2026-01-0455 Published 07 Apr 2026

Assessing Plug-in Electric Vehicle Adoption: Methodologies, Policy Effects, and Diverging Market Pathways in China, the U.S., and Europe

Wei Luo, Shiqi(Shawn) Ou, and Pan Zhou South China University of Technology

Tianpeng Wang Tsinghua University

Xiaodong Qian Wayne State University

Citation: Luo, W., Ou, S., Zhou, P., Wang, T. et al., "Assessing Plug-in Electric Vehicle Adoption: Methodologies, Policy Effects, and Diverging Market Pathways in China, the U.S., and Europe," SAE Technical Paper 2026-01-0455, 2026, doi:10.4271/2026-01-0455.

Received: 23 Oct 2025 Revised: 16 Dec 2025 Accepted: 21 Jan 2026

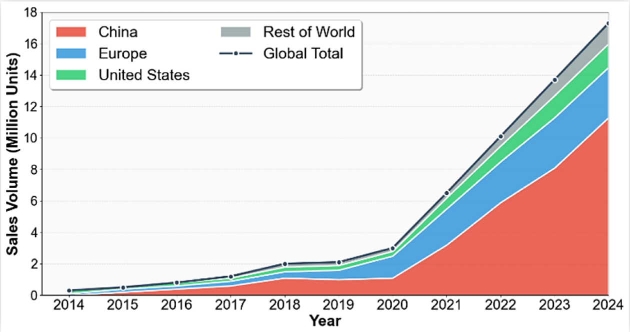
Abstract

Accurate projection of Plug-in Electric Vehicle (PEV) market sales share is vital for evidence-based policymaking, yet existing studies employ diverse and often fragmented methodologies, creating a need for a systematic review to clarify their analytical foundations and comparative strengths. This study classifies mainstream approaches to market projections into theory-driven and data-driven categories and reviews the merits, limitations, and future directions of five representative models. Analysis reveals that leading approaches increasingly employ cross-scale model coupling, theory-data fusion, and modular design to harness complementary strengths, improving model robustness and predictive accuracy. Furthermore, the study compares PEV policies and market outlooks in China, the United States, and Europe—the world's three largest automotive markets. The findings indicate a strong linkage between projection convergence and policy stability. China demonstrates the highest policy consistency and institutional consensus, with an average projected PEV share of new-vehicle sales of 81.3% by 2030. Europe's projections average 62.8%, driven by binding emissions mandates, whereas the U.S. exhibits greater uncertainty, averaging 31.1% amid fragmented regulations and policy uncertainty. These disparities highlight the decisive role of policy coherence and regulatory predictability in shaping PEV market outlooks.

I. Introduction

Driven by stringent CO_2 reduction targets, Plug-in Electric Vehicles (PEVs), including Battery Electric Vehicles (BEVs) and Plug-in Hybrid Electric Vehicles (PHEVs), have experienced rapid global market expansion. In 2024, global PEV sales exceeded 17 million units, with the PEV sales share surpassing 20% worldwide [1]. In China, the PEV share of new passenger vehicle sales increased from 5.7% in 2020 to 48.0% in 2024 [2]. Policy guidance, technological advancements, and resilient battery material supply chains have jointly driven the rapid expansion of PEVs, reinforcing their central role in the transition toward sustainable transportation.

FIGURE 1 PEV Sales in China, the U.S., Europe, and the Rest of the World, 2014-2024



China, the U.S., and Europe, as the three largest PEV markets globally, exhibit distinct market dynamics and policy frameworks. As shown in Figure 1, global PEV sales experienced rapid growth from 2014 to 2024 [3], yet the three markets display markedly different trajectories shaped by their respective policy approaches. China's market expansion, driven by the dual-credit scheme and carbon neutrality goals, has established it as the dominant player with accelerated growth since 2020. Europe pursues regulatory-led adoption through stringent frameworks, with the European Commission's "Fit for 55" package mandating a 55% reduction in passenger vehicle CO2 emissions by 2030 and zero emissions by 2035 [4]. In contrast, the United States exhibits substantially lower penetration rates, with policy intensity varying widely across states. While some states have adopted the Low-Emission Vehicle (LEV) standards and regional initiatives like REV West, many states lack binding mandates. This fragmented policy landscape contrasts sharply with the unified regulatory approaches in China and Europe. These three markets collectively represent distinct governance models: China employs centralized policy coordination, Europe operates under supranational regulation, and the U.S. exhibits fragmented federalism. This structural diversity provides an informative comparative setting for examining how policy design influences adoption patterns and forecasting reliability. Thus, comparative analysis across these regions provides essential insights into the role of regulatory frameworks in shaping global PEV development.

Numerous studies have examined policy impacts on PEV adoption across major markets. For China, Zhang et al. systematically reviewed national PEV policies and identified persistent gaps in policy design and implementation [5], particularly in subsidy allocation, infrastructure planning, and policy coordination. Wang et al. demonstrated that government subsidies significantly stimulate innovation [6], with effects varying across regions and ownership structures. Ou et al. developed a credit-based simulation model to analyze the dual-credit policy [7], showing how its credit structure reshapes technology choices, vehicle mix, and industry profitability. For the U.S., Stekelberg and Vance used experimental evidence to demonstrate that transferable tax credits can substantially increase consumer purchase intentions [8], while Sen et al. applied agent-based modeling to show that stringent CAFE standards [9], combined with financial incentives, can accelerate EV penetration. Jenn et al. quantified the effects of federal and state incentives and found measurable adoption elasticities as well as the critical role of consumer awareness [10]. For Europe, Harrison and Thiel used system-dynamics modeling to examine interactions among subsidies [11], infrastructure deployment, and emission regulations, revealing how these policy combinations influence long-term powertrain transitions. However, these studies predominantly focus on single-market policy effects without systematically comparing how different governance structures shape projection convergence and long-term market trajectories.

PEV market forecasting research has employed a wide range of analytical approaches, yet systematic comparative evaluation of these methodologies remains limited. Prior research has primarily examined a set of methodological approaches, though not exclusively, including traditional market penetration models such as Bass diffusion and S-curve models [12, 13, 14], time-series and regression-based approaches such as ARIMA [15,16], and emerging machine learning and deep learning methods such as neural networks and ensemble techniques [17,18]. While several studies have reviewed PEV forecasting methodologies, their analytical scopes remain fragmented. Sharma provides a descriptive overview of EV market trends with limited methodological comparison [19]; Domarchi and Cherchi offer a focused synthesis of diffusion-based models but give little attention to econometric or machine-learning approaches [20]; and Kemala et al. summarize multiple techniques without systematically contrasting their underlying assumptions or potential improvement pathways [21]. As a result, the literature still lacks a unified and structured comparative framework that situates theory-driven models and emerging machine-learning approaches within a coherent methodological landscape.

After collecting historical PEV policies from China, the U.S., and Europe, this study compares the mainstream policies across these three markets (Section II). It analyzes mainstream PEV forecasting approaches, including emerging machine learning and deep learning methods (Section III). By synthesizing the projections from different agencies, the study compares future market trajectories in the three regions over the next decade (Section IV). The policy implications, limitations, and future directions are discussed in Section V.

II. Policy Review in China, the U.S., and Europe

Policies play a critical role in shaping PEV market development and sales share projections. China has established a dual-pronged policy system combining supply-side regulations and demand-side incentives, exemplified by the dual-credit policy and the gradual phase-out of subsidies. The U.S. adopts a dual-track system with supply-side regulations such as the ZEV program and CAFE standards, alongside demand-side incentives including federal tax credits. However, this framework has undergone substantial changes since 2025. Europe, meanwhile, has accelerated automakers' electrification transition through increasingly stringent CO_2 emissions standards. This section provides a concise comparative analysis of core policy frameworks across these three major markets.

A. China's Policies

China's PEV policies can be divided into the Demand-Side Incentive Phase (2009-2016) and the Supply-Demand Driven Phase (2017-present). The earliest PEV policy implementation in China began with the "Ten Cities and Thousand Vehicles Project" in 2009, initially piloted in 13 cities and later expanded to 25 cities. The project accelerated PEV adoption in public transportation by providing purchase subsidies to institutional buyers [22]. Research indicates that the New Energy Vehicle Pilot City program also incentivized technological innovation among enterprises in these cities [23]. Beginning in 2011, major cities progressively lifted purchase restrictions and road access limitations on PEVs [24]. In 2012, the State Council issued the Energy-Saving and New-Energy Vehicle Industry Development Plan (2012-2020), targeting cumulative production and sales of 500,000 units by 2015 and over 5 million units by 2020 [25]. The 2014 vehicle purchase tax exemption policy for eligible PEVs and Fuel Cell Electric Vehicles (FCEVs) significantly reduced consumer costs, fueling rapid sales growth in subsequent years. However, in 2016, the subsidy system underwent significant restructuring with a gradual phase-down to control fiscal expenditures and incentivize manufacturer innovation. While this caused short-term declines in production and sales, it enhanced long-term industrial competitiveness.

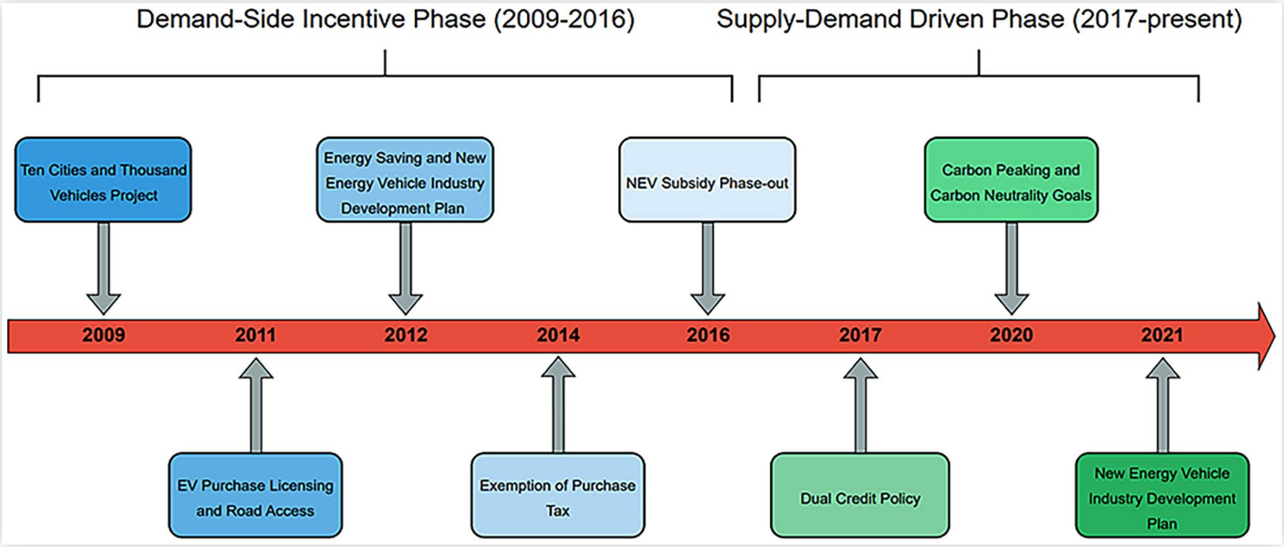
The dual credit policy introduced in September 2017 marked the transition to the Supply-Demand Driven Phase. The system comprises Corporate Average Fuel Consumption (CAFC) credits and New Energy Vehicle credits, requiring manufacturers to control fleet fuel consumption while incentivizing PEV production. Credit trading establishes a market-based mechanism compelling Original Equipment Manufacturers (OEMs) to accelerate technological transformation. China's carbon peaking and carbon neutrality goals elevated PEVs' strategic importance as a critical lever for decarbonizing transportation. The 2021 New Energy Vehicle Industry Development Plan (2021-2035) set targets of 20% PEV sales penetration by 2025 and established pure PEVs as the mainstream by 2035, with core technologies reaching internationally advanced levels [26]. Figure 2 illustrates the evolution of China's PEV policies.

B. U.S.'s Policies

Unlike China's centrally unified policy framework, U.S. PEV policies feature a dual-track system in which distinct federal and state-level approaches shape both supply- and demand-side dynamics. At the state level, California has pioneered supply-side regulations adopted by seventeen states and the District of Columbia. The Zero Emission Vehicle program, established in the early 1990s, mandates that automakers maintain a specified ratio of ZEV credits to total vehicle sales, with this ratio increasing annually to drive greater market penetration. California's Advanced Clean Cars I plan, covering 2012 to 2025, and Advanced Clean Cars II plan, for 2026 to 2035, establish progressively stringent targets, with the latter mandating 100% ZEV sales by 2035. Beyond ZEV mandates, states employ diverse policy instruments, including purchase rebates, sales tax exemptions, registration fee waivers, and high-occupancy vehicle lane access privileges to stimulate demand. They also use LEV standards in states such as California and Oregon to address supply-side emissions. These state-level regulations create substantial pressure on automakers to accelerate electrification in major regional markets.

At the federal level, policy mechanisms address both dimensions through complementary instruments. On the supply side, the Corporate Average Fuel Economy standards, established in 1975 and progressively tightened, impose fleet-wide fuel-efficiency requirements with penalties for noncompliance. By 2025, these standards mandate 53.40 miles per gallon for passenger cars and 38.20 miles per gallon for light-duty trucks, respectively [27]. Since BEVs and PHEVs receive favorable weighting in fleet calculations, these standards indirectly incentivize automakers to expand PEV production. On the demand side, the Federal Tax Credit policy, implemented from 2008 through September 2025, offered eligible consumers up to $7,500 toward the purchase of NEVs [28]. Stricter

FIGURE 2 Evolution of China's PEV Policies



requirements introduced in 2023 included domestic assembly mandates and income caps. Research demonstrates the significant positive impact of federal tax credits on U.S. PEV sales, with these incentives becoming increasingly important over time [29]. This dual-track architecture has historically created a regulatory environment where state mandates set ambitious electrification targets while federal policies provide supply-side pressure through efficiency standards and demand-side stimulus through consumer incentives.

However, beginning in 2025, a series of policy actions has substantially reshaped the regulatory landscape, introducing uncertainty into the framework. Following the enactment of the "One Big Beautiful Bill Act," the federal tax credit for electric vehicle purchases was terminated on September 30, 2025 [28]. Beyond demand-side incentives, supply-side regulations have also undergone substantial review. The Environmental Protection Agency has initiated reconsideration of multiple greenhouse gas regulations, proposing in June 2025 to repeal the 2024 emissions standards for fossil fuel-fired power plants [30]. Additionally, in July of the same year, EPA proposed to rescind the 2009 Endangerment Finding—the scientific determination that serves as the legal foundation for EPA's regulation of greenhouse gas emissions from motor vehicles under the Clean Air Act [31]. If finalized, this action would eliminate EPA's statutory authority to regulate motor vehicle emissions standards and could potentially affect its regulatory basis for greenhouse gas emissions from all transportation and stationary sources. Regulatory uncertainty further extends to the federal-state regulatory architecture itself. In June 2025, the President signed three Congressional Review Act resolutions (H.J. Res. 87, 88, and 89) revoking EPA's Clean Air Act waivers previously granted to California [32]. These actions directly affect the seventeen states and the District of Columbia that have adopted California's standards. The cumulative effect of these policy adjustments creates systemic uncertainty across multiple dimensions—demand-side incentives, supply-side standards, and federal-state regulatory architecture—posing significant challenges to the long-term development trajectory of the U.S. PEV market.

C. European Policies

PEV policies in Europe are predominantly shaped by European Union (E.U.) regulatory frameworks, particularly stringent CO_2 emissions standards aimed at accelerating corporate transformation. In 2009, the E.U. first established mandatory targets for passenger vehicle carbon emissions, initially requiring new passenger vehicles to achieve average emissions of 130 g CO_2/km by 2015. This target underwent revisions in 2014 and 2019, significantly tightening emission standards. The E.U.'s "Fit for 55" package, proposed in July 2021, explicitly mandates a 55% reduction in average passenger vehicle emissions by 2030 and a 50% reduction in van emissions [4]. By 2035, all new vehicles must be zero-emission, effectively banning the sale of internal combustion engine vehicles. To ensure compliance, the E.U. has established a stringent excess emissions penalty mechanism. Under current regulations, each gram per kilometer of emissions exceeding the standard incurs a €95 penalty per vehicle. In 2020, Volkswagen Group paid over €100 million in fines for failing to meet emissions targets. These punitive measures have compelled traditional automakers, including BMW and Volkswagen, to accelerate their electrification strategies. Another notable initiative within the "Fit for 55" package is the Alternative Fuels Infrastructure Regulation. This directive mandates that charging stations be installed every 60 kilometers along major trans-European transport corridors, with hydrogen refueling stations established every 200 kilometers by 2030, providing robust infrastructure support for large-scale PEV adoption across member states.

TABLE 1 Comparison of PEV Policies in China, the U.S., and Europe

Region	China	the U.S.	Europe
Policy Approach	Government-led, coordinated supply- and demand-side measures	Federal-state division, market-oriented policy mix	Regulation-driven, strong compliance enforcement
Supply-Side Policies	Dual-credit	CAFE (ZEV, EPA GHG standards under uncertainty)	CO_2 emission standards
Demand-Side Policies	Purchase subsidies (phased out 2022); Purchase tax exemption	Federal tax credit (ended 2025); state subsidies	National purchase incentives (country-specific)
Key Targets	20% PEV share by 2025	No federal target	100% zero-emission by 2035
New Sales Share in 2024	48% (passenger vehicles)	10% (light-duty vehicle)	22% (passenger car)

D. Summary

The analysis of PEV policies in China, the U.S., and Europe shows that, although all three regions aim to accelerate automotive electrification, they differ substantially in policy design philosophy, instrument choice, and implementation pathways. Table 1 summarizes the core characteristics of PEV policies in these three regions.

Policy differences among the three regions are substantial. China's dual-credit system and subsidy phase-out have enabled supply-demand coordination, propelling rapid market growth. The U.S. framework, historically combining ZEV programs, CAFE[1] standards, and federal

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[1] As of late 2025, California's ZEV program authority was revoked (H.J. Res. 87, 88, 89), and EPA proposed rescinding greenhouse gas vehicle emission standards. CAFE standards remain in effect.

tax credits, underwent substantial restructuring in 2025, with multiple policy reversals introducing significant regulatory uncertainty. Europe's carbon emission regulations, along with the 2035 ban on the sale of traditional gasoline-powered vehicles, constitute the strongest regulatory constraints. These differences reflect distinct governance models across regions and result in notable disparities in market penetration rates.

III. PEV Market Forecasting Methodologies

A. Classification Framework

Methods for forecasting the PEV market can be categorized across multiple dimensions. Previous research has predominantly classified approaches by modeling scale, distinguishing between top-down and bottom-up frameworks [33]. This study proposes a classification framework grounded in methodological foundations, dividing forecasting approaches into theory-driven and data-driven categories.

Theory-driven methods construct models based on established theoretical frameworks or causal mechanisms, emphasizing explanatory insights into market evolution. Rooted in classical theories in statistics, economics, and related disciplines, these models share several key characteristics, including clear theoretical assumptions, strong explanatory power, and parameters with explicit economic or sociological meanings. Representative approaches include the Bass Diffusion, ARIMA, System Dynamics, and Agent-Based models. Their strength lies in revealing the intrinsic mechanisms of market evolution, though their assumptions are often overly idealized and insensitive to volatility.

Data-driven methods have gained prominence with advances in machine learning. They do not rely on predefined theoretical frameworks; instead, they use algorithms to learn underlying trends from data and make predictions automatically. These encompass traditional machine learning approaches such as Random Forest and SVM, as well as deep learning methods including LSTM and GRU. Such methods effectively capture market nonlinearities and achieve high predictive accuracy with sufficient data, but they typically require large, high-quality datasets and often offer limited interpretability.

Methodological integration strategies that combine elements from both categories have become increasingly prevalent. These integrated approaches are classified according to their primary driving mechanism. When theory-driven models incorporate data-driven components as auxiliary tools to capture residual patterns or enhance specific modeling aspects while maintaining theoretical frameworks as the core predictive structure, they remain categorized as theory-driven methods. For instance, ARIMA models augmented with neural networks to model nonlinear residuals retain their classification as theory-driven approaches because the ARIMA framework provides the primary structure, and the neural network serves only to improve residual fitting. Conversely, when data-driven algorithms serve as the primary forecasting engine with theoretical knowledge embedded as constraints or interpretive layers, such approaches fall under the data-driven category. This classification principle ensures conceptual clarity while acknowledging the evolving nature of forecasting methodologies.

B. Method Overview

This section introduces and analyzes various methods based on the classification framework outlined above, which form the methodological foundation for PEV market forecasting research.

1. Theory-Driven Methods

a. Diffusion Model. Diffusion models represent a foundational class of PEV forecasting methods, originating from innovation diffusion theory. These models characterize product market diffusion using S-curves, with commonly used specifications including the Bass, Logistic, Gompertz, and Generalized Bass models. First proposed in 1969, the Bass model simulates new product diffusion by describing the behavior of innovators and imitators in the market [34]. Due to its parameters' clear economic significance and extensive validation across multiple fields, the Bass model has become one of the most widely used and recognized models. Numerous studies have applied the Bass model to forecast PEV markets across different countries and regions. Examples include Becker et al.'s projection of U.S. PEV market penetration through 2030 [14], Jenn et al.'s predictions for future BEV and PHEV penetration rates in multiple nations [35], and Ramadoss et al.'s simulation of early PEV adopters [36].

However, the traditional Bass diffusion model relies on simplified and often idealized assumptions about market dynamics, making it difficult to address uncertainties and dynamic market changes caused by external shocks. Recent studies have attempted to integrate policy, technology, and other influencing factors into the Bass model to enhance predictive performance. For instance, Fan et al. and Li et al. both employed the Generalized Bass model in their respective research to account for PEV market development in the context of green premiums [12,13]. Additionally, both research teams utilized an innovative parameter optimization method combining Nonlinear Least Squares (NLS) with Genetic Algorithms (GA), demonstrating its effectiveness through validation. Li et al. incorporated price factors into the Bass model and integrated grey system theory to propose the Grey Bass Extended Model (GBME) [37]. This model demonstrated superior performance in a comparative analysis of fitting accuracy across multiple models, including Bass and GM(1,1) models. Numerous studies have also explored other diffusion models, with the Gompertz and Logistic models being widely adopted. Dalkic-Melek et al. proposed a combined approach for countries experiencing rising motorization rates: first, predicting motorization rates using the Gompertz model; then, forecasting PEV penetration rates using the Logistic model [38].

b. Time-Series Model. Time-series forecasting models predict future trends by analyzing patterns in historical data, employing statistical methods to extract trends and seasonality. The most widely used time-series forecasting model for PEV sales is the Autoregressive Integrated Moving Average (ARIMA) model. Its autoregressive (AR) component captures patterns in historical data, the integration (I) component addresses non-stationarity, and the moving average (MA) component accounts for lag effects introduced by random errors. Multiple studies have applied this model to forecast PEV sales across various markets with promising results. For instance, Dhankhar et al. combined ARIMA with exponential smoothing to predict India's PEV sales over the next two years, noting the model's effectiveness in capturing short-term fluctuations in the PEV market [39]. Additionally, some studies have examined the effectiveness of other time-series models. For instance, Zhang et al. employed SSA and VAR time-series forecasting models for monthly and annual predictions of China's PEV sales, finding that the SSA model demonstrated strong noise reduction capabilities [40]. In contrast, the VAR model achieved higher prediction accuracy. Veysi validated the SARIMAX model's superior performance in forecasting UK PEV sales from 2015 to 2024, reaching an R-squared value of 0.98 [41]. However, time-series models have notable limitations; their reliance on historical data trends makes them ill-suited to adapt to structural market changes. Kemala noted that ARIMA models fail to capture interactions and dependencies among multiple variables [21]. Even VAR models, capable of handling multivariate relationships, suffer from critical drawbacks: substantial data requirements and an inability to explain nonlinear data relationships.

In recent years, multiple researchers have introduced innovations to the ARIMA framework to overcome these limitations. For instance, Yu et al. proposed the SARIMA-GRA-SVR model: SARIMA captures the temporal characteristics and seasonal patterns of PEV sales, GRA-SVR filters variables highly correlated with sales, and the final optimization combines these through serial and parallel arrangements [42]. Other scholars have proposed residual modeling and nonlinear enhancement methods. Yang et al. extracted linear trends and seasonality from data using ARIMA, then modeled nonlinear features in residuals with a BP neural network, achieving superior performance compared to single models [43]. Ning et al. employed LSTM to model the nonlinear components retained in the residual sequence of the ARIMA model [44]. The resulting ARIMA-IO-LSTM model, incorporating anomaly detection via the IO component, achieved lower forecasting errors for both annual and monthly data.

c. System Dynamics Model. The System Dynamics (SD) model treats the PEV market as an integrated system, describing market changes through differential equations. Unlike traditional forecasting methods, SD's core strength lies in its ability to capture feedback loops and causal relationships among system elements, making it particularly suited for analyzing complex systems with multiple feedback mechanisms. Early SD models primarily evaluated policy impacts through scenario comparisons, involving a limited number of entities. Liu and Xiao categorized PEV policies into direct policies (government programs, financial incentives, and industry regulations) and indirect policies (environmental and energy policies) [45]. They simulated four scenarios through 2040 to demonstrate the effects of different policy combinations on PEV diffusion. Xiang et al. integrated factors influencing PEV purchases into three modules—vehicle development, vehicle demand, and evolution—demonstrating SD's capability to synthesize multi-source data [46].

As research advanced, multi-agent SD models gained prominence. Kong et al.'s SD model captures interactions among governments, companies, and consumers through multi-layered feedback loops [47]. Harrison and Thiel employed a PTTMAM model to simulate automotive market evolution under varying CO_2 regulations and purchase subsidy intensities, emphasizing the critical role of minimal infrastructure deployment in PEV diffusion [11]. Li et al. constructed the most comprehensive four-agent SD model to date, introducing infrastructure operators as decision-makers for the first time [48]. It captures interactions among government, manufacturers, consumers, and infrastructure operators through four key feedback loops. This model demonstrated acceptable error margins of up to 7.8% when testing Chinese PEV sales and ownership data from 2015 to 2020, exhibiting strong short-term predictive capability. While SD models can simulate interactions among different groups, they remain limited in describing micro-level heterogeneity among individual consumers, particularly in capturing individual differences and social network effects.

d. Agent-Based Model. Agent-based modeling (ABM) simulates the behavior and interactions of micro-level agents to observe system dynamics. Unlike the macro-level approach of SD models, ABM excels at capturing decision-making heterogeneity and network effects among agents—characteristics crucial for studying the diffusion of socially influenced innovations like PEVs. Mehdizadeh et al. conducted a systematic review of 86 relevant studies, concluding that ABMs have reached a high level of maturity in PEV diffusion research [49]—the methodological strengths of ABM manifest in two primary aspects. First, ABM effectively captures consumer heterogeneity. Kangur et al. employed a psychological framework to classify the cognitive strategies of 1,795 consumer agents into repetition, imitation, inquiring, and optimizing based on satisfaction and certainty levels [50]. Second, ABM demonstrates particular strength in modeling social networks and word-of-mouth propagation. Liu et al. developed a multi-level social influence model—incorporating global influence and neighbor effect—to study the joint diffusion of PEVs and V2G in Beijing [51]. Additionally, this study innovatively employed a random forest model to generate agent preferences from questionnaire data, demonstrating recent advances in integrating machine learning with ABM.

However, pure ABM faces challenges in long-term forecasting due to high computational complexity and difficulties in effectively handling supply-side dynamics. Recognizing the limitations of single methodologies, recent research has explored hybrid approaches combining SD and ABM. SD-ABM hybrid models employ a "layered modeling" strategy, with most studies using the SD layer to address macro-level supply-side dynamics and the ABM layer to capture micro-level demand-side heterogeneity. Scorrano and Danielis developed an SD-ABM model that parameterized the ABM demand module using real data from 1,521 Italian respondents while employing SD to simulate changes in supply-side battery costs [52]. Zhan et al. proposed a data-driven framework that incorporates user-attribute heterogeneity to effectively evaluate the impacts of incentive schemes based on actual usage [53]. By integrating the system-level modeling capabilities of SD models with the micro-level heterogeneous decision-making simulation capabilities of ABM models, SD-ABM hybrid models offer a more comprehensive and realistic portrayal of PEV market dynamics. This integration emerges as another major research focus in PEV market adoption forecasting.

2. Data-Driven Methods Data-driven methods have flourished as PEV market data has accumulated and computing power has advanced. These methods can automatically uncover patterns and make predictions from data, with different algorithms exhibiting variations in model characteristics and complexity. In PEV market forecasting research, common traditional machine learning approaches include Linear Regression, Random Forest (RF), XGBoost, and SVM. Existing research has quantitatively compared these methods [18], indicating that Gradient Boosting Regressor and Random Forest significantly outperform Linear Regression in market fitting. Additional studies demonstrate that SVM and ANN models achieved outstanding R-squared values of 0.979 and 0.978, respectively, in predicting PEV market penetration in India, with RF closely following at 0.974 [17]. Kumar et al. employed the DEMATEL method to prioritize and weight PEV sales factors, utilizing multiple machine learning approaches to forecast future PEV sales [54]. They found that the Random Forest method achieved the best performance, with the lowest Root Mean Square Error (RMSE) and Mean Absolute Error (MAE).

Deep learning is a method based on multi-layer neural networks that automatically learns data representations and has gained significant attention in PEV forecasting in recent years. Recurrent neural networks (RNNs) are a mainstream choice for PEV forecasting, with the Long Short-Term Memory (LSTM) method favored by numerous studies for their ability to capture long-term data dependencies and achieve high prediction accuracy. Current research often combines LSTM with other models to further enhance prediction accuracy. Mishra et al. employed Gradient Boosted Regression Trees (GBRT) to learn and correct residual errors generated by LSTM predictions, demonstrating that the LSTM-GBRT model achieved lower prediction errors than stand-alone LSTM, Linear Regression, Support Vector Regression (SVR), and ARIMA models [55]. Simsek et al. proposed a combined LSTM-CNN model—EVs-PredNet. This model incorporates convolutional operations for feature extraction and outperforms models composed of individual LSTM or CNN components across four evaluation metrics: MAE, RMSE, MSE, and R-squared [56]. Afandizadeh et al. innovatively combined two-dimensional attention, residual networks, and LSTMs to enhance focus on key features while effectively reducing model complexity, achieving superior prediction performance compared to simple LSTM and ConvLSTM models [57]. Rahaman et al. proposed a Multi-Branch LSTM Architecture with Attention Mechanisms, where three branches process historical PEV sales data, infrastructure and policy signals, and economic trends, respectively [58]. Experiments demonstrated significant improvements over traditional models like single-branch LSTMs and ARIMAs. Bi-directional Long Short-Term Memory (BiLSTM), a model combining forward and backward LSTMs, learns bidirectional temporal dependencies in data, enabling better adaptation to complex dynamics. In both of Liu's two studies, BiLSTM outperformed unidirectional LSTMs [59,60]. Simultaneously, Liu introduced Grey Relational Analysis (GRA) to quantify the correlation between influencing factors and PEV sales volume. By applying the Discrete Wavelet Transform (DWT) to process nonlinear data features, the GRA-DWT-BiLSTM model demonstrated outstanding performance in predicting PEV sales volume in China.

C. Summary

This section systematically reviews and analyzes literature on five mainstream PEV market forecasting approaches: diffusion models, ARIMA-based time-series models, System Dynamics models, Agent-Based models, and deep learning methods. The analysis reveals distinct strengths and limitations inherent in each modeling paradigm. Table 2 summarizes the advantages, limitations, and potential improvement directions of these forecasting approaches.

Recognizing the inherent limitations of standalone models, contemporary research increasingly adopts methodological integration strategies to enhance forecasting performance. Within the theory-driven paradigm, researchers augment classical frameworks by incorporating data-driven components to address specific limitations. ARIMA models are enhanced with neural networks to capture nonlinear residual patterns. In contrast, system dynamics and agent-based models achieve cross-scale integration, simultaneously modeling macro-dynamics and micro-level heterogeneity. Within the data-driven paradigm, deep learning architectures are refined through modular enhancements that address fundamental limitations in model architecture. Additionally, approaches that embed theoretical knowledge into machine learning

TABLE 2 Advantages, Limitations, and Improvement Directions of PEV Market Forecasting Methods

Method	Advantages	Limitations	Improvement Directions
Bass Model [12,13]	Few parameters, clear theory, strong explanatory power	Difficulty in capturing the impact of technological change and policy interventions on market diffusion	Employing the Generalized Bass Model and incorporating external influence variables
ARIMA Time-Series Models [43,44]	High accuracy for short-term forecasts, computationally efficient	Difficulty in capturing underlying nonlinear patterns in data	Introducing neural networks to capture nonlinear residual patterns
System Dynamics (SD) [52,53]	Excels at macro-level system modeling and policy scenario analysis	Unable to describe consumer heterogeneity, social networks, and word-of-mouth effects	Introducing ABM to capture micro-level heterogeneity
Agent-Based Model (ABM) [52,53]	Excels at depicting micro-level heterogeneity and modeling social networks	Large-scale agent simulations face computational bottlenecks	Hybrid SD-ABM frameworks, where SD captures macro-level dynamics to reduce computational burden
Deep Learning [55, 56, 57, 58]	Automatic feature learning; strong ability to capture nonlinear relationships	Single architecture exhibits systematic bias	Overlay ensemble learning, feature extraction, feature selection, attention mechanisms, and other components

frameworks balance predictive accuracy with interpretability. These methodological enhancement strategies, whether through within-paradigm refinement or cross-paradigm integration, have demonstrated superior performance and reliability in PEV market forecasting compared to traditional single-model approaches.

IV. Future PEV Market Comparison

This section compares mainstream projections for PEV sales share through 2035 across China, the U.S., and Europe, synthesizing projections from institutional reports and academic research. The analysis reveals substantial regional differences in both projected share levels and projection consensus, with predictability of the policy framework emerging as the primary determinant of institutional agreement.

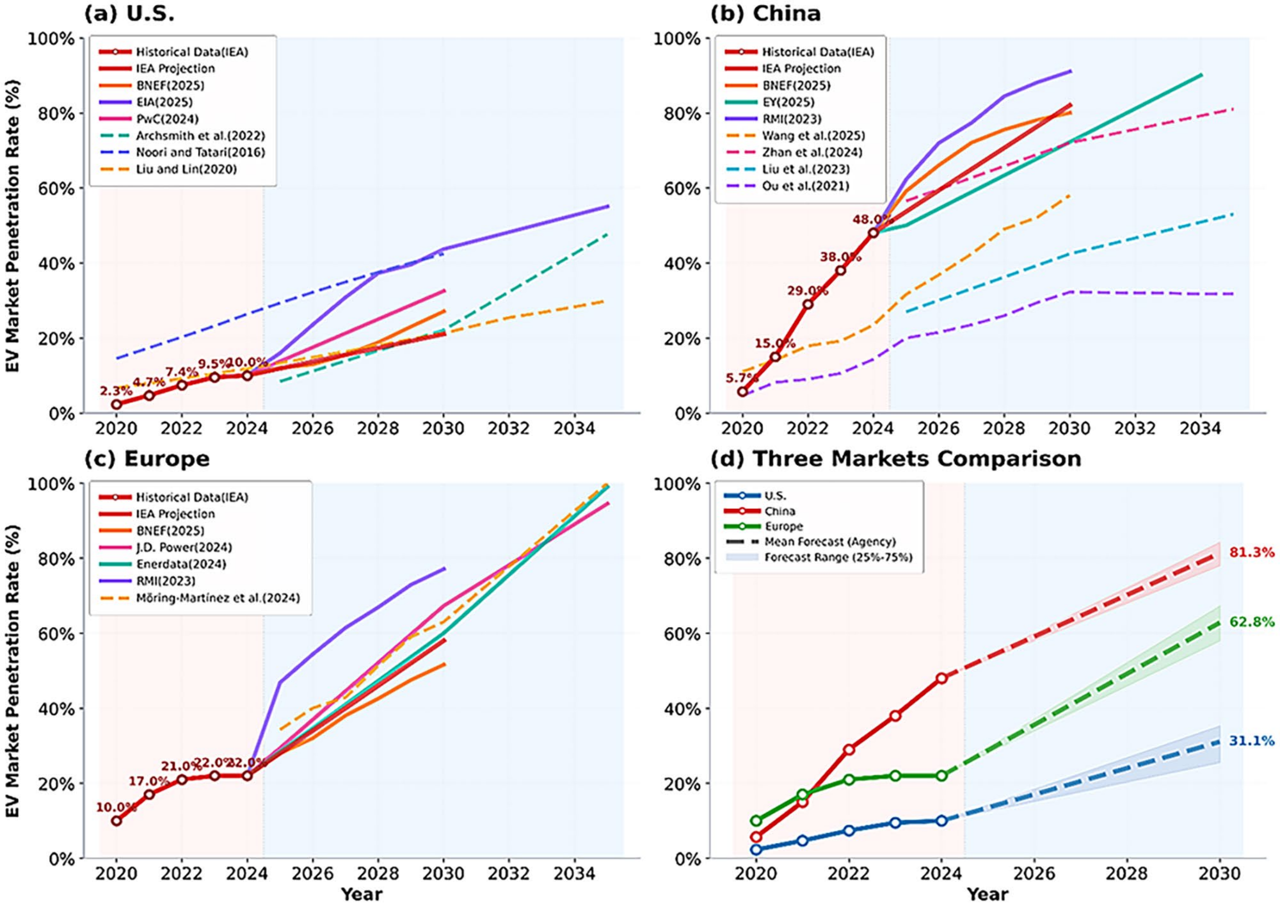
Figure 3 presents these regional projection results. Based on systematic analysis of market projections from major research institutions for China, the U.S., and Europe, this study reveals substantial differences in both projected share levels and the degree of institutional consensus across these three markets. To quantify projection divergence while accounting for baseline differences in market conditions, this study uses the coefficient of variation, defined as the standard deviation of institutional 2030 projections divided by their mean. For sources that present projection ranges instead of point estimates, the corresponding 2030 figures are inferred via linear interpolation between the range endpoints.

The findings demonstrate distinct patterns across regions. China shows the highest projected market share of 81.3%, coupled with the strongest institutional consensus, reflected in a coefficient of variation of only 9.49%. Europe's market shows intermediate characteristics with projections averaging 62.8% and a coefficient of variation of 15.54%, indicating moderate uncertainty. The U.S. presents a markedly different profile, combining the lowest average projected share of 31.1% with the highest degree of divergence, evidenced by a coefficient of variation reaching 31.01%. This threefold difference in variability coefficients across markets, coupled with the substantial gap in absolute sales share projections, reveals a key insight about institutional assessments. These assessments differ not merely in projection magnitude but also in their fundamental confidence regarding each market's development trajectory under prevailing policy and market conditions.

Analysis of 2030 institutional projections indicates that differing policy expectations represent the predominant driver of projection discrepancies, while technology cost assumptions represent secondary factors. Academic research, owing to earlier publication timelines and longer publication cycles, typically reflects earlier baseline years and is thus not directly comparable numerically to current institutional projections, yet it provides critical mechanistic insights into how policy uncertainty translates into projection divergence. The following analysis integrates both sources to illuminate the underlying mechanisms linking policy predictability to projection consensus.

For China's market, mainstream projection agencies have reached consensus on sustained and consistent policy support. IEA's projection of 82% is based on the continuation of the current policy framework and progress in vehicle affordability [1]. In comparison, BloombergNEF's 80% projection emphasizes that policy-driven cost advantages have made China the only major market where the average purchase price of PEVs is lower than that of comparable gasoline vehicles [66]. Limited projection divergence primarily stems from differing assessments of technological cost trajectories, with RMI's higher projection of 91% explicitly incorporating accelerated battery cost reductions and intensified environmental policy pressures [61]. This institutional consensus reflects confidence

FIGURE 3 Projection and Comparison of PEV Sales Share in China, the U.S., and Europe. Different data scopes were employed based on official reporting standards: passenger car data for China and Europe, and light-duty vehicle data for the U.S. Solid lines represent institutional projections, while dashed lines represent academic projections, distinguishing their different analytical functions and publication years. In subfigure (d), dashed lines represent averaged institutional projections, with shaded areas showing projection ranges (25th-75th percentiles). Data from selected sources were extracted using WebPlotDigitizer 5.2 because the raw numerical data were not publicly available. Historical data source: IEA [1]; Institutional projection sources: [1,61, 62, 63, 64, 65, 66, 67, 68]; Academic literature sources: [53,59,69, 70, 71, 72, 73, 74].



in China's structured policy evolution. Academic analyses reveal how the dual-credit system maintains market predictability through progressive policy transitions rather than disruptive shifts [59,69,70]. Studies further demonstrate that while significant provincial variation exists in adoption patterns, the centralized policy architecture ensures coordinated national trajectories [59], substantiating institutional confidence in long-term policy continuity.

For the U.S. market, the significantly higher projection uncertainty reflected in its coefficient of variation of 31.01% originates from fundamental disagreements among stakeholders regarding policy stability under the current federal administration. BloombergNEF's projection of 27.07% attributes the downside primarily to the rollback of federal fuel-economy standards, the elimination of federal tax credits [66], and reduced investment in charging infrastructure. It assumes that California retains its regulatory exemption for the Advanced Clean Cars II program, while noting that projections would need to be revised if the exemption were revoked. IEA's lower projection of 21% reflects its assessment that policy headwinds will cap growth at less than half the level projected in its previous analysis [1]. Academic research illuminates why this policy volatility generates such pronounced projection divergence by revealing that policy influences adoption through multiple compounding pathways beyond direct financial incentives [71,72]. Analyses demonstrate that policy signals affect not only purchase economics but also consumer confidence in technology maturity, social network diffusion patterns, and infrastructure investment expectations [72,73]. This multiplicity of transmission mechanisms means that policy instability creates cascading uncertainty across the full spectrum of adoption drivers, explaining why institutional projections diverge more dramatically in the U.S. than in markets with stable policy frameworks [71].

For Europe's market, an intermediate pattern of projection divergence emerges. In response to recent relaxations in European carbon emission reduction requirements, BloombergNEF has, for the first time, lowered its long-term and near-term PEV sales share projections to 51.6% [66]. IEA acknowledges that recent policy revisions offer automakers greater flexibility, but maintains that the fundamental regulatory impetus for mandatory zero-emission requirements by 2035 remains unchanged, projecting 58% [1]. J.D. Power's projection of 67.3% incorporates detailed analysis of subsidy program reductions across multiple member states from 2023 to 2024 [64], including Germany's elimination of purchase incentives and France's reduced support levels, while noting that temporary compliance flexibility allows automakers to de-prioritize PEV sales in favor of higher-margin internal combustion engine models. This moderate divergence reflects the tension between near-term implementation flexibility and long-term regulatory certainty. Academic scenario analyses confirm that the binding 2035 zero-emission mandate provides a strategic anchor, constraining projection variability despite tactical policy adjustments [74]. The contrast between adjustable compliance pathways and the immovable regulatory endpoint explains why European institutional projections exhibit intermediate rather than high divergence.

These market-specific analyses reveal a strong systematic association between policy framework predictability and projection consensus, suggesting that policy stability plays a central role in shaping institutional agreement. The striking contrast across the three markets—from China's strong institutional agreement to the U.S.'s pronounced divergence and Europe's intermediate pattern—closely aligns with differences in policy stability and regulatory certainty. This systematic relationship between policy predictability and projection convergence has critical implications for both market projection methodologies and policy design. It suggests that the credibility and consistency of regulatory frameworks strongly influence institutional confidence in market trajectories.

V. Conclusions

PEV sales share projections hold critical significance for government policy formulation, automakers' production capacity planning, and infrastructure operators' facility development strategies. This study addresses gaps in existing literature by proposing a classification framework that categorizes mainstream forecasting methods into theory-driven and data-driven approaches. The framework systematically reviews five key methodologies: diffusion models, represented by the Bass model; ARIMA time-series models; System Dynamics models; Agent-Based models; and deep learning models, including LSTM-based approaches. Analysis reveals that contemporary research increasingly adopts methodological enhancement strategies that incorporate auxiliary components to address limitations inherent in standalone models. Within the theory-driven paradigm, researchers augment classical frameworks with data-driven elements to capture nonlinear residual patterns, exemplified by ARIMA models integrated with neural networks and cross-scale SD-ABM coupling. Within the data-driven paradigm, deep learning architectures employ modular stacking and ensemble techniques to reduce systematic bias. These within-paradigm refinements and cross-paradigm integrations demonstrate superior predictive performance compared to traditional single-method approaches. Additionally, this study systematically analyzes major PEV policies across China, the U.S., and Europe. It synthesizes the latest market projections from leading research institutions and academic studies for these three markets.

Cross-market comparative analysis reveals a strong systematic relationship between policy framework characteristics and projection consensus, with policy stability emerging as the central determinant of institutional agreement. China’s sustained policy consistency, characterized by stable implementation of the dual credit system and continuous purchase tax exemptions, is associated with the highest projection convergence, with 2030 sales share projections averaging 81.3%. Academic scenario analysis demonstrates how China's structured policy transition from supply-side to demand-side incentives maintains stakeholder confidence through progressive, phased evolution. Europe’s binding 2035 zero-emission mandate provides long-term regulatory certainty, yielding an intermediate level of projection consensus, with projected sales shares averaging 62.8%. This regulatory anchor effectively contains projection divergence despite near-term implementation adjustments. In contrast, the U.S. exhibits the greatest projection divergence, with projections averaging only 31.1%, reflecting fundamental disagreement stemming from fragmented federal-state policy architecture and multiple policy reversals in 2025 that affect both supply-side and demand-side mechanisms.

The cross-national patterns yield two critical policy implications. First, policy stability and long-term commitment mechanisms are essential for market trajectory predictability, as consistent regulatory frameworks reduce projection divergence and strengthen stakeholder confidence in electrification pathways. Second, successful policy transitions require gradual, structured mechanisms rather than abrupt shifts. China's progressive policy evolution exemplifies how phased adjustments maintain market momentum while mitigating disruptive uncertainty. Across both institutional and academic assessments, policy framework stability consistently correlates with market trajectory predictability, underscoring that policy credibility serves as a foundational determinant of projection consensus and effective policy design for accelerating PEV market transitions.

This study has certain limitations that suggest future research directions. The geographic scope is limited to China, the U.S., and Europe, leaving many other markets unexplored. Future research could expand coverage to emerging markets, including Japan, South Korea, and India, to test whether the policy predictability-consensus relationship generalizes across different institutional contexts. Additionally, longitudinal tracking of projection revisions could provide empirical evidence on how different modeling approaches adapt to policy changes and technological developments. Moreover, systematic accuracy analysis across temporal horizons could guide method selection for specific forecasting contexts.

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Contact Information

Shiqi(Shawn) Ou
sou@scut.edu.cn; oushiqi@pazhoulab.cn
Phone number: +86-020-81181684
Mailing address:
1. South China University of Technology, School of Future Technology, 777 Xingye Ave East, Panyu District, Guangzhou, Guangdong, 511442, China
2. Guangdong Artificial Intelligence and Digital Economy Laboratory (Guangzhou), 70 Yuean Road, Haizhou District, Guangzhou, Guangdong 510335, China

Acknowledgments

This work is funded by the Development Agreement between Saudi Aramco Technologies Company and South China University of Technology (SCUT) (SATC 2024-006) and used the facilities of the Pazhou Laboratory. All opinions expressed in this paper are the authors' and do not necessarily reflect the policies and views of SCUT, Pazhou Laboratory, or Saudi Aramco.

ISSN 0148-7191