frontiers | Frontiers in Sustainable Energy Policy

TYPE Original Research
PUBLISHED 03 December 2024
DOI 10.3389/fsuep.2024.1457743

Check for updates

OPEN ACCESS

EDITED BY
Sanjay Kumar Kar,
Rajiv Gandhi Institute of Petroleum Technology, India

REVIEWED BY
Elżbieta Macioszek,
Silesian University of Technology, Poland
Giacomo Di Foggia,
University of Milano-Bicocca, Italy
Richard Kotter,
Northumbria University, United Kingdom

*CORRESPONDENCE
Hermas Abudu
17720170155924@stu.xmu.edu.cn

RECEIVED 01 July 2024
ACCEPTED 08 November 2024
PUBLISHED 03 December 2024

CITATION
Abudu H, Sai R, Hossin MA and Botah EB (2024) China's electric vehicles adoption: implications for sustainable electricity, transportation, and net-zero emissions. *Front. Sustain. Energy Policy* 3:1457743. doi: 10.3389/fsuep.2024.1457743

China's electric vehicles adoption: implications for sustainable electricity, transportation, and net-zero emissions

Hermas Abudu[1]*, Rockson Sai[2], Md Altab Hossin[3] and Elvis Banoemuleng Botah[4]

[1]College of Overseas Education, Chengdu University, Chengdu, China, [2]Department of Engineering Management, School of Management, Guangzhou University, Guangzhou, Guangdong, China, [3]School of Innovation and Entrepreneurship, Chengdu University, Chengdu, China, [4]Center for Peace and Security Research, University of Professional Studies, Accra (UPSA), Madina, Ghana

Introduction: The rapid adoption of electric vehicles in China is a key strategy for decarbonizing the transportation sector, facilitating the transition to sustainable energy, and meeting the country's net-zero emissions goals. Notwithstanding this, limited research has explored how technological advancement influences electric vehicle adoption in the context of achieving sustainable electricity.

Methods: This study addresses this gap by integrating vehicle range, smart charging infrastructure, and battery electric vehicles into an econometric count framework utilizing countrywide data-driven insights.

Results: The findings demonstrate that technological advancements-specifically in vehicle range and the expansion of charging infrastructure-are vital solutions in driving battery electric vehicles acceptance. These advancements are essential for revolutionizing the transportation industry and contributing to the country's emissions reduction targets.

Discussion: However, this presents a dual challenge: balancing increased electricity demand while capitalizing on these technologies to meet net-zero goals. The study highlights critical policy implications, particularly the need to advance electric vehicle material technologies through the use of critical minerals including aluminum and lithium. By prioritizing these materials, producers can improve electric vehicles' efficiency and support the integration of renewable energy sources. The study concludes that incorporating renewable energy solutions, like solar-powered charging stations, is crucial for ensuring sustainable electricity. Policies encouraging public-private partnerships and investments in research on materials and smart charging technologies are crucial for reducing charging times and improving vehicle range. Additionally, fostering public-private collaborations to install smart charging infrastructure equipped with Internet-of-Things technology at parking slots can create a synergistic effect, significantly boosting electric vehicle adoption in China.

KEYWORDS

vehicle range electricity demand nexus, China net-zero emissions goals, charging infrastructure matters, sustainable energy policy, electric vehicle adoption strategies, econometric count model framework

1 Introduction

The urgent global need to combat climate change has intensified the focus on energy transition and industrial decarbonization. Therefore, several studies (Franzò and Nasca, 2021; Haidar and Rojas, 2022; Xu and Lin, 2024) emphasize that achieving net-zero emissions and carbon neutrality heavily depends on the decarbonization of the transport and energy industries. In this regard, China has demonstrated a strong commitment to meeting the goals of environmental sustainability through ambitious energy transition strategies aimed at achieving net-zero emissions. As the world's largest carbon emitter, China has made a pivotal shift in its energy policies by pledging to peak emissions by 2030 and achieve carbon neutrality through decarbonization by 2060 (Li et al., 2018, 2019). Central to this transition is a large-scale adoption of renewable energy sources (Lin and Abudu, 2020; Zou et al., 2024), such as solar, wind, and hydropower, as well as promoting electric vehicles (EVs) to decarbonize the transportation sector (Tao, 2024). China's commitment to these initiatives is reflected in its aggressive investments in clean energy technologies, energy-efficiency programs, and carbon capture and storage (CCS) systems (Li et al., 2022; Liu et al., 2023). China's adoption of EVs as early as 2010 marked a significant step toward industrial decarbonization and sustainable transportation (Li et al., 2018; Tao, 2024).

Despite significant attention to electric vehicle adoption (EVA) in China, research gaps remain in understanding the role of technological advancements in driving this transition (Tao, 2024). Existing studies have largely focused on socioeconomic factors, including consumer choices, initial costs, and incentive programs (Li et al., 2019; Guo et al., 2021). However, this focus leaves a gap in research on critical technological factors, such as vehicle range (VR), charging infrastructure (CI), and battery electric vehicles (BEVs; Franzò and Nasca, 2021; Squalli, 2024; Li et al., 2022). Although research has examined battery materials and EV durability, challenges around CI and city readiness for widespread EV integration remain, particularly in developing countries (Gohlke et al., 2022; Li et al., 2018). For instance, underdeveloped e-mobility infrastructure in Poland's Górnośląsko-Zagłębiowska Metropolis underscores the need for expanded networks to meet increasing demand (Kowalski et al., 2020). Similarly, many cities worldwide struggle with inadequate urban planning, complicating the integration of charging stations into existing transportation systems (Kaminski and Szczepaniak, 2021). Even with incentive programs, inconsistent implementation and low public awareness hinder EVA in many regions (Lewicki and Nowak, 2021). Other persistent barriers, such as high costs, limited battery lifespans, and slow charging speeds, further complicate global EV promotion efforts (Jurczak and Kowalski, 2021). Addressing these challenges demands coordinated efforts in infrastructure development, innovative policy, and technological advancements.

While studies in Spain, France, the United States, and Germany have explored EV integration (Buhmann and Criado, 2023; Haidar and Rojas, 2022; Squalli, 2024), fewer studies examine the impacts of these factors on EVA in China. This gap presents an opportunity to investigate how technological advancements specifically influence EVA in China, a country with a long-standing commitment to EV market growth. Research on VR, smart CI, and BEVs in EVA remains limited, as does analysis on how EVA affects electricity demand (ED) and contributes to net-zero emissions goals, particularly using national data-driven insights (Pirmana et al., 2023; Tao, 2024). The objectives of this study are to fill these gaps by addressing the following research questions: (1) how do VR, CI, and BEV technologies impact EVA? and (2) How do EVA, ED, and oil displacement (OD) interact to support net-zero emissions in China? This study uniquely models the synergistic effects of VR and CI, particularly focusing on smart-charging solutions (Buhmann and Criado, 2023). By incorporating socioeconomic factors as control variables, it contributes to the literature through a count model framework that deepens understanding of technological impacts on EVA (Yang et al., 2017; Khan et al., 2022). The study provides insights for policymakers and researchers on EVA trends, Internet of Things (IoT)–enabled CI deployment, OD, and electricity consumption from 2010 to 2022. Furthermore, it formulates hypotheses linking technological factors to EVA, thereby enhancing research design and scientific replicability. Leveraging nationwide data-driven insights, this research expands the literature on EV integration (Li et al., 2018; Buhmann and Criado, 2023) and offers valuable applications for sustainable transportation and net-zero policy development (Haidar and Rojas, 2022; Tao, 2024).

2 Literature review and hypothesis development strategy

2.1 Nexus between EVA, ED, and OD

Studies indicate that the widespread adoption of EVs has the potential to significantly reduce the consumption of fossil fuels in the transportation sector (Axsen et al., 2020). In this regard, scholars have analyzed the growth of the EV market and its impact on the substitution of fossil fuels with electricity, and the findings highlight substantial reductions in greenhouse gas emissions in other countries (Li et al., 2018; Bakhtyar et al., 2023). The literature shows that the shift toward environmentally friendly transportation in China may have far-reaching implications on relying on imported oil and making China a pioneer in the EV industry (Fuinhas et al., 2021; Gohlke et al., 2022; Li et al., 2018). Also, studies have emphasized the environmental benefits (Vaishnav, 2023) of EVs in terms of reduced emissions and the cost savings associated with using electricity instead of gasoline or diesel fuel. Researchers have explored the impact of electric buses and other forms of electric public transportation on fossil fuel displacement and air quality improvements in urban areas (Pirmana et al., 2023). Similarly, the literature indicates that the widespread adoption of EVs significantly may increase ED and has shown that the extent of this impact depends on factors such as charging patterns, battery technology, and the overall growth rate of EVs (Li et al., 2018). Researchers have examined regional variations in the impact of EVs on ED, emphasizing the role of government policies and incentives in shaping adoption rates (Buhmann and Criado, 2023) and charging behavior (Ge and MacKenzie, 2022). So, investigations have highlighted the importance of smart CI and grid integration to optimize the use of renewable energy sources (Amuakwa-Mensah and Näsström, 2023) on the impact of EVs on the grid. The literature findings suggest that scholars have explored the role of time-of-use pricing in managing the impact of EVs on ED and suggest that this dynamic pricing strategies encourage off-peak charging, thereby reducing stress on the grid during peak hours (Ge and MacKenzie, 2022). In conclusion, integrating EVs into China's transportation sector is a promising avenue for addressing the Sustainability Development Goals (SDGs), particularly, 7 and 11–13 (Abudu et al., 2023). However, only a few empirical studies have focused on the ramifications of widespread EVA in China concerning ED and OD data-driving experiences, which are central to achieving net-zero carbon emissions and neutrality (Ge and MacKenzie, 2022; Squalli, 2024). Literature suggests the adoption of EVs, particularly BEVs, over plug-in hybrid electric vehicles (PHEVs) and internal combustion engine vehicles (ICEVs; Franzò and Nasca, 2021; Buhmann and Criado, 2023) directly influences ED dynamics. The question arises of whether China's electricity generation mix aligns with the sustainability goals of reducing carbon emissions (Xu and Lin, 2024). Also, the extent to which EVA may lead to cleaner energy sources as a crucial determinant in the carbon footprint of electricity consumption remains unexplored. Moreover, theoretical literature shows (Franzò and Nasca, 2021; Buhmann and Criado, 2023) that EVA holds the potential to reduce oil displacement. Therefore, this study aims to explore the research gap in understanding the holistic impact of EVA in the context of China.

2.2 Technological factors influencing EVA

The move toward sustainable transportation and decarbonization of industry, particularly in the context of EVs, marks a significant turning point in the global automotive sector. Notably, China, renowned as the world's largest automotive market, stands as a leader in spearheading this transformative journey (Xu et al., 2020). As China embraces EVA, various technological factors have come to the forefront, shaping the trajectory of this shift (Li et al., 2022; Mastoi et al., 2022). One of the primary factors influencing EVA in China and globally is VR and battery technology. Research by Li et al. (2018) emphasizes the critical role of increasing the driving range of EVs in consumer acceptance. Moreover, the domain of battery technology innovations, which include extended VR and accelerated charging capabilities, is primed to exert a significant impact on EVA, thereby bringing the world closer to meeting sustainable transportation (Haidar et al., 2020). Studies have explored how advancements in battery technology, particularly in extending VR, influence the adoption of EVs. The literature has examined the relationship between increasing VR and EVA rates, by providing insights into consumer preferences (Oliveira et al., 2019; Barkenbus, 2020). This study employs a stated choice experiment to investigate how varying VR affects consumers' preferences and choices when it comes to EVs (Barkenbus, 2020). Also, technological factors through governments' initiatives to invest in CI have been critical in addressing the VR anxiety of potential EV buyers where studies have shown that the availability of charging stations significantly influences the willingness of consumers to switch to EVs (Sovacool et al., 2018; Xue et al., 2021). Also, CI is another significant technological factor, Hardman et al. (2018) conducted a study on CI deployment, highlighting the importance of accessible charging stations. Literature shows that BEVs have gained prominence in China's EV landscape. Barkenbus (2020) explored the growth of BEVs, emphasizing that as they become more affordable and widely available, adoption rates increase, underscoring the role of technological advancements in battery technology. Smart-charging systems are revolutionizing the EV industry. Xu et al. (2020) investigated the impact of smart charging systems on EVA in China, indicating that such systems enhance consumer confidence by making charging more convenient and efficient. Battery-swapping technology and renewable charging stations are other areas of innovation (Barkenbus, 2020). These technologies address range anxiety by allowing quick and efficient battery replacement, further promoting EVA. Literature showed that policy support for advanced EV technologies accelerates adoption rates, providing a clear link between government actions and technological progress. Challenges related to charging tariffs may influence adoption rates (Liu et al., 2023). Finally, emerging EV technologies, such as solid-state batteries and wireless charging or the IoT, are discussed by Xue et al. (2021). These innovations are expected to shape the future of EVA in China (Xue et al., 2021). Similarly, the presence of charging stations, particularly the availability of smart chargers, renewable charging stations, and their correlation with EVA rates have not yet received ample scholarly attention (Xue et al., 2021; Squalli, 2024).

In conclusion, the literature underscores the need for EVA on ED and oil displacement, with China emerging as a key player in this transition. Studies highlight that EVA may contribute to reducing greenhouse gas emissions, displacing fossil fuel consumption, and enhancing urban air quality. However, challenges remain in aligning China's electricity generation mix with sustainability goals, and there is a gap in understanding the precise effects of EVA on ED. Technological advancements, particularly in battery technology, extended VR, and CI, have been crucial in driving EVA, and hereafter, further research is needed to explore the holistic effects of these innovations. Finally, while advancements in battery swapping, smart-charging systems, and renewable energy integration are promising, there is a lack of comprehensive databases to conduct empirical studies on EVA in China, which is essential for achieving carbon neutrality and net-zero goals.

2.3 Hypotheses development

In contributing to the literature, this study developed the following logical hypotheses, aligned with the literature (Buhmann and Criado, 2023) to strengthen the empirical analysis:

Hypothesis 1: The availability and accessibility of CI may significantly enhance EVA in China.

Hypothesis 2: VR anxiety negatively impacts BEV adoption in the Chinese EV market.

10.3389/fsuep.2024.1457743

Hypothesis 3: BEVs have a greater impact on ED relative to PHEVs, HEVs, and other EV types in China.

Hypothesis 4: Optimizing both smart CI and VR has a positive synergistic effect in EVA.

Hypothesis 5: Increased adoption of EVs in China is expected to significantly increase the country's overall electricity consumption.

Hypothesis 6: The adoption of EVs in China will lead to a substantial displaced oil consumption and a corresponding reduction in emissions.

3 Model design and data strategy

This study employs a comprehensive data modeling approach in analyzing China's EVA and its implications for sustainable electricity, transportation, and net-zero emissions. Using data from the International Energy Agency (IEA) covering the period from 2010 to 2022, the analysis focuses on key factors such as ED, electricity prices (EPX), EV prices (PX), government subsidies (SD), EV stock shares (ST), charging infrastructure (CI), and oil displaced (OD). A Poisson regression model (PRM) is used to estimate the count of EVs in China and assess the relationship between EVA and these variables, particularly focusing on BEVs, VR, and CI density. The charging stations are classified into fast and slow chargers, allowing the study to investigate the influence of fast charging on EV uptake. The model also incorporates autoregressive terms to capture temporal growth patterns in China's EV market. In ensuring the study's robustness, a negative binomial model (NBM) is employed to address potential over dispersion in the data, providing a reliable basis for evaluating the impact of EVA on this topic on China's transition toward net-zero emissions.

3.1 Data modeling strategy

In responding to the research questions and hypotheses, the study utilizes various socioeconomic factors as control variables, data sourced from the IEA covering the period from 2010 to 2022 in China. This data set provides a comprehensive, data-driven perspective on EVA in China. The key socioeconomic control variables include ED, EPX, and PX, which are based on the framework presented in the literature (Haidar et al., 2020). These variables are crucial in understanding the broader context of EVA as they directly influence consumer costs and infrastructure demands. In addition to these factors, the study incorporates data on EV stock share and government rebates or SD. *EV stock shares* refer to the stocks of companies involved in the production and supply of EVs. Including this variable is important because investments in the EV sector expose stakeholders to a rapidly growing market driven by the increasing demand for eco-friendly transportation and advancing technology (Haidar et al., 2020). Government subsidies and rebates are another critical factor, as the Chinese government has implemented a wide range of policies to incentivize the EVA, including subsidies, tax benefits, rebates, and preferential regulations, such as license plate policies. These policies aim to encourage both consumers and manufacturers to transition toward EV uptake (Pirmana et al., 2023). The primary model centers on the count of EVA, which is a key variable in this analysis. The adoption of EVs is particularly focused on BEVs, which is coded as 1 in the data set if there is a positive growth rate from 2010 to 2022 and 0 otherwise. This coding also applies a dummy effect (Long and Freese, 2014) for PHEVs and ICEVs, reflecting the distinct technological and market conditions for these vehicle types.

Furthermore, the variable VR is included, with BEVs being coded at an average range of 300 miles and PHEVs being coded as having a range of 300-plus miles, including ICEVs. The study also distinguishes between different types of CI, coding 1 for smart/fast-charging stations and 0 for slower charging stations, which significantly impacts EVA rates and usage patterns. This classification of CI enables the study to investigate the role of fast-charging technology in the EV ecosystem. Another unique feature of the study is its focus on four key vehicle categories—buses, vans, cars, and trucks—which are significant due to their substantial energy consumption and frequent use. These vehicle categories are essential to understanding the broader impact of EVA on energy consumption and emissions (Barkenbus, 2020; Li et al., 2018). By incorporating these factors, the study provides a broader view of the dynamics driving the transition to EVs in China and offers insights into how different types of vehicles contribute to the overall impact on energy infrastructure and environmental outcomes. Consequently, this study is unique because it incorporates a wide range of control variables while focusing on the diverse factors that influence EVA, including market forces, government policies, technological advancements, and vehicle-specific characteristics. By coding these variables effectively, the study provides a robust framework for econometric analysis, which is used to evaluate the impacts of BEVs, CI, and government incentives on the growing EV uptake in China. Also, in contributing to the literature with novelty to the research, the authors employed advanced Stata techniques for coding and analyzing the data set (Long and Freese, 2014). By leveraging Stata, the authors ensured accuracy in data processing and hypothesis testing, using modern data analytics to understand EVA in China. The Stata code used in this study is available upon request from the corresponding author, allowing for reproducibility and further exploration of the data set.

3.2 Basic statistics and summary

Table 1 provides a detailed breakdown of EVA from 2010 to 2022, categorized by vehicle type (bus, car, truck, and van) and powertrain type (BEV and PHEV).

As of 2022, the data in Table 1 reveals that China has sold a total of 11,937,980 BEVs and 3,138,850 PHEVs, bringing the total number of EVs to 15,076,830. According to Table 2, this widespread adoption of EVs has displaced approximately 59.6 million barrels of oil, measured in liquefied gas equivalent. This significant reduction in oil consumption highlights China's growing commitment to reducing reliance on fossil fuels, curbing carbon emissions, and advancing its transition to a more sustainable and energy-efficient transportation system. The large-scale integration of EVs in China also sets an important precedent for industrial decarbonization in the transportation sector, promoting cleaner air, lowering greenhouse gas emissions, and encouraging global

TABLE 1 Total type of electric vehicle adoption in China.

	Year	2010	2011	2012	2013	2014	2015	2016	2017	2018	2019	2020	2021	2022	Total
BUS	BEV	1,900	450	1,400	2,000	4,100	94,000	90,000	90,000	94,000	75,000	62,000	48,000	52,000	**614,850**
BUS	PHEV	0	330	1,000	3,500	12,000	26,000	15,000	530	2,400	2,600	3,600	1,700	2,300	**70,960**
CAR	BEV	0	0	9,600	15,000	49,000	150,000	260,000	470,000	820,000	830,000	920,000	2,700,000	4,400,000	**10,623,600**
CAR	PHEV	0	0	0	0	24,000	61,000	79,000	110,000	270,000	230,000	220,000	550,000	1,500,000	**3,044,000**
TRUCK	BEV	0	0	430	860	340	17,000	15,000	67,000	54,000	35,000	33,000	36,000	50,000	**308,630**
TRUCK	PHEV	0	0	0	0	0	0	0	14,000	3,600	2,400	420	1,000	1,500	**22,920**
VAN	BEV	0	0	670	750	480	15,000	11,000	68,000	54,000	27,000	26,000	58,000	130,000	**390,900**
VAN	PHEV	0	0	0	0	0	0	0	0	0	0	0	0	1,500	**1,500**
Total	**BEV**	**1,900**	**450**	**12,100**	**18,610**	**53,920**	**276,000**	**376,000**	**695,000**	**1,022,000**	**967,000**	**1,041,000**	**2,842,000**	**4,632,000**	**11,937,980**
Total	**PHEV**	**0**	**330**	**1,000**	**3,500**	**36,000**	**87,000**	**94,000**	**124,000**	**276,000**	**235,000**	**224,020**	**552,700**	**1,505,300**	**3,138,850**

Data Source: https://www.iea.org/data-and-statistics/data-tools/global-ev-data-explorer and https://ourworldindata.org/electric-car-sales. BEV, battery electric vehicle; PHEV, plug-in hybrid electric vehicle. Table 2 presents the total amount of oil displaced (in millions of barrels) by each EV category from 2010 to 2022.

TABLE 2 Total oil displaced by electric vehicle types in China.

	2010	2011	2012	2013	2014	2015	2016	2017	2018	2019	2020	2021	2022	Total
BUS	0	1.5	5.8	14	73	230	450	840	1,600	2,300	2,800	5,300	11,000	**24,614.3**
CAR	68	67	91	120	190	1,700	2,700	3,400	4,300	4,100	3,900	4,100	4,700	**29,436**
TRUCK	0.088	0.67	3.1	8	8.9	93	150	430	640	630	620	730	860	**4,173.758**
VAN	0.59	0.76	1.7	2.8	3.2	27	39	130	200	210	200	270	310	**1,395.05**
Total	**68.678**	**69.93**	**101.6**	**144.8**	**275.1**	**2,050**	**3,339**	**4,800**	**6,740**	**7,240**	**7,520**	**10,400**	**16,870**	**59,619.11**

Data Source: https://www.iea.org/data-and-statistics/data-tools/global-ev-data-explorer and https://ourworldindata.org/electric-car-sales.

efforts toward eco-friendly mobility solutions, which are essential for long-term climate and net-zero goals.

Table 3 presents a summary of descriptive data statistics and variables used in the study. The variables include EVA, ST, CI, fast charging (FC), and BEV measured in millions of count unit; PX, SD, and EPX measured in millions of dollars; ED measured in kilowatt-hours (kWh); VR measured in kilometers; vehicle range*charging Infrastructure (VRCI) measured in charging station density; and OD measured in million barrels of oil/liquefied gas equivalent.

Before we integrated the data into the empirical model, we processed and standardized data using Stata Software. This involved converting the data from yearly to quarterly frequency, as the entire data set usually included count indicators typically recorded quarterly. This standardization process effectively shifted the data from a higher frequency to a lower one. This technique expanded the observations for each EV type (BEV and PHEV) to four quarters, resulting in 52 total data observations (Liu et al., 2023; Shao et al., 2023) shown in Table 3.

3.3 Model design strategy

3.3.1 Poisson regression model estimation

Literature suggests that selecting the best model equation for estimating count data depends on several key factors, including the data's characteristics, the nature of the count process, and the assumptions about the data distribution. Based on the time-series data for 2010–2022 on China's EVA and ED (Fache and Bhat, 2024), the authors have employed a PRM framework (Yang et al., 2017; Khan et al., 2022) to analyze the count of EVAs in China, with the predictor variables outlined in Table 3. The PRM is commonly used for count data, where the discrete outcome of interest is the frequency of events occurring within a specific time period. In this study, the authors extended the basic PRM to incorporate temporal dependence by including autoregressive terms, reflecting the data's time-series nature. As recommended in the literature, the PRM is suitable for count data as it handles non-negative integer values and follows a Poisson distribution, where the mean and the variance of the counts are assumed to be approximately equal (Khan et al., 2022). The Poisson model is expressed as follows: Let EVA follow a Poisson distribution with the parameter lambda (λ). That is, $EVA_t \sim$ Poisson (λ_t). Therefore, we express:

$$P\left(EVA_t = eva_t\right) = \frac{e^{-\lambda *}\lambda^{eva_t}}{eva_t!} \tag{1}$$

For eva = 0, 1, 2, ... and $\lambda > 0$, where

$$E\left(eva_t\right) = \lambda_t = e^{eva_t}\beta. \tag{2}$$

From Equations 1, 2, λ is the number of events (count), t is the length of the time interval, and the λ is the average rate (intensity) of the events per unit time. Also, $P(EVA_t = eva_t)$ represents the probability of observing the λ events in the interval (0, t). The e is the base of the natural logarithm, and the $eva_t!$ denotes the factorial of λ, which is the product of all positive integers from 1 to λ. To model the relationship between the EVA and the main independent variables (BEV, VR, CI, VRCI, and FC). Literature shows that the PRM is appropriate for count data, such as the number of EVs sold, where the dependent variable is a count of events (EVA) and the independent variables are used to explain the variation in the count (Coxe et al., 2009; Khan et al., 2022).

$$\begin{aligned}\log\left(\lambda_t\right) &= \alpha + \beta_1 VR_t + \beta_2 CI_t + \beta_3 VRCI_t \\ &+\beta_4 BEV_t + \beta_5 FC_t + \beta_6 BZ_t + \log\beta_7 eva_{t-1} + \varepsilon_t,\end{aligned} \tag{3}$$

where the dependent variable, λ (lambda), is the Poisson parameter of the expected count sales of EVs at time t. The independent variables are those explained in Section 3.1 at time t. Also, β_1-β_5 are the parameter coefficients associated with the main independent variables to be estimated. Also, β_6 denotes the included controlled variables to be determined including the intercept, α. Note that from Equation 3, the authors have extended the general Poisson model by including temporal dependence: The β_7 parameter introduces the temporal dependence, capturing the effect of past EVA on current adoptions (offset), and ε_t is the error term. Expressing this model equation allows the authors to explain the relationship between EVA and the given independent variables while accounting for potential temporal dependencies through the autoregressive terms. Also, to determine the total ED (Fache and Bhat, 2024) and fossil fuels displaced by the EVs, we apply the same PRM estimated in Equations 1, 2 as shown in Equations 4, 5. For the objectives of this study, using the PRM, the authors employed an incidence rate ratio ($IRR = e^{\beta_1}$) reporting technique to explain the impact of VR, CI, VRCI, FC, and BEV under sustainable transportation. The authors employed the IRR reporting analysis to test hypotheses about the EVA based on whether the introduction of VRCI technology may increase EVA rates. Also, apply the IRR in this study provides interpretable results relevant to policymakers without necessarily using the predicted log count. So, Equations 4, 5 present electricity and oil displaced by adoption of EVs.

Let $ED_t \sim$ Poisson (λ_t); then,

$$\begin{aligned}\log\left(\lambda_t\right) &= \alpha + \beta_1 VR_t + \beta_2 CI_t + \beta_3 VRCI_t \\ &+\beta_4 BEV_t + \beta_5 BZ_t + log\beta_6 ed_{t-1}) + \varepsilon_t.\end{aligned} \tag{4}$$

Let $OD_t \sim$ Poisson (λ_t); then,

$$\begin{aligned}\log\left(\lambda_t\right) &= \alpha + \beta_1 VR_t + \beta_2 CI_t \\ &+\beta_3 VRCI_t + \beta_4 BEV_t + \beta_5 BZ_t + log\beta_6 od_{t-1}) + \varepsilon_t.\end{aligned} \tag{5}$$

Finally, the authors conducted the PRM analysis using Stata Software, employing the following commands "poisson eva vr ci vrci bev + control variables, vce(robust) irr" to estimate the variable parameter adoption. To analyze ED and OD, the dependent variables were replaced, and the outcomes are detailed in Tables 3–5.

3.3.2 Robustness, sensitivity tests, and study limitations

In empirical research, each model may exhibit limitations that can lead to biased parameter estimates and potentially affect the validity of conclusions. To enhance the validity of this study, a robustness test was conducted by employing the NBM to

TABLE 3 Data statistics.

Variables	Obs.	Mean	Std. Dev.	Min	Max
EVA	52	289,939	428,558.1	195	1,534,325
BEV	52	0.7692308	0.4254356	0	1
PX	52	353,361.6	241,360.1	148,390	751,043.3
ST	52	786,864.6	1,137,348	1,064	3,957,925
SD	52	4.69e+09	4.06e+09	8.55e+08	1.18e+10
CI	52	95,057.69	132,830.2	0	440,000
EPX	52	0.7661538	0.086004	0.65	0.98
ED	52	9,017.173	4,766.649	2,290	16,555
VR	52	346.1538	85.08713	0	1
VRCI	52	3.05e+07	4.09e+07	0	1.32e+08
FC	52	0.692308	0.466041	0	1
OD	52	1,146.521	1,237.174	17.1695	4,217.5

Data Source: https://www.iea.org/data-and-statistics/data-tools/global-ev-data-explorer and https://ourworldindata.org/electric-car-sales. EVA, electric vehicle adoption; BEV, battery electric vehicle; PX, EV price; ST, EV stock shares; SD, government subsidies; CI, charging infrastructure; EPX, electricity prices; VR, vehicle range; VRCI, vehicle range*charging Infrastructure; FC, fast charging; OD, oil displacement.

authenticate the findings of the PRM, mainly in the context of overdispersion. The NBM was utilized to assess overdispersion within the data, ensuring that the conclusions regarding the variables and the model are unbiased. The main model PRM, together with NBM as a robustness test, is presented in Tables 3–5 (Coxe et al., 2009; Payne et al., 2017). Furthermore, a sensitivity analysis was conducted by omitting the VRCI interaction term in investigating whether the synergistic effects of these variables significantly impact EVA (Barman et al., 2023). Finally, this study has few limitations and could be addressed by future studies. First, the applied model framework did not account for regional disparities in charging infrastructure and economic conditions because regional data for the variables were not available at the time of the study, meaning that these findings are not applicable to rural or less developed areas in China. Second, the research did not get real-time data integration, limiting its ability to capture dynamic changes in ED, charging behavior, and EVA trends. Third, the study's focus on BEVs may overlook the transitional role that PHEVs and other EVs play in meeting net-zero emissions. Finally, while the research emphasizes OD and net-zero emissions, the study could not account for broader environmental impacts, such as life-cycle effects of battery production and recycling. Consequently, addressing these limitations in future studies may broaden the literature for understanding EVA in China.

4 Results presentation and analysis

4.1 Model estimation and EVA result analysis

Table 4 presents EVA estimation results using two distinct techniques, PRM and NBM. The two techniques, PRM and NBM, are applied in Model 1 and Model 2, respectively, to estimate the EVA results. These same techniques are then applied in Model 3 and Model 4 for sensitivity analysis, ensuring the robustness of the findings. The comparison between Models 1 and 3 (for PRM) and between Models 2 and 4 (for NBM) allows for an evaluation of how sensitive the EVA results are to changes in model specifications and estimation approaches (Franzò and Nasca, 2021; Ge and MacKenzie, 2022). The model results indicate that the likelihood ratio chi-squared test confirms that the full models are a significant improvement over the null (no predictors) model ($p < 0.001$). First, the results show that the lag EVA (lagEVA) is not statistically significant, meaning that past adoption rates do not influence current uptake. This finding is consistent with the Poisson distribution assumption, where the occurrence of events is independent of subsequent events (Khan et al., 2022). Moreover, all control variables in Model 1 are statistically significant, suggesting their relevance in explaining EVA. The robustness test in Model 2 confirms that the primary predictors VR and CI and the interaction term between VRCI, BEV, and FC are significant determinants of EVA in the Chinese market. Furthermore, the NBM results indicate that there is no over dispersion in the data, implying that the variability aligns with theoretical expectations and that the counts do not exhibit unexpected spread. This supports using the chosen statistical model PRM, affirms its suitability for the data, and suggests that the parameter estimates are unbiased due to data variability. Additionally, the sensitivity analysis in Model 3, along with the robustness test in Model 4, demonstrates that even when the interaction term VRCI is excluded, the significance of the primary predictors remains unchanged. This highlights that EVA is dominantly driven by factors such as VR, availability of smart CI, battery storage capacity, and advancements in both range and charging technologies. As a result, the findings in Model 1 were utilized in the main analysis. To ensure empirical rigor, Equation 3 is presented in logarithmic form, and consistent with the literature, we report the IRR as exp (β) rather than the raw coefficients (Yang et al., 2017). This transformation, as explained in Section 3, converts logarithmic predictors into a linear scale, facilitating more transparent reporting and interpretation of results. Reporting only the log count could obscure the full magnitude of parameter effects,

TABLE 4 EVA results.

Estimate technique	Model 1	Model 2	Model 3	Model 4
Variable	PRM	NBM	PRM	NMB
VR	0.982***	0.981***	0.993***	0.988***
	(0.000)	(0.000)	(0.000)	(0.000)
CI	0.999***	0.999***	0.999***	0.999***
	(0.000)	(0.000)	(0.000)	(0.000)
VRCI	1.002***	1.004***	Sensitivity	Robustness
	(0.000)	(0.000)	Test	Test
BEV	0.626***	0.500***	0.635***	1.664**
	(0.000)	(0.000)	(0.000)	(0.008)
FC	3.376***	4.781***	4.364***	5.480***
	(0.000)	(0.000)	(0.000)	(0.000)
lagEVA	1.000	0.999	1.000	1.000
	(0.182)	(0.584)	(0.881)	(0.896)
PX	1.000***	1.000***	1.000***	1.000*
	(0.000)	(0.000)	(0.000)	(0.033)
ST	1.000***	1.000***	1.000***	1.000***
	(0.000)	(0.000)	(0.000)	(0.000)
EPX	26.175***	0.052***	167.38***	347.821***
	(0.000)	(0.000)	(0.000)	(0.000)
ED	1.000***	1.000***	1.000***	1.000***
	(0.000)	(0.000)	(0.000)	(0.000)
Constant	37,124.05***	629,436***	156.669***	370.922***
	(0.000)	(0.000)	(0.000)	(0.000)
R^2	0.9997	0.6077	0.9987	0.613

Values in parentheses are p-values. PRM, Poisson regression model; NBM, negative binomial model; VR, vehicle range; CI, charging infrastructure; VRCI, vehicle range*charging Infrastructure; BEV, battery electric vehicle; FC, fast charging; lagEVA, lag EVA; PX, EV price; ST, EV stock shares; EPX, electricity prices; ED, electricity demand. $^{*}p < 0.1$. $^{**}p < 0.05$. $^{***}p < 0.01$.

but using the IRR provides an accurate representation (Abudu et al., 2023).

The study's primary finding underscores the crucial role of VR in shaping EVA decisions and behaviors (Ge and MacKenzie, 2022; Haghani et al., 2023). Specifically, the results indicate that for each additional percentage increase in the distance drivers need to cover, the predicted adoption of battery electric vehicles BEVs decreases by a factor of 0.982, or a 1.8% reduction in adoption [(0.982 − 1) * 100%]. This result confirms the developed hypothesis 2 and suggests that as customers anticipate longer trips or require extended driving ranges, they show a slight 1.8% preference for PHEVs or ICEVs over BEVs. This consumer shift is often associated with "range anxiety," a phenomenon in which potential EV buyers worry about running out of battery charge before reaching their destination or the next charging station (Lee et al., 2020; Haghani et al., 2023). As a result, many consumers gravitate toward PHEVs, which offer the reassurance of a fossil fuel backup. However, recognizing that this shift toward PHEVs may not represent a full transition to sustainable transportation or net-zero emissions is important, as PHEVs still rely on fossil fuels (Tao, 2024; Squalli, 2024). To promote widespread EVA and a more sustainable mode of transportation, technological innovations that enhance the driving range of both BEVs and PHEVs are urgently needed (Barman et al., 2023; Squalli, 2024). Additionally, renewable energy–based recharging technologies, such as battery-swapping systems along major roads, should be encouraged to alleviate range anxiety (Lee et al., 2020; Barkenbus, 2020). Addressing these challenges will help the transportation industry facilitate a more effective transition to eco-friendly BEVs and contribute to sustainable mobility solutions. Moreover, the increased adoption of BEVs can spur the development and use of CCS technologies. By capturing and storing emissions that would otherwise be released by individual vehicles, CCS can play a key role in reducing overall emissions and enhancing environmental sustainability.

The results in Table 4 suggest that improvements in CI have a negative impact on EVA, raising concerns among potential EV buyers (Liu et al., 2023; Squalli, 2024). This finding is counterintuitive, as a 1% improvement in charging accessibility and availability is associated with a marginal 0.1% reduction in EVA. While CI is improving, it is currently insufficient to drive a proportional increase in EVA within the Chinese market (Shao et al., 2023). This is evidenced by the nationwide ratio of electric vehicles to charging stations, which stands at 3.1:1. This imbalance suggests that the current CI is insufficient to meet the demands of the growing EV market, leading to a slower adoption rate (Guo et al., 2021; Li et al., 2022). The relationship between CI and EVA is complex and influenced by factors such as charging station tariffs, charging speed, and station distribution. For instance, high public charging fees may discourage users, reducing EVA, as higher costs lower demand (Haidar and Rojas, 2022). Consequently, an increase in public charging stations may not significantly enhance EVA if consumers prefer the convenience and lower costs of home charging (Haidar and Rojas, 2022). In effectively promoting EVA in China, policies should prioritize diversifying charging technologies (Vaishnav, 2023; Fache and Bhat, 2024). This could include inductive charging (IoT-enabled), conductive charging, and battery swapping, supported by multiple charging levels such as residential Levels 1 and 2, public Level 2, and direct fast-charging Level 3 (Mastoi et al., 2022). Also, the findings also show a slight positive effect (0.2%) from the interaction between VR and CI, as observed in China's data-driven EV market. This VRCI effect significantly enhances the convenience of owning and using EVs, contributing to the transition toward sustainable transportation in China (Liu et al., 2023). With advancements in VR technology combined with a well-developed CI network, users would gain confidence in their ability to easily locate charging stations and benefit from improved battery performance. As a result, consumers in the Chinese economy are more likely to switch to EVs when they perceive them as a viable and convenient alternative to ICEVs (Liu et al., 2023; Shao et al., 2023).

Additionally, the findings presented in Table 4 demonstrate that an increase in the supply of BEVs results in a significant decline in adoption rate compared to the control group (PHEVs and ICEVs) than expected in the Chinese market. In this finding, several factors contribute to this result, including limitations in VR, concerns related to range anxiety, and consumer preferences favoring PHEVs (Liu et al., 2023; Fatemi et al., 2023). That is, BEVs typically have a limited driving range on a single charge compared to PHEVs, which operate on both electric power and internal combustion engines (Squalli, 2024). The recommendation is that Chinese consumers, much like their global counterparts, express apprehension regarding the limited range of BEVs, despite their positive impact on achieving net-zero emissions. This limitation has a significant drawback for potential EV buyers who need to travel long distances regularly, such as commuters or individuals living in rural areas, particularly for vans, cars, and trucks. Even with advancements in charging stations, there are still concerns about the availability and accessibility of charging stations, particularly in less densely populated areas where BEV owners heavily rely on CI, and this negatively impacts BEV adoption in the Chinese market. Therefore, in response to range limitations and range anxiety, consumers rather prefer PHEVs over BEVs (Shao et al., 2023). Because PHEVs offer the flexibility of using electricity and gasoline, they provide a greater sense of security for longer trips. This inclination for PHEVs leads to a decrease in BEV adoption, as consumers opt for vehicles aligning better with their driving expectations.

Finally, the research findings indicate that an increase in the availability of smart or FC systems positively correlates with higher EVA rates within the Chinese market. The positive effect of fast CI on EVA is that it significantly reduces charging time and enhances the convenience of owning an EV (Fatemi et al., 2023; Shao et al., 2023). Smart-charging stations allow EV owners to recharge their vehicles much more quickly compared to standard charging methods, which may take several hours (6–8). As a result, the availability of smart CI assists in overcoming "range anxiety," which is one of the barriers to EVA, as drivers may recharge their vehicles more easily during long trips (Haidar and Rojas, 2022).

4.2 EVA impact on ED analysis

Table 5 presents the electricity demand estimation results using two distinct techniques, PRM and NBM. The two techniques, PRM and NBM, are applied in Model 1 and Model 2, respectively, to estimate the primary results. These same techniques are then applied in Model 3 and Model 4 for sensitivity analysis, ensuring the robustness of the findings. The comparison between Models 1 and 3 (for PRM) and between Models 2 and 4 (for NBM) allows for an evaluation of how sensitive the results are to changes in model specifications and estimation approaches. In Table 5, the result suggests that ST and SD are the significant control variables. Also, the results show that ED is independent of the lag demand, and this is consistent with the PRM distribution assumption (Khan et al., 2022).

The analysis reveals that for every percentage increase in VR technology, or the greater the distance drivers desire to travel, there is a corresponding 0.3% increase in ED. This suggests that increased demand for VR technology necessitates additional electricity, which potentially creates competition with other sectors for the available electrical resources (Fatemi et al., 2023). This increase in VR subsequently increases ED as more EVs hit the road (Li et al., 2018; Liu et al., 2023). Overall, the positive effect of increased VR on ED stems from a combination of reduced charging frequency, higher EVA, and expanded usage scenarios (Li et al., 2018). These factor advancements collectively contribute to an uptake in electricity consumption, highlighting the interplay between EV technology advancements and the electric grid's capacity and resilience. This, therefore, presents the need for alternative energy sources particularly from renewable charging stations to meet this growing EVA in a sustainable manner (Seyyedeh-Barhagh et al., 2023; Vaishnav, 2023). Also, the results in Table 5 show that a percentage increase in the supply of BEVs in the Chinese economy required more than a 27.8% increase in ED (Fatemi et al., 2023). That is, having more BEVs on the road requires a higher demand for electricity, particularly during charging. This surge in ED presents energy challenges and emissions consequences if the energy is not a renewable source (Seyyedeh-Barhagh et al., 2023; Zhou et al., 2023). To therefore, accommodate the increased ED from BEVs, China requires investment in the development of smart grids and advanced energy management systems (Squalli, 2024). These technologies enhance grid efficiency, reduce energy losses, and enable better integration of renewable energy to accelerate China's sustainable transportation (Zhou et al., 2023).

4.3 Impact of EVA on OD in China

Table 6 presents oil displaced estimation results using two distinct techniques, PRM and NBM. The two techniques, PRM and NBM, are applied in Model 1 and Model 2, respectively, to estimate the primary results. These same techniques are then applied in Model 3 and Model 4 for sensitivity analysis, ensuring the robustness of the findings. The comparison between Models 1 and 3 (for PRM) and between Models 2 and 4 (for NBM) allows for an evaluation of how sensitive the results of oil displaced by EVA are to changes in model specifications and estimation approaches.

These findings suggest that an increase in VR, or a greater preference among consumers for longer EV trips, reduces the total amount of oil displaced in the Chinese economy by 1.9%. This reduction occurs because longer VR allows EVs to travel greater distances on a single charge, decreasing the reliance on gasoline or diesel. As a result, oil consumption in the transportation sector decreases, contributing to oil displacement (Liu et al., 2023; Mastoi et al., 2022). Consequently, increased adoption of EVs with longer ranges has further implications for China's oil imports. As a major oil importer, China could reduce its dependence on foreign oil sources as it shifts toward renewable energy through increased EVA. This transition may have economic and geopolitical significance, as reduced reliance on oil imports can strengthen energy security. Additionally, the technological advancements in VR for EVs may not only contribute to lower oil imports but also enhance net-zero goals (Mastoi et al., 2022; Squalli, 2024).

Also, the finding shows that a percentage increase in CI tends to reduce the total amount of oil displaced in the Chinese economy by a marginal amount of 0.1%. This means that as the availability and accessibility of charging stations for EVs improve, there is a corresponding decrease in the reliance on oil for transportation (Li et al., 2018). Charging infrastructure supports the adoption and usage of EVs, which are typically powered by electricity rather than fossil fuels like gasoline or diesel (Lin and Abudu, 2020). Therefore, an expansion of charging infrastructure contributes to the displacement of oil in the transportation sector, as more people choose to drive EVs and rely less on traditional ICEVs (Liu et al., 2023). Therefore, the implication of reducing the total amount of oil displaced in the Chinese economy due to an increase in CI has several important implications for carbon emissions and carbon neutrality. Many countries, including China, have set ambitious targets for carbon neutrality, aiming to balance carbon emissions with carbon removal or offsetting measures (Li et al., 2019; Squalli, 2024). Thus, the reduced reliance on oil and the adoption of EVs align with these goals. So, policy measures must be put in place to enhance the CI across the country to meet climate action, carbon emissions reduction, and neutrality (Mastoi et al., 2022). Finally, an increase in CI leads to a reduction in oil displacement, thereby supporting industrial decarbonization and the transition to cleaner and more sustainable transportation options like EVs (Squalli, 2024). This transition aligns with global efforts to reduce carbon emissions, achieve carbon neutrality, and promote sustainable energy sources, ultimately benefiting both the environment and public health in China (Li et al., 2019; Vaishnav, 2023). Finally, the finding shows that the combined policy technologies in improving both VR and CI are currently constant with the total fossil fuel displaced. Furthermore, the results reveal that a percentage increase in the adoption of BEVs in the Chinese economy has displaced oil by a great deal of 88.1%. The effect of a percentage increase in BEVs' adoption on the total oil displaced in the Chinese economy has significant policy implications (Squalli, 2024). First, the high adoption rate of BEVs is believed to be sourced from low-carbon or renewable sources and therefore a significant reduction in oil consumption for transportation. This would have positive implications for carbon emissions reduction and efforts to achieve carbon neutrality, as BEVs produce zero tailpipe emissions relative to PHEVs and ICEVs (Li et al., 2019; Mastoi et al., 2022; Shao et al., 2023). Also, BEVs contribute to industrial decarbonization by lowering greenhouse gas emissions in the transportation sector. As more BEVs replace ICEVs, there is a direct reduction in carbon emissions associated with transportation, a sector that significantly contributes to industrial emissions in China and in the case of the United States (Squalli, 2024).

4.4 Result discussion and policy implication

China's growing adoption of EVs is a key driver in its push toward decarbonizing the energy sector, enhancing sustainable electricity, and reducing greenhouse gas emissions, in line with its commitment to achieve carbon neutrality by 2060. The rise in EVA has significant implications for sustainable electricity generation, the transformation of the transportation sector, and the attainment of net-zero emissions (Lin and Abudu, 2020; Liu et al., 2023). As more EVs hit the road, the demand for electricity is increasing, particularly as VR expands and the supply of BEVs grows. Every improvement in VR leads to a proportional rise in electricity consumption, which, combined with a higher availability of BEVs, presents both a challenge and an opportunity for China's energy setting. The challenge lies in meeting growing ED through sustainable sources, as the environmental benefits of EVs can only be fully realized if the energy that powers them is derived from renewables like solar, wind, and hydropower (Xue et al., 2021). By ensuring that EVs are charged with clean energy is crucial to advancing China's renewable energy transition. The integration of EVA is pivotal in reducing oil consumption, offering a direct pathway toward transforming China's transportation sector (Guo et al., 2021). With each increase in VR, there is a corresponding reduction in oil usage, which will be further driven down by the supply of BEV. This shift has the potential to reduce China's reliance on fossil fuels and significantly lower transportation-related carbon emissions, which currently account for over 10% of the country's emissions in this sector (Liu et al., 2023). However, the persistence of PHEVs in the market, due to concerns over range anxiety and insufficient charging infrastructure, presents barriers to fully transitioning to zero-emission transportation. PHEVs offer a temporary solution for reducing oil consumption; however, their reliance on fossil fuels limits their contribution to China's net-zero emissions goals. To address this, China should prioritize the adoption of BEVs by advancing VR through critical materials technologies and enhancing the accessibility of CI (Fuinhas et al., 2021).

Furthermore, continuous improvement in CI is essential for the successful implementation of EVA, as it strengthens the

TABLE 5 Electricity demand results.

Estimate technique	Model 1	Model 2	Model 3	Model 4
Variable	PRM	NBM	PRM	NMB
VR	1.003***	1.000***	1.002***	1.003***
	(0.000)	(0.000)	(0.000)	(0.000)
CI	1.000***	1.000***	1.000***	1.000***
	(0.000)	(0.000)	(0.000)	(0.000)
VRCI	1.000***	1.000*	Sensitivity	Robustness
	(0.000)	(0.021)	Test	Test
BEV	1.278**	1.578*	1.028	1.155
	(0.008)	(0.010)	(0.642)	(0.250)
lagED	0.999	0.999	1.000	0.999
	(0.206)	(0.530)	(0.301)	(0.637)
EVA	0.999	1.000*	0.999	1.000*
	(0.566)	(0.030)	(0.312)	(0.057)
EPX	3.007	7.443*	0.666	1.436
	(0.191)	(0.032)	(0.446)	(0.573)
SD	1.000***	1.000***	1.000***	1.000***
	(0.000)	(0.000)	(0.000)	(0.0000
ST	0.999**	0.999***	0.999*	0.999***
	(0.007)	(0.000)	(0.027)	(0.000)
Constant	433.874***	94.912***	2,379.159***	756.525***
	(0.000)	(0.000)	(0.000)	(0.000)
R^2	0.8903	0.60	0.8815	0.75

Values parentheses are p-values. PRM, Poisson regression model; NBM, negative binomial model; VR, vehicle range; CI, charging infrastructure; VRCI; BEV, battery electric vehicle; EVA, electric vehicle adoption; lagED, lag ED; EPX, electricity prices; SD, government subsidies; ST, EV stock shares. $^{*}p < 0.1$. $^{**}p < 0.05$. $^{***}p < 0.01$.

synergy between VR and the availability of smart charging options. This interaction emphasizes the need for a robust and accessible charging network, made possible through by integrating IoT technologies. Although China has made advances in intensifying its CI, gaps remain, particularly in regions where charging stations are scarce. Additionally, issues such as high public-charging tariffs and slow charging speeds further impede the widespread adoption of EVs (Fuinhas et al., 2021; Haidar and Rojas, 2022). In addressing these challenges, China needs to invest in developing fast-charging networks, integrated with renewable energy sources, to encourage broader EVA. Such advancements will help alleviate range anxiety and ensure that EV charging aligns with the country's sustainability objectives. The success of EVA in contributing to China's sustainable development and net-zero emissions efforts depends on several strategic actions. First, accelerating the transition from ICEVs and PHEVs to BEVs is essential, as BEVs offer greater potential for reducing fossil fuel dependence and emissions (Fuinhas et al., 2021). That is, while VR anxiety is an important concern for customers, achieving net-zero emissions takes precedence in advancing sustainable energy and carbon neutrality. This, therefore, can be achieved through technological advancements in BEVs and a transition to cleaner energy sources. Also, this may be achieved through implementing consumer incentives, subsidies, and public awareness campaigns that emphasize the long-term environmental and economic benefits of BEVs. Second, as ED continues to grow with EVA, meeting this demand through renewable energy sources is critical. That is, expanding renewable energy–based charging stations and developing smart grid systems will ensure that EVs are powered by sustainable electricity (Lewicki and Nowak, 2021; Li et al., 2022). Finally, significant improvements in CI, particularly fast-charging networks, are necessary to support higher levels of BEV adoption and reduce oil dependence in the Chinese economy.

5 Conclusion and policy recommendations

In conclusion, China's EVA is central to its efforts to decarbonize the transportation sector, transition to sustainable energy, and achieve net-zero emissions. However, the success of EVA in contributing to sustainable electricity and transportation depends on advancing technologies focusing on promoting BEVs adoption over PHEVs and ICEVs, continued investment in renewable energy and boosting infrastructure. Also, the study concludes that advancements in EV materials technology in critical minerals (aluminum, carbon fiber, lithium, nickel, cobalt, and neodymium) and energy-efficiency technologies are

TABLE 6 Oil displaced results.

Estimation technique	Model 1	Model 2	Model 3	Model 4
Variable	PRM	NBM	PRM	NMB
VR	0.981***	0.980***	0.990***	0.990**
	(0.000)	(0.000)	(0.000)	(0.006)
CI	0.999***	0.999***	0.999***	0.999*
	(0.000)	(0.000)	(0.000)	(0.069)
VRCI	1.000***	1.000***	Sensitivity	robustness
	(0.000)	(0.000)	Test	Test
BEV	0.119***	0.119***	0.252*	0.588
	(0.000)	(0.000)	(0.031)	(0.346)
lagOD	1.000	1.000	1.000	0.999
	(0.942)	(0.992)	(0.980)	(0.789)
PX	1.000***	1.000***	1.000***	1.000***
	(0.000)	(0.000)	(0.000)	(0.000)
ST	1.000*	1.000***	1.000***	1.000*
	(0.076)	(0.000)	(0.000)	(0.065)
EVA	0.999	0.999**	0.999***	0.999
	(0.519)	(0.001)	(0.000)	(0.370)
SD	1.000*	1.000***	1.000	1.000
	(0.020)	(0.000)	(0.966)	(0.982)
EPX	0.019*	0.019*	200.818*	131.626*
	(0.043)	(0.066)	(0.012)	(0.094)
ED	1.000***	1.000***	1.000***	1.000***
	(0.000)	(0.000)	(0.000)	(0.000)
Constant	125,833.8***	125,833.8***	1.212	3.344
	(0.000)	(0.000)	(0.776)	(0.584)
R^2	0.9933	0.7129	0.9910	0.5364

Values parentheses are p-values. PRM, Poisson regression model; NBM, negative binomial model; VR, vehicle range; CI, charging infrastructure; BEV, battery electric vehicle; lagED, lag ED; EVA, electric vehicle adoption; EPX, EV price; SD, government subsidies; ST, EV stock shares; EPX, electricity prices; VRCI, FC, OD, oil displacement. $^{*}p < 0.1$. $^{**}p < 0.05$. $^{***}p < 0.01$.

crucial to the success of EV uptake in China. The study concludes that technological innovations such as lightweight materials and improved battery technologies enhance vehicle performance, increase range, and reduce energy consumption. These improvements may not only contribute to more efficient transportation but also help in reducing the overall environmental impact. Furthermore, through continued investment in material science and energy-efficient technologies, China may further support its goals for sustainable mobility and achieve significant progress toward net-zero emissions and a greener economy. Consequently, the study recommends policymakers actively integrate advanced technologies such as artificial intelligence, the IoT, blockchain, and smart grid systems in using real-time data, swappable battery services to further promote EVA and drive progress in the energy and transport sectors. As these advanced technologies may play a crucial role in optimizing EV infrastructure, supporting the country's digital economy drive, and advancing its goals of sustainable electricity, transportation, and net-zero emissions. Together with renewable energy solutions, these technological advancements will maximize the environmental benefits of EVs, reduce reliance on fossil fuels, and accelerate China's transition toward sustainable transportation and net-zero emissions targets.

Data availability statement

Publicly available datasets were analyzed in this study. This data can be found here: https://www.iea.org/data-and-statistics/data-tools/global-ev-data-explorer.

Author contributions

HA: Conceptualization, Data curation, Formal analysis, Investigation, Methodology, Software, Supervision, Validation, Writing – original draft, Writing – review & editing. RS: Conceptualization, Data curation, Formal analysis, Investigation, Methodology, Software, Supervision, Validation, Writing – original draft, Writing – review & editing. MAH: Formal analysis, Funding acquisition, Investigation, Project administration, Resources, Software, Supervision, Validation, Visualization, Writing – review & editing. EBB: Formal analysis, Investigation, Resources, Validation, Visualization, Writing – review & editing.

Funding

The author(s) declare that no financial support was received for the research, authorship, and/or publication of this article.

Conflict of interest

The authors declare that the research was conducted in the absence of any commercial or financial relationships that could be construed as a potential conflict of interest.

Publisher's note

All claims expressed in this article are solely those of the authors and do not necessarily represent those of their affiliated organizations, or those of the publisher, the editors and the reviewers. Any product that may be evaluated in this article, or claim that may be made by its manufacturer, is not guaranteed or endorsed by the publisher.

References

Abudu, H., Wesseh, P. K., and Lin, B. (2023). Are African countries on track to achieve their NDCs pledges? Evidence from difference-in-differences. *Environ. Impact Assess. Rev.* 98:106917. doi: 10.1016/j.eiar.2022.106917

Amuakwa-Mensah, F., and Näsström, E. (2023). Role of banking sector performance in renewable energy consumption. *Appl. Energy* 306:118023. doi: 10.1016/j.apenergy.2021.118023

Axsen, J., Plötz, P., and Wolinetz, M. (2020). Crafting strong, integrated policy mixes for deep CO2 mitigation in road transport. *Nat. Clim. Chang* 10, 809–818. doi: 10.1038/s41558-020-0877-y

Bakhtyar, B., Qi, Z., Azam, M., and Rashid, S. (2023). Global declarations on electric vehicles, carbon life cycle and Nash equilibrium. *Clean Technol. Environ. Policy.* 25, 21–34. doi: 10.1007/s10098-022-02399-7

Barkenbus, J. (2020). Prospects for electric vehicles. *Sustainability* 12:5813. doi: 10.3390/su12145813

Barman, P., Dutta, L., Bordoloi, S., Kalita, A., Buragohain, P., Bharali, S., et al. (2023). Renewable energy integration with electric vehicle technology: a review of the existing smart charging approaches. *Renew. Sustain. Energy Rev.* 183:113518. doi: 10.1016/j.rser.2023.113518

Buhmann, K. M., and Criado, J. R. (2023). Consumers' preferences for electric vehicles: the role of status and reputation. *Transport. Res. Part D* 114:103530. doi: 10.1016/j.trd.2022.103530

Chai, J., Lu, Q.-Y., Wang, S.-Y., and Lai, K. K. (2016). Analysis of road transportation energy consumption demand in China. *Transp. Res. Part D Transp. Environ.* 48, 112–124. doi: 10.1016/j.trd.2016.08.009

Coxe, S., West, S. G., and Aiken, L. S. (2009). The analysis of count data: a gentle introduction to Poisson regression and its alternatives. *J. Pers. Assess.* 91, 121–136. doi: 10.1080/00223890802634175

Fache, A., and Bhat, M. G. (2024). Temperature sensitive electricity demand and policy implications for energy transition: a case study of Florida, USA. *Front. Sustain. Energy Policy* 2:1271035. doi: 10.3389/fsuep.2023.1271035

Fatemi, S., Ketabi, A., and Mansouri, S. A. (2023). A four-stage stochastic framework for managing electricity market by participating smart buildings and electric vehicles: towards smart cities with active end-users. *Sustain. Cities Soc.* 93:104535. doi: 10.1016/j.scs.2023.104535

Franzò, S., and Nasca, A. (2021). The environmental impact of electric vehicles: a novel life cycle-based evaluation framework and its applications to multi-country scenarios. *J. Clean. Prod.* 315:128005. doi: 10.1016/j.jclepro.2021.128005

Fuinhas, J. A., Koengkan, M., Leitão, N. C., Nwani, C., Uzuner, G., Dehdar, F., et al. (2021). Effect of battery electric vehicles on greenhouse gas emissions in 29 European Union countries. *Sustainability* 13:13611. doi: 10.3390/su132413611

Ge, Y., and MacKenzie, D. (2022). Charging behavior modeling of battery electric vehicle drivers on long-distance trips. *Transport. Res. Part D.* 113:103490. doi: 10.1016/j.trd.2022.103490

Gohlke, D., et al. (2022). *Energy Systems and Infrastructure Analysis Division, Argonne National Laboratory*.

Guo, Z., Li, T., Peng, S., and Zhang, H. (2021). Environmental and economic consequences of the incentive policy on electric vehicle industry: a CGE based study in China. *Resour. Conserv. Recycl.* 169:105542. doi: 10.1016/j.resconrec.2021.105542

Haghani, M., Sprei, F., Kazemzadeh, K., Shahhoseini, Z., and Aghaei, J. (2023). Trends in electric vehicles research. *Transp. Res. Part D Transp. Environ.* 123:103881. doi: 10.1016/j.trd.2023.103881

Haidar, B., da Costa, P., Lepoutre, J., and Vidal, F. (2020). *Which Combination of Battery Capacity and Charging Power for Battery Electric Vehicles: Urban Versus Rural French Case Studies.* Available at: https://centralesupelec.hal.science/hal-03071656

Haidar, B., and Rojas, M. T. A. (2022). The relationship between public charging infrastructure deployment and other socio-economic factors and electric vehicle adoption in France. *Res. Transpor. Econ.* 95:101208. doi: 10.1016/j.retrec.2022.101208

Hardman, S., Jenn, A., Tal, G., Axsen, J., Beard, G., and Daina, N. (2018). A review of consumer preferences of and interactions with electric vehicle charging infrastructure. *Transp. Res. Part D Transp. Environ.* 62, 508–523. doi: 10.1016/j.trd.2018.04.002

Jurczak, M., and Kowalski, M. (2021). "Electric vehicles-Problems and issues," in *Emerging Technologies and Applications for a Sustainable Electric Mobility*, ed. A. Grabowski (Cham: Springer), 443–455.

Kaminski, R., and Szczepaniak, A. (2021). "Analysis of trends in development of electromobility in Poland: current problems and issues," in *Electromobility in Poland: Status and Perspectives,* eds. P. Kotlarz and B. Kubica (Cham: Springer), 165–175.

Khan, A., Ullah, M. A., Amin, M., Muse, A. H., Aldallal, R., and Mohamed, M. S. (2022). Empirical examination of the Poisson regression residuals for the evaluation of influential points. *Mathem. Prob. Eng.* 2022:6995911. doi: 10.1155/2022/6995911

Kowalski, M., Macher, M., and Adamski, M. (2020). "E-mobility infrastructure in the Górnoślasko-Zagłebiowska Metropolis, Poland, and potential for development," in *Proceedings of the 5th World Congress on New Technologies*, 762–772.

Lee, J. H., Chakraborty, D., Hardman, S. J., and Tal, G. (2020). Exploring electric vehicle charging patterns: mixed usage of charging infrastructure. *Transpor. Res. Part D.* 79:102249. doi: 10.1016/j.trd.2020.102249

Lewicki, W., and Nowak, B. (2021). "The role of incentive programs in promoting the purchase of electric cars-Review of good practices and promotion methods from the world," in *Research methods in modern urban transportation systems and networks*, eds. M. Turkay and C. Kahraman (New York: Springer), 295–306.

Li, C., Shan, Y., Zhang, L., Zhang, L., and Fu, R. (2022). Techno-economic evaluation of electric vehicle charging stations based on hybrid renewable energy in China. *Energy Strat. Rev.* 41:100850. doi: 10.1016/j.esr.2022.100850

Li, W., Yang, M., and Sandu, S. (2018). Electric vehicles in China: a review of current policies. *Energy Environ.* 29, 1512–1524. doi: 10.1177/0958305X18781898

Li, Y., Du, Q., Lu, X., Wu, J., and Han, X. (2019). Relationship between the development and CO2 emissions of transport sector in China. *Transport. Res. Part D* 74, 1–14. doi: 10.1016/j.trd.2019.07.011

Lin, B., and Abudu, H. (2020). Can energy conservation and substitution mitigate CO2 emissions in electricity generation? Evidence from middle east and North Africa. *J. Environ. Manage.* 275:111222. doi: 10.1016/j.jenvman.2020.111222

Liu, Y., Zhao, X., Lu, D., and Li, X. (2023). Impact of policy incentives on the adoption of electric vehicle in China. *Transport. Res. Part A* 176:103801. doi: 10.1016/j.tra.2023.103801

Long, S., and Freese, J. (2014). *Regression Model for Categorical Dependent Variables Using Stata (3rd ed.).* College Station: Stata Press.

Mastoi, M. S., Zhuang, S., Munir, H. M., Haris, M., Hassan, M., Usman, M., et al. (2022). An in-depth analysis of electric vehicle charging station infrastructure, policy implications, and future trends. *Energy Rep.* 8, 11504–11529. doi: 10.1016/j.egyr.2022.09.011

Oliveira, G., Roth, R., and Dias, L. (2019). Diffusion of alternative fuel vehicles considering dynamic preferences. *Technol. Forecast. Soc. Change* 147, 83–99. doi: 10.1016/j.techfore.2019.06.002

Payne, E. H., Gebregziabher, M., Hardin, J. W., Ramakrishnan, V., and Egede, L. E. (2017). An empirical approach to determine a threshold for identification of over dispersion in count data. *Commun. Stat. Simul. Comput.* 47, 1722–1738. doi: 10.1080/03610918.2017.1323223

Pirmana, V., Alisjahbana, A. S., Yusuf, A. A., Hoekstra, R., and Tukker, A. (2023). Economic and environmental impact of electric vehicles production in Indonesia. *Clean Technol. Environ. Policy* 25, 1871–1885. doi: 10.1007/s10098-023-02475-6

Seyyedeh-Barhagh, S., Abapour, M., Mohammadi-Ivatloo, B., and Shafie-khah, M. (2023). Risk-based peer-to-peer energy trading with info-gap approach in the presence of electric vehicles. *Sustain. Cities Soc.* 99:104948. doi: 10.1016/j.scs.2023.104948

Shao, J., Jiang, C., Cui, Y., and Tang, Y. (2023). A game-theoretic model to compare charging infrastructure subsidy and electric vehicle subsidy policies. *Transport. Res. Part A.* 176:103799. doi: 10.1016/j.tra.2023.103799

Sovacool, B. K., Noel, L., Axsen, J., and Kempton, W. (2018). The neglected social dimensions to a vehicle-to-grid (V2G) transition: a critical and systematic review. *Environ. Res. Lett.* 13:013001. doi: 10.1088/1748-9326/aa9c6d

Squalli, J. (2024). Environmental hypocrisy? Electric and hybrid vehicle adoption and pro-environmental attitudes in the United States. *Energy* 293:130670. doi: 10.1016/j.energy.2024.130670

Tao, M. (2024). Dynamics between electric vehicle uptake and green development: understanding the role of local government competition. *Transport Policy* 146, 227–240. doi: 10.1016/j.tranpol.2023.11.020

Vaishnav, P. (2023). How can quantitative policy analysis inform the energy transition? The case of electrification. *Front. Sustain. Energy Policy* 2:1271301. doi: 10.3389/fsuep.2023.1271301

Xu, B., and Lin, B. (2024). Exploring the role of green finance in wind power development: using the nonparametric model. *Front. Sustain. Energy Policy* 3:1344166. doi: 10.3389/fsuep.2024.1344166

Xu, G., Wang, S., Li, J., and Zhao, D. (2020). Moving towards sustainable purchase behavior: examining the determinants of consumers' intentions to adopt electric vehicles. *Environ. Sci. Pollut. Res. Int.* 27, 22535–22546. doi: 10.1007/s11356-020-08835-9

Xue, C., Zhou, H., Wu, Q., Wu, X., and Xu, X. (2021). Impact of incentive policies and other socio-economic factors on electric vehicle market share: a panel data analysis from the 20 countries. *Sustainability* 13:2928. doi: 10.3390/su13052928

Yang, W., Jepson, C., Xie, D., Roy, J. A., Shou, H., Hsu, J. Y., et al. (2017). Statistical methods for recurrent event analysis in cohort studies of CKD. *Clin. J. Am. Soc. Nephrol.* 12, 2066–2073. doi: 10.2215/CJN.12841216

Zhou, X., Mansouri, S. A., Jordehi, A. R., Tostado-Véliz, M., and Jurado, F. (2023). A three-stage mechanism for flexibility-oriented energy management of renewable-based community microgrids with high penetration of smart homes and electric vehicles. *Sustain. Cities Soc.* 99:104946. doi: 10.1016/j.scs.2023.104946

Zou, P., Zhang, B., Yi, Y., and Wang, Z. (2024). How does travel satisfaction affect preference for shared electric vehicles? An empirical study using large-scale monitoring data and online text mining. *Trans. Policy* 146, 59–71. doi: 10.1016/j.tranpol.2023.10.027