traffic congestion. The promotion of electric vehicles can significantly reduce the emissions of key precursor pollutants, such as VOC_s and NO_x, thus lowering the concentration of $PM_{2.5.}$ Zhang (2023) pointed out that there is regional heterogeneity in the impact of new energy vehicle technology innovation on air pollution. In cities with high population density and motorization, such as the Beijing-Tianjin-Hebei, Yangtze River Delta, and Pearl River Delta regions, the upgrade of the new energy vehicle industry structure has a more significant effect on improving air quality (El Hafdaoui *et al*., 2024). The promotion of electric vehicles is particularly effective in reducing $PM_{2.5}$ concentrations.

Fourth, policy support is a key factor to promote the development of new energy vehicles. By implementing policies such as car purchase subsidies, tax incentives, and subsidies for infrastructure construction, the popularization of new energy vehicles can be effectively promoted, thereby reducing urban atmospheric pollutant emissions (Lyu *et al*., 2014). The study by Wu *et al*. (2022) indicates that subsidies and driving restriction policies reduce air pollution by increasing the sales of new energy vehicle and alleviating road congestion, respectively. Han *et al*. (2020) suggests that new energy vehicle subsidy policies can more effectively facilitate the replacement of internal combustion engine vehicles with new energy vehicles. Zheng *et al*. (2020) proposes that unit subsidy policies can increase the market demand for new energy vehicles, while sales incentive policies can improve the market outcomes of unit subsidies and enhance the performance of government subsidies. Differentiated unit subsidy policies can reduce demand for low-quality vehicles and increase demand for high-quality vehicles without reducing the overall market demand, thus optimizing the market demand structure.

Fifth, public acceptance of new energy vehicles is one of the key factors to promote its popularity. Research by Xiao *et al*. (2016) and Asgarian (2024) indicates that the influencing factors of consumers' choice to purchase new energy vehicles include environmental awareness, availability of charging facilities, and openness to innovation. Efforts to enhance consumer environmental consciousness, strengthen the promotion of new energy vehicles, and optimize car purchasing policies aim to further promote the healthy development of the new energy vehicle market, ultimately reducing vehicle emissions and their impact on air pollution.

This study takes 286 prefecture-level cities in China as the research sample, employing empirical research and large-scale sample data analysis to reveal the impact of new energy vehicles on urban air pollution and provide systematic evidence to support the sustainable development of new energy vehicles in China. Considering that the influencing factors of new energy vehicles and air pollution are complex and diverse and interact with each other, the study incorporates regional characteristic variables into the analytical framework. By setting interaction terms, it avoids the interference caused by differences in numerical distribution trends and explores the regional development heterogeneity effect of new energy vehicle adoption on air pollution, ensuring the comparability of results. This study extends the existing literature in the following ways: First, it constructs a multidimensional analytical framework that includes population size, the stock of traditional fuel vehicles, and industrial emissions, breaking through the traditional research paradigm of a single causal chain. Second, it applies the Spatial Durbin Model to reveal the spatial spillover effect of new energy vehicles on $PM_{2.5}$ reduction and verifies the emission reduction advantages of economically developed cities and resource-based cities. Third, through the integration of spatial weight matrices and heterogeneity analysis, this study empirically validates the synergistic interplay among "policy incentives, technological diffusion, and environmental enhancement," thereby establishing a robust theoretical framework for designing interregional collaborative governance mechanisms.

2. Methodology and data

2.1. Data sources and research approach

To examine the impact of the development level of new energy vehicle on urban air quality and its spatial effects, this study utilizes statistical data from the National Bureau of Statistics of China, as well as various regional sources such as the *China Statistical Yearbook*, *China Automotive Industry Yearbook*, *Energy Saving and New Energy Vehicle Yearbook*, *China Energy Statistical Yearbook*, provincial and municipal statistical yearbooks, statistical bulletins, and the EPS database. Missing data were supplemented using linear interpolation where necessary. This study collected data on the level of new energy vehicle development, the $PM_{2.5}$ index, and a total of seven variables characterizing provincial features. Based on the current state of new energy vehicle development in China, a panel dataset was constructed, covering 286 prefecture-level cities from 2013 to 2022, yielding a total of 28,600 samples.

The dependent variable is the PM2.5 index, which is one of the key indicators for measuring urban air pollution and a primary cause of smog. Emissions from motor vehicles are a major source of PM2.5. PM2.5 has a significant spatial spillover effect and can be diffused across regions through atmospheric circulation. This requires the use of the Spatial Durbin Model (SDM) to capture its geographical correlation. The original data for this study comes from the Atmospheric Composition Analysis Team at Washington University in St. Louis, and the mean values of the PM2.5 index were obtained after organizing the data according to China's prefecture-level administrative boundaries.

Core explanatory variable: The development level of new energy vehicles. The development of the new energy vehicle industry can effectively reduce the dependence of automobile industry on oil resources and reduce environmental pollution, making it a key driver for the green transformation and upgrading of the automotive industry. Therefore, this study uses the proportion of new energy vehicle production to total automobile production to represent the development level of new energy vehicles.

Control Variables: To minimize bias caused by omitted variables and ensure the accuracy of the estimation results, this study includes the following eight variables as control factors to evaluate their impact on urban air quality. The specific variables are as follows: (1) Urban Population Size: The population size directly influences the urban activity levels and energy consumption, which in turn indirectly affects air quality. When assessing the impact of new energy vehicles on air quality, it is essential to control the variable of urban population size to eliminate interference from population growth or decline. (2) Economic Development Level: The economic development level of a city is closely related to energy consumption and environmental pollution. Cities with higher levels of economic development tend to have more vehicles and higher energy consumption, which may have an impact on air quality. (3) Number of Traditional Fuel Vehicles: Traditional fuel vehicles are one of the main sources of urban air pollution. When assessing the impact of new energy vehicles on air quality, it is necessary to control the number of traditional fuel vehicles in order to more accurately measure the environmental benefits brought by new energy vehicles replacing traditional fuel vehicles. (4) Expenditure on Science and Education: Regions with higher expenditures on science and education and with more educated populations are more likely to perceive the risk of environmental deterioration. They are more willing to pay for improvements in air quality and more likely to purchase new energy vehicles. (5) Urban Green Coverage Rate: Green plants have a certain capacity to absorb and purify air pollutants. Therefore, the urban green coverage rate is an important control variable, as it can help assess the relative contribution of new energy vehicles in reducing air pollution. (6) Industrial Dust Emissions: In addition to transportation, industrial production is a significant source of urban air pollution. Controlling the intermediary variable of industrial emissions can exclude the impact of industrial production on air quality, and thus assess the environmental protection effect of new energy vehicles more accurately.

Mediating Variables: This study selects three mediating variables. (1) Environmental Regulation Intensity: Regions with high industrial emissions or serious ecosystem degradation are likely to adopt more stringent environmental regulations, and are more inclined to recognize the restoration ability of new energy vehicles. (2) Industrial Structure Upgrading: Promoting new energy vehicles may accelerate the transformation and upgrading of industrial structure and reduce air pollution to a certain extent. (3) Level of Technological Innovation: The technological innovation of new energy vehicles can promote the improvement of the urban environment, significantly reduce air pollution and promote green travel by reducing emissions and improving energy efficiency, thus realizing sustainable development.

The purpose of this study is to empirically test the impact of the New Energy Vehicle Development Index and its control variables on urban air quality in China. The dependent variable in this study is determined according to the estimation results of the air quality of Chinese cities, combined with GDP data provided by the National Bureau of Statistics and municipal statistical bureaus. The descriptive statistical results for these foundational data are shown in **Table 1**.

Table 1. Descriptive Statistics of All Empirical Test Variables

Variable Coincidence	Mean	Standard Deviation	Minimum	Maximum
PM2.5	45.2734	12.8346	18.3453	89.7112
NEVE	18.5663	10.2460	2.1147	45.3214
UPZ	5.7548	0.698 7	2.9374	8.1734
LED	7.7344	0.937 0	4.7458	10.5463
NTFV	5.4738	1.7878	0.0890	8.7494
ESE	13.3044	0.8436	9.6754	16.568 8
UGCR	38.5011	8.2221	12.4301	55.6204
IDE	3.2418	2.1328	0.5339	12.5417
ER	51.2653	21.5944	22.5894	89.2939
ISU	45.3499	11.006 3	10.6790	89.7501
LTI	5.5165	1.7933	0.0906	8.8950

2.2. Theoretical model and research hypotheses

In the context of the “dual-carbon” goal, economic growth is no longer the sole indicator of development, and the urgent challenge is to reconcile the relationship between environment and development (Aqib *et al*., 2023). Furthermore, reducing pollutant emissions and building an environmentally friendly society are important paths to achieve sustainable development and maintain competitiveness. New energy vehicles, especially electric vehicles, use electricity as a power source, which greatly reduces greenhouse gas emissions compared to traditional fuel vehicles (Zahoor *et al*. 2023; Abdul-Manan 2015). New energy vehicles do not produce exhaust emissions during operation, thus avoiding the pollution of air quality by harmful substances in exhaust gases, which has a positive effect on improving urban air quality (Williams *et al*. 2023; Güzel,2024). The development of new energy vehicles has obvious heterogeneous characteristics for the improvement of urban air quality. Managers can leverage new energy vehicle technology advancements to address regional disparities and effectively reduce the concentration of $PM_{2.5}$ in the air, thereby achieving urban air quality enhancement. Based on the above theoretical analysis, we can establish the first research hypothesis regarding the impact of the development of new energy vehicles on urban air quality. Research Hypothesis H1: New energy vehicles can reduce carbon emissions, lower the concentration of $PM_{2.5}$ in the air, and improve urban air quality. The impact of the development of new energy vehicles on $PM_{2.5}$ in urban air includes both direct and indirect effects. The direct effect is generated through the role of explanatory and control variables, while the indirect effect is primarily through the role of mediating variables.

According to the current state of China's economic development, in the process of reducing the $PM_{2.5}$

concentration in the air by the use of new energy vehicles in China, the impact of new energy vehicles on reducing the concentration of $PM_{2.5}$ in the air is primarily mediated by three variables: environmental regulation (ER), industrial structure upgrading (ISU), and the level of technological innovation (LTI). Thus, this study proposes the second research hypothesis, H2: environmental regulation, industrial structure upgrading, and technological innovation level are mediating variables in the impact of new energy vehicles on urban air quality. In the process of the impact of new energy vehicles on urban air quality, there is a significant spatial spillover effect, which is mainly manifested through the following characteristics: new energy vehicle industry correlation effect, technological innovation spillover effect, industrial correlation effect, resource-sharing effect and etc. Therefore, the development of new energy vehicles can improve urban air quality through resource integration, industrial structure adjustment and green technology progress. Accordingly, this study proposes the third research hypothesis, H3: there is an obvious spatial spillover effect of new energy vehicles on the improvement of urban air quality.

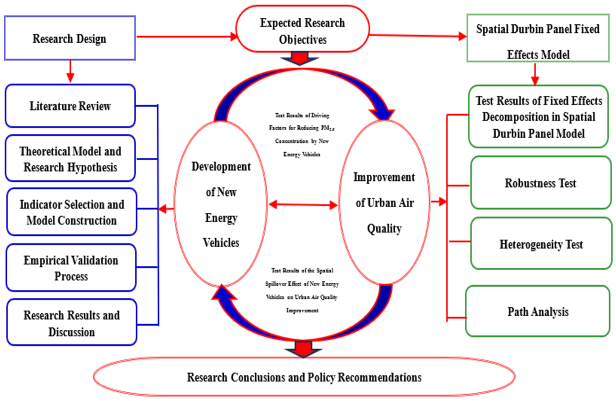

Figure 1. Framework diagram of the research concept

2.3. Construction of the spatial durbin model

2.3.1. Construction of the spatial relative weight model

In order to test the existence of spatial spillover effects of the impact of the development level of new energy vehicles on air quality, this paper proposes the Durbin spatial model based on the spatial model, which is selected on the basis of a comprehensive analysis: spatial adjacency matrix, economic weight matrix, and spatial economic and geographic weight matrix. The SDM can effectively deal with the spatial dependence of urban air quality data. By introducing spatial weighting matrices (e.g., adjacency matrix, economic-geographical matrix), the model captures the spatial spillover effect of $PM_{2.5}$ concentration and avoids the estimation bias caused by ignoring the geographic or economic correlations in traditional linear regression. By explicitly decomposing effects into direct impacts (local policy-driven changes) and indirect spillovers (cross-regional diffusion through adjacency or economic linkages), the SDM provides a more precise quantification of the net air quality improvements attributable to new energy vehicle adoption. The spatial adjacency matrix reflects the relationship between neighboring cities, assigning a value of 1 to neighboring cities and 0 to non- neighboring cities. The economic weight matrix reflects the economic development level relationship between two cities, represented as the reciprocal of the GDP difference between them. The spatial economic-geographic weight matrix is the weighted average of the spatial adjacency matrix and the economic weight matrix. If W1 represents the spatial adjacency matrix, W2 represents the economic weight matrix, and W3 represents the spatial economic-geographic weight matrix, the three matrices can be expressed as follows:

$$
\begin{gathered}
W_1=\begin{pmatrix} 1 & 0 & 0 & 0 \\ 0 & 1 & 0 & 0 \\ 0 & 0 & \vdots & 0 \\ 0 & 0 & 0 & 1 \end{pmatrix};\ W_2=\left(GDP_j-GDP_i\right)^{-1}; \\
W_3=\xi\begin{pmatrix} 1 & 0 & 0 & 0 \\ 0 & 1 & 0 & 0 \\ 0 & 0 & \vdots & 0 \\ 0 & 0 & 0 & 1 \end{pmatrix}+(1-\xi)W_2
\end{gathered}
\tag{1}
$$

In the above equation, ξ represents the weight coefficient of W_3. According to the spatial weight theory, it is generally set ξ as 0.4, which makes the value of W_3 biased towards W_2. To examine the spillover effect of the development level of new energy vehicles and its control variables on air quality in Chinese cities, the Moran's I index is introduced. The spatial test results of Moran's I index are used to assess the impact of the independent variables on the dependent variables. Moran's I is a statistical test method proposed and first applied in 1950. According to Moran's I theory, when the value of Moran's I lies within the range [-1, 1], Moran's I > 0 indicates positive spatial correlation, the larger the value of Moran's I suggests stronger spatial correlation; Moran's I < 0 indicates negative spatial correlation, the smaller the value of Moran's I suggests greater spatial disparity. When Moran's I = 0, the spatial pattern is random. The formula for calculating Moran's I is as follows:

$$
I=\frac{n\sum_{i=1}^{n}\sum_{j=1}^{n}w_{ij}\left(x_i-\bar{x}\right)\left(x_j-\bar{x}\right)}{\sum_{i=1}^{n}\sum_{j=1}^{n}w_{ij}\sum_{i=1}^{n}\left(x_i-\bar{x}\right)^2}=\frac{\sum_{i=1}^{n}\sum_{j\neq i}^{n}w_{ij}(x_i-\bar{x})(x_j-\bar{x})}{S^2\sum_{i=1}^{n}\sum_{j\neq i}^{n}w_{ij}}
\tag{2}
$$

According to statistical theory and methods, the standard statistic Z is generally used to test the significance level of the indicator. The standard statistic for Moran's I uses the following model to calculate the Z value. The specific econometric model is as follows:

$$
Z=\frac{I-E(I)}{\sqrt{VAR(I)}}=\frac{\sum_{j\neq i}^{n}w_{ij}(d)(x_j-\bar{x}_i)}{S_i\sqrt{w_i(n-1-w_i)/(n-2)}}\quad j\neq i
\tag{3}
$$

To improve the effectiveness of spatial testing for variables, this paper introduces the spatial statistic of C, denoted as Geary's C. This indicator is commonly referred to as the Geary's Contiguity Ratio, and the calculation formula for this spatial statistic is as follows:

$$c = \frac{(n-1)\sum_{i=1}^{n}\sum_{j=1}^{n} w_{ij}\cdot\left(x_i - x_j\right)^2}{2\sum_{i=1}^{n}\sum_{j=1}^{n} w_{ij}\cdot\sum_{i=1}^{n}\left(x_i-\bar{x}\right)^2} = \frac{(n-1)\sum_{i=1}^{n}\sum_{j=1}^{n} w_{ij}\cdot\left(x_i - x_j\right)^2}{2nS^2\sum_{i=1}^{n}\sum_{j=1}^{n} w_{ij}} \quad (4)$$

In the equation, W_{ij} is the relative weight of the squared difference between variables, n is the number of variables, and S represents the standard deviation of the variable. The value range of this indicator can be expressed as Geary's C in [0, 2]. When Geary's C = 1, it indicates no spatial autocorrelation. When Geary's C < 1, it suggests positive spatial autocorrelation, and when Geary's C > 1 indicates negative spatial autocorrelation. Based on statistical theory and methods, the standard statistic for the Geary's C index is calculated as follows:

$$C^{*} = \frac{C-1}{\sqrt{Var[C]}} = (C-1)\cdot\left[\left(\left(2W_2+W_3\right)\cdot(n-1)-4W_1^2\right)\cdot\left(2(n+1)\cdot W_1^2\right)^{-1}\right]^{-1/2} \quad (5)$$

In the equation: $W_1 = \sum_{i=1}^{m}\sum_{j=1}^{n} w_{ij}$, $W_2 = \frac{1}{2}\sum_{i=1}^{m}\sum_{j=1}^{n}\left(w_{ij}+w_{ji}\right)^2$, $W_3 = \sum_{i=1}^{m}\left(\sum_{j=1}^{n} w_{ij} + w_{ji}\right)^2$. Under the null hypothesis, the calculation formula for *p* is as follows:

$$p = erfc\left(\frac{\left|C - E[C]\right|}{\sqrt{2Var[C]}}\right) \quad (6)$$

Given that urban air quality in Chinese cities is influenced by numerous factors, this paper focuses on analyzing the impact of selected core explanatory variables on the dependent variable. As there are various forms of the Spatial Durbin Model constructed in this study, we draw on the structure of the Spatial Durbin Model and, after adjustments, obtain the following expression for the Spatial Lag Model:

$$Y_{it} = \rho WY_{it-1} + \delta_1 X_{it} + \beta_1 WX_{it} + \delta_2 X_{it} + \beta_2 WX_{it} + \mu_i + \eta_t + \varepsilon_i \quad (7)$$

The above formula is the general form of the Spatial Lag Model (SLM). In this equation: Y_{it} is the dependent variable, also known as the explained variable. On the right side of the equation, Y_{it-1} is called the lagged term. X_{it} represents the vector of driving factors, W_{it} denotes the spatial weight matrix, ρ, δ and β is the coefficient to be determined, μ_i represents individual fixed effects, ηt indicates time fixed effects, and ε_{it} is the error term. Based on the actual conditions of cities in China, seven control variables are selected: the development level of new energy vehicles (NEVE), urban population size (UPZ), level of economic development (LED), number of traditional fuel vehicles (NTFV), science and education expenditure (ESE), urban green coverage rate (UGCR), and industrial dust emissions (IDE). Substituting these variables into the Spatial Durbin Lag Model yields the following test equation:

$$\begin{aligned} PM_{2.5it} &= \rho WPM_{2.5it-1} + \delta_1 NEVE_{it} + \delta_2 UPZ_{it} + \delta_3 LED_{it} \\ &+ \delta_4 NTFV_{it} + \delta_5 ESE_{it} + \delta_6 UGCR_{it} + \delta_7 IDE_{it} + \beta_1 W_{it} NEVE_{it} \\ &+ \beta_2 W_{it} UPZ_{it} + \beta_3 W_{it} LED_{it} + \beta_4 W_{it} NTFV_{it} + \beta_5 W_{it} ESE_{it} \\ &+ \beta_6 W_{it} UGCR_{it} + \beta_7 W_{it} GRC_{it} + \varepsilon_{it} \end{aligned} \quad (8)$$

The indirect impact of new energy vehicles on urban air quality is primarily realized through mediating variables. This paper selects three mediating variables: environmental regulation (ER), industrial structure upgrading (ISU), and level of technological innovation (LTI). The model for the indirect effects of the mediating variables is as follows:

$$\begin{aligned} ER_{it} &= \rho WPM_{2.5it-1} + \delta_1 NEVE_{it} + \delta_2 UPZ_{it} + \delta_3 LED_{it} \\ &+ \delta_4 NTFV_{it} + \delta_5 ESE_{it} + \delta_6 UGCR_{it} + \delta_7 IDE_{it} + \beta_1 W_{it} NEVE_{it} \\ &+ \beta_2 W_{it} UPZ_{it} + \beta_3 W_{it} LED_{it} + \beta_4 W_{it} NTFV_{it} + \beta_5 W_{it} ESE_{it} \\ &+ \beta_6 W_{it} UGCR_{it} + \beta_7 W_{it} GRC_{it} + \varepsilon_{it} \end{aligned} \quad (9)$$

$$\begin{aligned} ISU_{it} &= \rho WPM_{2.5it-1} + \delta_1 NEVE_{it} + \delta_2 UPZ_{it} + \delta_3 LED_{it} \\ &+ \delta_4 NTFV_{it} + \delta_5 ESE_{it} + \delta_6 UGCR_{it} + \delta_7 IDE_{it} \\ &+ \beta_1 W_{it} NEVE_{it} + \beta_2 W_{it} UPZ_{it} + \beta_3 W_{it} LED_{it} + \beta_4 W_{it} NTFV_{it} \\ &+ \beta_5 W_{it} ESE_{it} + \beta_6 W_{it} UGCR_{it} + \beta_7 W_{it} GRC_{it} + \varepsilon_{it} \end{aligned} \quad (10)$$

$$\begin{aligned} LTI_{it} &= \rho WPM_{2.5it-1} + \delta_1 NEVE_{it} + \delta_2 UPZ_{it} + \delta_3 LED_{it} + \delta_4 NTFV_{it} \\ &+ \delta_5 ESE_{it} + \delta_6 UGCR_{it} + \delta_7 IDE_{it} + \beta_1 W_{it} NEVE_{it} + \beta_2 W_{it} UPZ_{it} \\ &+ \beta_3 W_{it} LED_{it} + \beta_4 W_{it} NTFV_{it} + \beta_5 W_{it} ESE_{it} + \beta_6 W_{it} UGCR_{it} \\ &+ \beta_7 W_{it} GRC_{it} + \varepsilon_{it} \end{aligned} \quad (11)$$

The mediating variables have a direct impact on urban air quality in Chinese cities and reflect the indirect effects of driving factors on urban air quality. The mechanism of mediating factors is illustrated in **Figure 1**. The impact of these mediating factors on urban air quality in China is determined through empirical tests, which show that making full use of these mediating indicators to reduce the concentration of $PM_{2.5}$ is an effective approach to improving air quality in Chinese cities.

Table 2. Results of Spatial Correlation Tests Between Variables

variable	Moran's I	P	Geary's C	P
PM2.5	0.3457***	0.0021	0.3216***	0.0001
NEVE	0.2853***	0.0016	0.3024***	0.0002
UPZ	0.3188***	0.0022	0.3429**	0.0011
LED	0.2786***	0.0017	0.3110***	0.0001
PTFV	0.2897***	0.0019	0.2899***	0.0001
ESE	0.3219***	0.0020	0.3119***	0.0003
UGCR	0.3126***	0.0027	0.3307**	0.0040
IDE	0.3206***	0.0023	0.3227**	0.0029
ER	0.2814***	0.0031	0.3052**	0.0035
ISU	0.2967***	0.0024	0.3184***	0.0018
LTI	0.2675***	0.0018	0.2973***	0.0009

3. Analysis of research results

3.1. Testing for spatial correlation of empirical variables

To examine the impact of driving factors on urban air quality across Chinese cities, all test variables in the study were normalized. Based on this normalization, spatial correlation tests were conducted on the selected variables. Using the specified test models (2) and (5) from the research design, Moran's I and Geary's C tests were applied to all variables to assess their spatial correlation. The specific test results are shown in **Table 2**.

To verify the validity of the variables and model, this study selects the LM (Lagrange Multiplier), LR (Likelihood Ratio), and Hausman tests to examine the spatial correlation of variables. The LR and LM tests aim to determine whether the variables exhibit spatial lag and the extent of the spatial error effect, while the purpose of the Hausman test is to assess whether the variables follow a fixed effects model or a random effects model, thus identifying the appropriate spatial test model. Detailed results of the LM, LR, and Hausman tests are presented in **Table 3**.

Table 3. Tests for Variable Lag, Error Effect, and Model Selection

Inspection method	Coefficient	P Value	
LM Test	LM (error) test	45.327	0.000***
	Robust LM（error）test	38.216	0.000***
	LM (lag) test	22.154	0.001***
	Robust LM (lag) test	18.743	0.002***
LR Test	SDM&SAM chi2	36.529	0.000***
	SDM&SEM chi2	64.817	0.000***
Hausman Test	19.452	0.004***	

Table 4. Decomposition Test Results of Fixed Effects in the Spatial Lag Model

Variables	Direct Effect	Indirect Effect	Total Effect
NEVE	-2.800*** (-2.076)	-0.1796*** (-4.868)	-2.9796*** (-3.557)
UPZ	0.3926** (2.973)	0.2368** (2.557)	0.6294*** (2.215)
LED	-0.4757*** (-4.538)	-0.1853*** (-4.294)	-0.6610*** (-3.547)
NTFV	0.4826** (2.499)	0.2133** (2.270)	0.6959** (2.234)
ESE	-0.3149*** (-4.174)	-0.1795*** (-3.817)	-0.4944* (-3.283)**
UGCR	-0.4147*** (-4.428)	-0.1643*** (-4.184)	-0.5790*** (-3.437)
IDE	0.4615** (5.333)	0.1248*** (4.184)	0.5863*** (3.654)
$W\cdot PM_{2.5t-1}$	0.3723*** (4.455)	0.1726*** (4.089)	0.5449*** (2.864)
W· NEVE	-0.5143** (4.286)	-0.1784** (-3.874)	-0.6927** (3.674)
W· UPZ	0.3575*** (2.898)	0.1908*** (2.474)	0.5483*** (2.163)
W· LED	-0.4746** (3.465)	-0.1850*** (3.337)	-0.6596*** (3.175)
W· NTFV	0.4818*** (3.663)	0.2100*** (3.264)	0.6918*** (3.175)
W· ESE	-0.3083*** (-2.884)	-0.1732** (-2.685)	-0.4815*** (-2.603)
W· UGCR	-0.4076*** (-4.333)	-0.1554*** (-4.184)	-0.5630*** (-3.653)
W·IDE	0.4467*** (5.333)	0.1137** (4.184)	0.5604*** (3.654)
Rho	0.2284*** (3.684)	0.1878*** (3.522)	0.4162*** (3.487)
R^2	0.4527	0.4328	0.4237
$sigma^2$	0.0895	0.0881	0.0874
log L	-10.1738	-54.9837	-47.8536

*Note: ***, **, and * denote significance levels of 1%, 5%, and 10%, respectively. Values in parentheses represent T-statistics. The corresponding probability for significance is P < 0.05.*

According to the test results in **Table 3**, it is evident that the P-values of the LM test (LM-error=0.000, LM-lag=0.001) are significantly smaller than 0.05, which means that the null hypothesis is rejected. This indicates the existence of spatial autocorrelation effect (both error terms and lagged terms are present). Based on the test results, the Spatial Durbin Model (SDM), which can simultaneously include both spatial lag and error terms, is chosen. The LR test results show that the comparisons between SDM and SAR (Chi^2 = 36.529, P = 0.000) and between SDM and SEM (Chi^2 = 64.817, P = 0.000) are all significant at the 1% level, indicating that the SDM cannot be reduced to either the SAR or SEM model, and thus the full model form should be retained. The Hausman test statistic of 19.452 (P=0.004) is significant at the 5% level, leading to the rejection of the random effects null hypothesis and supporting the fixed effects model. Based on the comprehensive test results, the Spatial Durbin Fixed Effects Model is ultimately chosen for empirical analysis.

3.2. Test results of the spatial lag model

According to the analysis results, fixed effects can be decomposed into direct effects and indirect effects. Based on this effect decomposition, test model (10) is applied to examine the different effects (Yang *et al.*, 2022). The specific test results are shown in **Table 4**.

In **Table 4**, Total Effect = Direct Effect + Indirect Effect. To improve the accuracy of the test, the results are retained to four decimal places. According to the results for direct effects, the level of new energy vehicle development (NEVE) has the most significant impact on urban air quality, with a direct effect coefficient of -2.800***. The total effect further expands to -2.9796***, indicating a significant contribution to emission reduction. The direct effects of the number of traditional fuel vehicles (PTFV) and the level of economic development (LED) on $PM_{2.5}$ concentrations are 0.4826 and -0.4757*, respectively, with total effects of 0.6959 and -0.6610*, ranking second and third, respectively. Expenditure on science and education (ESE) and urban greening coverage rate (UGCR) show significant negative impacts on $PM_{2.5}$ concentrations, with total effects of -0.4944 and -0.5790, suggesting that investments in science and education and improvements in greening can collaboratively suppress pollution. Among other driving factors, industrial dust emissions (IDE) have the most prominent positive impact (total effect 0.5863***), followed by urban population size (UPZ, total effect 0.6294***). The lagged term of $PM_{2.5}$ concentration (W $PM_{2.5t-1}$) has a total effect of 0.5449***, further validating the spatial spillover effect of air pollution. The coefficients of weighted terms (such as W NEVE, W PTFV) have the same direction as the non-weighted terms, but their absolute values are slightly reduced, indicating that the introduction of spatial weight matrices weakens the spatial aggregation of local pollution.

3.3. Discussion of fixed effects test results

To examine the impact of different combinations of all independent variables on the $PM_{2.5}$ concentration index of urban air quality in China, the Spatial Durbin Lag Model is simplified by omitting spatial weights, modifying it to a general lag model. The simplified lag model can be represented as follows:

$$\begin{aligned} PM_{2.5it} &= \rho PM_{2.5it-1} + \delta_1 NEVE_{it} + \delta_2 UPZ_{it} + \delta_3 LED_{it} \\ &+ \delta_4 NTFV_{it} + \delta_5 ESE_{it} + \delta_6 UGCR_{it} + \delta_7 IDE_{it} + \varepsilon_{it} \end{aligned} \tag{11}$$

In this framework, variables from the model above are combined in various forms, with common elements including the coefficient of the test equation and the lagged term of provincial energy carbon emission intensity $PM_{2.5it-1}$. Based on this, independent variables are added one by one: NEVE, UPZ, LED, NTFV, ESE, UGCR, and IDE to form the test equations with seven distinct combinations of variables. The specific test results are presented in **Table 5**.

Table 5. Test Results of Fixed Effects Model with Different Variable Combinations

Variables	Model (1)	Model (2)	Model (3)	Model (4)	Model (5)	Model (6)	Model (7)
	0.5152*** (4.574)	0.5228*** (4.476)	0.5435*** (4.416)	0.5567*** (4.340)	0.5651*** (4.190)	0.5765*** (4.230)	0.5813*** (4.071)
$PM_{2.5it-1}$	-0.5078*** (-4.451)	-0.5137*** (-4.348)	-0.5263*** (-4.264)	-0.5367*** (-4.365)	-0.5535*** (-4.265)	-0.5563*** (-4.165)	-0.5698*** (-4.408)
NEVE		0.4780*** (4.562)	0.4906*** (4.485)	0.5083*** (4.372)	0.5175*** (4.276)	0.5237*** (4.187)	0.5156*** (4.467)
UPZ			-0.5108*** (-2.467)	-0.5256*** (-2.376)	-0.5246*** (-2.217)	-0.5358*** (-2.086)	-0.5467*** (-2.563)
LED				0.5026*** (5.863)	0.5085*** (5.637)	0.5101*** (5.464)	0.5129*** (5.376)
NTFV					-0.4861*** (-5.354)	-0.5064*** (-4.782)	-0.5146*** (-4.026)
ESE						-0.4968*** (-4.539)	-0.4376*** (-4.571)
UGCR							0.4782*** (4.877)
IDE	0.5152*** (4.574)	0.5228*** (4.476)	0.5435*** (4.416)	0.5567*** (4.340)	0.5651*** (4.190)	0.5765*** (4.230)	0.5813*** (4.071)

*Note: ***, **, and * denote significance levels of 1%, 5%, and 10%, respectively. Values in parentheses represent T-statistics.*

According to the test results in **Table 5**, the results of Model (1) show that the constant δ, the lagged term of the $PM_{2.5}$ concentration index for urban air quality in China, and NEVE jointly have an impact on the $PM_{2.5}$ index for urban air quality in China, with an impact coefficient of -0.4968 for the explanatory variable NEVE. The results of Model (2) primarily reflect the combined impact of NEVE and UPZ on $PM_{2.5}$, with impact coefficients of -0.5484* and 0.4780, respectively. Model (3) mainly reflects the combined impact of NEVE, UPZ, and LED on $PM_{2.5}$, with impact coefficients of -0.5327, 0.4906, and -0.5108, respectively. Model (4) reflects the combined impact of NEVE, UPZ, LED, and NTFV on $PM_{2.5}$, with coefficients of -0.5427, 0.5083, -0.5256, and 0.5026. Model (5) reflects the combined impact of NEVE, UPZ, LED, NTFV, and ESE on $PM_{2.5}$, with coefficients of -0.5535, 0.5175, -0.5246, 0.5085, and -0.4861. Model (6) shows the effects of NEVE, UPZ, LED, NTFV, ESE, and UGCR, with coefficients of -0.5563, 0.5237, -0.5358, 0.5101, -0.5064, and -0.4968. Model (7) reflects the combined impact of all driving factors on urban air quality, with corresponding impact coefficients of -0.4980, 0.5156, 5.5467, 0.5129, -0.5146, -0.4376, and 0.4782. Therefore, the results of Model (7) represent the final test results.

3.4. Test results of mediation effects

Although the complete elimination of fossil energy is the key to realizing the green transformation of China's cities, clean energy currently constitutes less than 20% of total energy consumption in China. Therefore, a comprehensive shift to clean energy is not feasible in the short term. Under these circumstances, China must also rely on environmental regulation, industrial structure upgrading, and technological innovation to reduce the $PM_{2.5}$ concentration index. In this study, three mediating variables are selected: environmental regulation (ER), industrial structure upgrading (ISU), and the level of technological innovation (LTI). The mediating effects of these variables on the $PM_{2.5}$ concentration in urban air quality are shown in **Table 6**.

The test results in **Table 6** clearly show that the mediating effect on urban air quality through environmental regulation is -0.2190, through industrial structure upgrading is -0.2362, and through the level of technological innovation is -0.3941. This demonstrates that these mediating variables are able to inhibit the $PM_{2.5}$ concentration, thereby contributing to the improvement of urban air quality in China.

Table 6. Test Results of Mediation Effects

Indicator	Environmental Regulation (ER)		Industrial Structure Upgrading (ISU)		Level of Technological Innovation (LTI)	
	ER	$PM_{2.5}$	ISU	$PM_{2.5}$	LTI	$PM_{2.5}$
NEVE	0.898*** (4.295)	-0.765*** (-4.202)	0.825*** (4.008)	-0.765*** (-4.435)	0.778*** (3.916)	-0.659*** (-4.555)
ER		-0.219*** (-4.358)				
ISU				-0.2362*** (-4.2570)		
LTI						-0.394*** (-4.189)
Constant	3.238*** (4.673)	2.829*** (4.347)	2.183*** (4.236)	2.138*** (4.158)	1.901*** (4.096)	1.796*** (3.928)
Control Variables	Controlled	Controlled	Controlled	Controlled	Controlled	Controlled
Individual Effects	Controlled	Controlled	Controlled	Controlled	Controlled	Controlled
Time Effects	Controlled	Controlled	Controlled	Controlled	Controlled	Controlled
N	28,600	28,600	28,600	28,600	28,600	28,600
R2	0.382	0.317	0.354	0.298	0.415	0.336

*Note: *** indicates significance at the 1% confidence level, ** at the 5% confidence level, and * at the 10% confidence level. Values in parentheses represent T-test results.*

4. Discusssion of research findings

4.1. Robustness analysis of research results

In order to verify the validity of the driving factors affecting urban air quality, it is necessary to conduct a robustness test on the equation and its variables by using the empirical testing theory of quantitative economics. According to the principles of robustness testing, there are multiple testing methods. This study selects the alternative variable method, fixed effects control method, and lag period test method for verification. Carbon emission intensity is used as a substitute for the $PM_{2.5}$ index as the dependent variable. By reducing carbon emission intensity to decrease fossil energy consumption, improving energy efficiency and developing renewable energy, not only can greenhouse gas emissions be reduced, but also the concentrations of other pollutants can be significantly decreased, thereby improving air quality. Charging station density is used as a substitute for the level of new energy vehicle development. Infrastructure adequacy is a key support for promoting new energy vehicles. The high density indirectly promotes the demand for car purchases and reduces the use of traditional fuel vehicles. Furthermore, the study applies the fixed effects control method to enhance stability, mainly controlling the fixed effects of each city as well as the interaction effect between the city and year variables. The specific test results are shown in **Table 7**.

From the above test results, it is evident that using the natural logarithm of urban industrial dust emissions as a substitute for the urban air quality index ($PM_{2.5}$) passed the significance test at the 10% confidence level and exhibited a positive impact effect. The results of other robustness tests all passed the significance test at the 1% confidence level, strongly indicating the robustness of the model and its variables.

4.2. Heterogeneity analysis of research results

New energy vehicles can alleviate urban air pollution, significantly reducing the $PM_{2.5}$ index. Next, this study further analyzes the clean energy effects of new energy vehicles from the perspective of urban heterogeneity. This approach aims to strengthen the causal relationships between variables, highlight the impact of differences in development levels across cities, and provide empirical evidence for the new energy vehicle support policies implemented by national and local governments. To conduct the heterogeneity test, this study categorizes 269 cities across 30 provinces in China into two groups based on average GDP: high-level cities and low-level cities. High-level cities, with GDP above the average, include 104 cities, while low-level cities, with GDP below the average, comprise 165 cities. Based on the list of resource-dependent cities published by the State Council, Chinese cities are also classified into resource-based and non-resource-based cities. Using these two city classifications, the study conducts heterogeneity tests employing the pre-constructed test model and prepared foundational data. The specific test results are shown in **Table 8**.

Table 7. Results of Robustness Analysis

Variable	Alternative Variable Method		Fixed Effects Control Method		Lag Test Method		
	Carbon emissions (substitute for PM2.5)	Charging station density (substitute for NEVE)	Control for City Effects	Control for Year Effects	1-Period Lag	2-Period Lag	3-Period Lag
NEVE	-0.484*** (-4.852)	0.632*** (-4.158)	0.483*** (5.080)	0.367*** (4.820)	0.378*** (4.271)	0.367*** (3.871)	0.387*** (3.967)
UPZ	0.392** (2.973)	-0.546*** (-2.173)	0.236** (2.557)	0.185** (2.084)	0.332*** (4.186)	0.338*** (4.064)	0.341*** (4.236)
LED	-0.475*** (-4.852)	0.616** (2.205)	-0.185*** (-4.294)	-0.173** (-2.685)	0.367*** (3.871)	0.356*** (3.616)	-0.155*** (-4.184)
PTFV	0.482** (2.499)	0.506** (2.231)	0.213** (2.270)	0.210** (3.264)	0.333*** (4.423)	0.328*** (4.232)	0.124*** (4.184)
ESE	-0.314*** (-4.852)	-0.571** (-2.182)	-0.179*** (-3.817)	-0.173** (-2.685)	0.349*** (4.326)	0.345*** (4.152)	-0.164*** (-4.184)
UGCR	-0.414*** (-4.428)	0.561** (2.262)	-0.164*** (-4.184)	-0.155** (-4.184)	0.341*** (4.426)	0.339*** (4.236)	0.113** (4.184)
IDE	0.461*** (5.333)	0.513*** (4.876)	0.124* (4.184)	0.118* (3.954)	0.586* (3.654)	0.579* (3.587)	0.602* (3.721)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes
City effect	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year effect	Yes	Yes	Yes	Yes	Yes	Yes	Yes
City-F	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year-F	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	28,600	28,600	28,600	28,600	28,600	28,600	28,600
R2	0.44	0.4	0.39	0.38	0.39	0.42	0.45

*Notes: Significance levels are indicated by ***, **, and * for the 1%, 5%, and 10% levels, respectively. T-test values are shown in parentheses.*

Table 8. Test Results of Heterogeneity in New Energy Vehicle Development Levels and Urban Classification

Variable	Classified by Urban Type		Classified by Average GDP per Capita	
	Resource-based City	Non-Resource-based City	High GDP per Capita City ECI	Low GDP per Capita City ECI
NEVE	-0.819*** (-3.754)	-0.657** (-2.456)	-0.784*** (-4.026)	-0.622••• (-2.528)
Constant	0.995*** (3.347)	1.621** (2.273)	1.089*** (3.634)	1.520*** (2.179)
Control Variables	Controlled	Controlled	Controlled	Controlled
Individual Effects	Controlled	Controlled	Controlled	Controlled
Time Effects	Controlled	Controlled	Controlled	Controlled
N	28600	28600	28600	28600
R^2	0.329	0.213	0.148	0.282

*Notes: Significance levels are indicated by ***, **, and * for the 1%, 5%, and 10% levels, respectively. T-test values are shown in parentheses.*

From the table above, it is clear that the impact of new energy vehicle development on urban air quality is more significant in high-level cities and resource-based cities, while the corresponding effect is relatively lower in other cities. Additionally, the significance of new energy vehicle development on urban air quality is higher in high-level and resource-based cities, with both passing the 1% significance level test. In contrast, the significance of the corresponding impact in other cities is lower, passing only at the 5% or 10% significance levels.

5. Summary and recommendations

In order to investigate the impact of new energy vehicles on urban air quality and to explore effective strategies to maximize urban air quality improvement in China, this study estimated the concentration of $PM_{2.5}$ across urban areas by making full ues of city-level $PM_{2.5}$ concentration measurements and provincial GDP statistics. Based on these estimates, the effects of selected drivers on the concentration of $PM_{2.5}$ in urban air were examined by using the spatial Durbin panel model, the test-determined fixed-effects model, and the basic statistics. The findings reveal that four driving factors—the development level of new energy vehicle (NEVE), the level of economic development (LED), the expenditure on science and education (ESE), and urban greening coverage ratio (UGCR)—all exhibit a negative impact on $PM_{2.5}$ concentration, indicating a suppressive effect on urban air $PM_{2.5}$ levels. The corresponding coefficients are -2.9796, -0.6610, -0.4944 and -0.5790, respectively. Conversely, three other driving factors show a positive association with increased urban $PM_{2.5}$ concentration, with coefficients of 0.6330, 0.6959, and 0.5863, respectively. The study also found that: environmental regulation (ER), industrial structure upgrading (ISU) and the innovation technology level (LTI) have an intermediate suppressive effect, the corresponding impact coefficients are: -0.2190, -0.2362 and -0.3941, each significant at the 1% level. To further advance the development of the new energy vehicle industry and maximize its positive impact on urban air quality, this research proposes the following policy recommendations and implementation strategies:

Enhance Policy Support: Provide financial subsidies to consumers purchasing new energy vehicles to reduce purchase costs and increase the market competitiveness of new energy vehicles. Continue to implement the new energy vehicle purchase tax exemption policy, extending it through the end of 2027, with a gradual reduction in exemption rates to facilitate a smooth market transition. Additionally, intensify the promotion of new energy vehicle initiatives in rural areas to stimulate the consumption potential in these markets.

Strengthen Market Regulation and Legislation: First, the government should formulate and enhance regulations and standards relevant to the new energy vehicle industry to ensure environmental performance, safety, and compliance throughout the production process. Second, accelerate the legislation on the recycling and reuse of power batteries by establishing comprehensive management systems for battery transport and storage, repair and maintenance, safety inspection, decommissioning and withdrawal, re and etc. This would facilitate lifecycle monitoring, so as to promote the development of the industry in terms of resource-efficient, high-value, and greening.

Enhance the Construction of Charging Infrastructure: Increase the construction of charging stations by leveraging technologies such as big data analysis to accurately forecast charging demand and optimize infrastructure layout, accelerate the construction of a high-quality charging infrastructure system, thereby addressing issues like “difficult to find piles”. Reasonable plan and establish charging stations across urban areas, promoting the construction of charging infrastructure in public areas such as parking lots, gas stations, tourist attractions, etc. Ensure that 100% of fixed parking spaces in newly built residential areas are equipped with charging infrastructure or reserved for installation.

Strengthen Research and Development in Technology and Innovation: Increase R&D investment in battery technology to improve energy density, cycle life, and safety while reducing battery costs. Promote the deep integration of new energy vehicles with the energy, transportation, and information and communication sectors, supporting cross-industry collaboration among enterprises. This approach focuses on diverse production and application needs, fostering the development of ecosystem-leading enterprises that cover key segments of the industry chain, including solution design, R&D and production, usage support, and operational services.

Enhance Public Awareness of Environmental Protection: Strengthen publicity and education, popularize the environmental advantages and use of new energy vehicles to the public through various channels and means, and increase the public's awareness of environmental protection and willingness to purchase vehicles. Promote the concept of green travel by advocating for eco-friendly transportation methods and encouraging citizens to opt for public transportation, cycling, or walking as low-carbon travel options to reduce the frequency of private car use.

In summary, the new energy vehicle industry has a significant positive impact on urban air quality. To fully leverage its environmental benefits, coordinated efforts from the government, enterprises, and the public are essential. A series of policy measures and implementation strategies are needed to drive the development and widespread adoption of new energy vehicles.

Data availability statements

Due to the nature of this research, participants of this study did not agree for their data to be shared publicly, so supporting data is not available.

Conflict of interest

This paper is a phased achievement of the author's participation in National Bureau of Statistics Optimal Project (2024LY054). Five authors cooperate to complete it. The authors rank according to their contributions. There is no conflict of interest between the author and any individual or organization. This paper conforms to the research scope of this journal. All authors agree to submit the manuscript to this journal.

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