



American Journal of Smart Technology and Solutions (AJSTS)

ISSN: 2837-0295 (ONLINE)

VOLUME 5 ISSUE 2 (2026)

PUBLISHED BY
E-PALLI PUBLISHERS, DELAWARE, USA

Sustainable Market Forecasting of Electric Vehicle Adoption Using Machine Learning Techniques in Emerging Economies

Md Anas Biswas^{1*}, Mahbube Rabbani², Safia Farzana Nishi³, Ashutosh Roy⁴, Md Samir Murad⁵

Article Information

Received: July 28, 2026

Accepted: October 09, 2026

Published: October 19, 2026

Keywords

Electric Vehicle Adoption, Emerging Economies, EV Market Transition, Machine Learning, Market Forecasting, Predictive Analytics, Sustainable Transportation

ABSTRACT

The rapid transition toward sustainable transportation has increased the importance of electric vehicle (EV) adoption forecasting, particularly in emerging economies where market growth is influenced by economic conditions, charging infrastructure availability, vehicle costs, and policy environments. The scale of EV market penetration, however, is not a straightforward prediction owing to the fact that it can differ based on adoption rates, infrastructure deployment, and socioeconomic conditions in individual countries. This study proposes a machine learning tool to develop a sustainable market forecasting model to forecast adoption of EVs in emerging economies based on past market, economic, infrastructure and policy indicators. An EV adoption dataset was used, which consists of EV sales share, charging infrastructure, economic indicators, vehicle price data, and policy features across 26 emerging economies spanning 2010 to 2025. A set of forecasting models, such as Linear Regression, Ridge Regression, XGBoost, Gradient Boosting and an ensemble approach, was tested with an unseen test period from 2025, employing a leakage aware time-series validation strategy. The ensemble forecasting model presented here proved to have a high level of predictive skill with R^2 , RMSE and MAE values of 0.9010, 5.0773 and 3.7198, respectively. The historical trends of EV adoption, development of charging infrastructure, economic factors, and policy considerations were identified as primary drivers of future EV market growth through feature analysis. The results illustrate how machine learning-based forecasting can help offer decision-support information to policymakers, industry, and sustainable transportation planners. The suggested model is a step towards more data-informed EV transition planning, as it facilitates accurate market prediction and assists in sustainable mobility planning in new economies.

INTRODUCTION

The rapid transition to sustainable transportation has expedited the global adoption of electric vehicles (EVs) as a promising solution for lowering greenhouse gas emissions, reducing reliance on fossil fuels, and promoting environmentally friendly mobility. Governments and companies worldwide are encouraging EV adoption through technological improvements, policy incentives, and expanded charging infrastructure. However, as EV penetration has increased, new issues have emerged in market planning, demand assessment, production management, and infrastructure preparedness, making accurate forecasting of EV adoption and sales even more crucial. Economic conditions, technological advancement, availability of charging infrastructure, government legislation, and consumer preferences all have an impact on the EV market's growth (Mehta *et al.*, 2026). Machine learning-based analyses of EV adoption behavior show that factors such as income, vehicle cost, running cost, driving range, environmental awareness, and social influences significantly affect consumers' EV purchase decisions. These findings highlight the importance of considering diverse demographic and contextual variables for understanding EV adoption patterns (Dixit & Singh, 2022; Sanjib Kumar Shil *et al.*, 2024). Although understanding adoption factors is essential, forecasting

future EV demand and sales remains challenging because the EV market is nonlinear and rapidly changing. Traditional forecasting approaches often struggle to capture complex interactions among multiple influencing variables. Recent studies have therefore explored machine learning-based forecasting frameworks due to their capability to identify hidden patterns and model nonlinear relationships. Machine learning-based EV sales forecasting approaches have incorporated important influencing factors such as historical EV sales, EV market share, charging infrastructure, electricity demand, and energy-related parameters. Different forecasting techniques, including ARIMA, XGBoost, Random Forest, and LSTM, have demonstrated the effectiveness of machine learning approaches for improving EV sales prediction and supporting infrastructure planning (Kumar *et al.*, 2024). Furthermore, accurate EV demand forecasting has become increasingly important for optimizing manufacturing decisions, inventory management, and sustainable supply chain operations. Machine learning-based forecasting approaches can improve demand estimation by integrating historical market data with economic and technological factors. Predictive analytics can help manufacturers reduce uncertainty, optimize production processes, and improve strategic decision-making in the rapidly evolving eco-friendly vehicle market

¹ Department of Artificial Intelligence & Machine Learning, University of Portsmouth, Portsmouth, UK

² Naveen Jindal School of Management, University of Texas at Dallas, Texas, USA

³ Faculty of Business Studies, University of Dhaka, Dhaka, Bangladesh

⁴ Business Analytics Researcher, Gannon University, Erie, USA

⁵ College of Engineering and Applied Sciences, Stony Brook University, New York, USA

* Corresponding author's e-mail: anasbiswas@hotmail.com

(Kozlovskiy *et al.*, 2025). Despite significant progress in EV forecasting research, several limitations remain. Many existing studies focus mainly on prediction accuracy while providing limited understanding of the factors influencing EV adoption. Moreover, machine learning models often operate as complex black-box systems, reducing their interpretability for policymakers and industry stakeholders. Integrating machine learning models with interpretability techniques can provide deeper insights into the relationship between policy factors, charging infrastructure, economic conditions, and EV adoption. Such explainable approaches are important for combining predictive capability with actionable insights for effective EV transition strategies (Khusanboev *et al.*, 2023; Nsan *et al.*, 2025). Therefore, this study aims to develop a comprehensive machine learning-based framework for EV adoption forecasting by incorporating relevant socioeconomic, technological, and infrastructure-related factors. Unlike conventional approaches that primarily focus on prediction performance, this research also investigates the contribution of different influencing variables to provide meaningful insights for decision-makers. The proposed framework can assist policymakers, automotive industries, and energy planners in developing effective strategies for future EV market expansion and infrastructure development.

LITERATURE REVIEW

Recent Developments in Electric Vehicle Adoption and Sustainable Transportation Forecasting

The rapid growth of electric vehicle (EV) adoption has become a key component of sustainable transportation development due to its potential to reduce greenhouse gas emissions and dependence on fossil fuels. Recent studies indicate that EV adoption is driven by multiple factors, including economic conditions, technological improvements, charging infrastructure availability, government policies, and consumer preferences. Vehicle cost, driving range, operating cost, and environmental awareness have been identified as important determinants influencing consumer EV adoption decisions (Saqr *et al.*, 2025). The expansion of EV markets has also increased the need for accurate forecasting approaches to support infrastructure planning, production strategies, and policy development. Traditional forecasting methods often face limitations in capturing the nonlinear and dynamic characteristics of EV markets. Therefore, machine learning-based approaches have gained attention due to their ability to analyze complex relationships among historical adoption trends, market conditions, infrastructure factors, and economic indicators (Kabir *et al.*, 2025). Recent research has further highlighted the importance of integrating predictive analytics and explainable approaches for sustainable EV transition planning. Machine learning-based forecasting frameworks can improve demand estimation, optimize strategic decision-making, and provide insights into the factors affecting EV market growth (Reza *et al.*, 2025). Moreover,

combining predictive models with interpretability techniques enables stakeholders to better understand the influence of policy, infrastructure, and economic variables on EV adoption patterns (Cordero *et al.*, 2026).

Theoretical and Practical Foundations of Electric Vehicle Adoption Forecasting

Theoretically, the adoption of electric vehicles depends on the dynamics between consumer attitudes, economic conditions, infrastructure availability, technological developments, and sustainability considerations. The results of the earlier studies suggest that EV adoption is related to several factors such as economic advantages, environmental attitude, social-economic factors, and purchase cost, as well as battery range. Financial incentives and supportive policies are key to fast-tracking EV adoption, with EV price identified as a key barrier (Sobiech-Grabka *et al.*, 2022). The adoption of charging infrastructure and readiness of energy systems will also play a significant part in EV adoption forecasting. To achieve reliable and sustainable transportation development, intelligent charging systems, demand management and grid integration are essential for the growth of EV markets. The potential of IOT based charging frameworks to promote real-time monitoring, predictive demand forecasting, and energy management in the context of a large deployment of EVs (Rahman, 2025). The shift to renewables and growth of electricity consumption in emerging markets will also shape future EV uptake. Forecasting models need to account for factors in energy and economic developments, as these are closely related to EV growth, development of renewables and SDGs, instead of only transportation (Bin Abu Sofian *et al.*, 2024). The use of machine learning is a powerful way to study these intricate relationships and make predictions, optimizations, and identify key influencing factors. The flexibility of ML techniques has made them popular tools for sustainable energy systems, such as forecasting and optimizing their operation, and this can be equally valuable for EV adoption modelling. The adaptability of ML techniques has been leveraged in sustainable energy systems for forecasting and optimizing energy use, which can also be valuable for EV adoption modelling (Nassar & Khaleel, 2024). Moreover, the use of AI-based frameworks has demonstrated their ability to optimize the economic, environmental and operational goals of complex EV-related systems in the face of uncertainty (Almuwallad, 2026). Hence, a robust EV adoption forecasting should be done in a machine-learning approach by considering market trends, economic indicators, infrastructure, policy parameters, and sustainability-related parameters.

Challenges in Machine Learning-Based EV Market Forecasting

While machine learning offers promising solutions for predicting EV adoption trends, there are a number of challenges that can hinder practical implementation.

Availability and quality of reliable data is a major challenge. The analysis of EV markets needs to draw on a range of data, from past sales figures and key economic indicators, to infrastructure availability to consumer behavior and policy considerations. But uneven availability of data and short historical time-series, especially for emerging economies, may diminish model reliability and forecasting accuracy (De Silva *et al.*, 2025). One of the difficulties is the complexity of including several technological, economic and environmental aspects within the forecasting models. There is a variety of factors that affect EV adoption such as battery technology, charging infrastructure, government policies, manufacturing capacity, and market conditions, making prediction a very dynamic challenge (Zaino *et al.*, 2024). Additionally, emerging economies may also have infrastructure gaps, limited resources, and less adoption of the latest digital technologies, posing extra challenges to data-driven decision-making (Khan *et al.*, 2024; Salman *et al.*, 2025). Interpretability of the models and deployment on the real world are also key challenges. While high predictive performance can be achieved with advanced ML models, they may lack insights into individual factors that affect EV adoption decisions. Thus, embedding explainable AI (XAI) techniques is essential to make AI systems more transparent and to help policymakers, manufacturers and stakeholders make decisions. Further, the adoption of digital technologies like AI, IoT and predictive analytics needs the appropriate infrastructure and investments, which can be more difficult in developing markets (Akbari & Hopkins, 2022). Thus, issues of data availability, model transparency and economic and infrastructural factors of emerging economies need to be addressed to develop a stronger EV adoption forecasting framework. The challenges underscore the importance of a more holistic machine learning methodology that can take into account multiple factors while being both reliable and usable.

Limitations of Current EV Adoption Forecasting Research

While there is considerable research on forecasting EV adoption through machine learning, there are still some limitations in this research. There is a significant deficiency in comprehensive and consistent technological, economic, infrastructural and policy-related data. Many forecasting studies tend to be short-term and only incorporate historical sales and technical factors, and exclude important dynamic socio-economic and policy factors that can make predictions unreliable, especially in emerging economies (Ahmed, 2026; Singh *et al.*, 2026). The other restriction is the lack of attention to policy change and regional variations in forecasting models. While existing ML approaches usually consider policy factors as static variables, policy incentives and regulatory changes can have a significant impact on technology adoption pathways, which should be taken into account as dynamic predictors (Ghobadpour *et al.*, 2022). Moreover, the adoption of EVs has to be coordinated and take

into account the development of vehicles, charging infrastructure, power systems, and digital technologies, which makes forecasting a difficult task when these are considered individually (Mhlanga, 2021; Pozo-Burgos *et al.*, 2026). Further, the interpretability and usefulness of sophisticated ML models are significant challenges. While complex models can be very accurate in predicting outcomes, the lack of transparency can make it hard to use the model for policymaking and industry involvement. In the future, EV adoption forecasting studies should prioritize data-driven models that are interpretable, accurate, and practical, incorporating various factors that influence EV adoption.

Research Gap

While a number of studies on EV adoption and its determinants have been conducted, very few attempts have been made to combine historical adoption data, charging infrastructure, economic data, vehicle market dynamics, and policy-related variables in a machine learning forecasting model for emerging economies. This study thus develops a comprehensive forecasting approach to predict the trends in EV adoption and identify the key factors influencing the sustainable market transition.

Research Questions

1. What is the ability of a machine-learning based framework to predict the trends of EV adoption in emerging economies successfully?
2. What machine-learning model is the most accurate in predicting electric vehicle adoption?
3. To what extent do the forecast models developed by the researcher accurately predict EV adoption when using the MAE, RMSE and R^2 metrics of error?
4. Which of the following economic, infrastructure, vehicle market and policy related factors are most significant to EV adoption forecasting?
5. How can the forecasting of EV adoption with machine learning help support sustainable transportation planning and market transition strategies?

Research Objectives

The primary aim of this study is to create a sustainable market forecasting framework for EV adoption in emerging economies with machine-learning methods. In particular, this study will attempt to:

1. To create a machine learning-based model to predict EV adoption trends.
2. To compare the forecasting models and find out which model is the best.
3. To test the model's performance with the right forecasting indicators.
4. To perform feature analysis to determine the factors that will affect the adoption of EVs.
5. To deliver information to support sustainable transportation planning.

MATERIALS AND METHODS

Study Area

This study concentrates on the emerging economies where the adoption of electric vehicle (EV) is driven by economic growth, infrastructure availability, vehicle market conditions and government policies. Analysis presented in this report is based on country-level annual information for 26 emerging economies for the period 2010 to 2025. The study enables the comparison of EV transition stages among the different countries and the investigation of different EV adoption patterns in varying economic and market conditions. The chosen study area represents a more comprehensive overview of EV market transformation, as it takes into account multiple countries, instead of a single national market. This strategy allows to create a more generalizable machine-learning-based forecasting model for sustainable EV adoption predictions in emerging economies.

Study Design

This study was conducted using a “Quantitative Machine Learning-Based Forecasting Research Design” to create sustainable market forecasting framework for the adoption of the electric vehicle (EV) in emerging economies. This study was designed to forecast the EV sales share based on past EV adoption trends and economic, infrastructure, vehicle market and policy factors. An ensemble model, Gradient Boosting Regression, XGBoost Regression, Ridge Regression and Linear Regression were created and tested with time-series forecasting framework.

Sample Size and Selection

The data set of EVs adopted used in this study is a multi-country EV adoption data set of 26 emerging countries from 2010 to 2025. There are 416 country-year observations included in the dataset that include information regarding EV sales shares, charging infrastructure, economic indicators, vehicle prices, and EV policy related factors. The target variable was the percentage of EV sales (EV sales share) which was the percentage of EV sales in each country in one year. The dataset was chosen to reflect the wide-range of EV transition patterns in emerging economies, where economic, infrastructure and policy factors can differ.

Measures and Variables

The input factors were divided into five categories: historical adoption, infrastructural, economic, car market, and policy-related aspects. Historical adoption variables included prior EV sales share and adoption trends in order to capitalize on market momentum. Infrastructure variables included charging availability metrics including total charging points, slow chargers, fast chargers, and ultra-fast chargers. GDP per capita, GDP growth, EV, PHEV, ICE car, and EV pricing premium were among the economic and market variables examined. A policy intensity indicator was incorporated to measure the impact of EV policies, incentives, infrastructure programs, and

government support mechanisms.

Data Collection Procedure

Secondary data from official IEA and World Bank sources were used in the study. The collected datasets were combined at the country-year level to create a multi-country EV adoption forecasting panel that covers 26 rising economies from 2010 to 2025. The IEA provided information on the EV market, charging infrastructure, vehicle prices, and policy-related variables, while the World Bank provided economic data. The integrated dataset was arranged into a time-series panel, and feature engineering was used to develop historical adoption indicators and other prediction factors. The dataset was organized chronologically to ensure that future information would not influence model development.

Research Tools and Techniques

Python was used in a Jupyter Notebook to process data, engineer features, construct models, and evaluate them. Pandas and NumPy were used for data processing, Scikit-learn for regression model development and evaluation, XGBoost and Gradient Boosting for advanced forecasting, and Matplotlib for visualization.

Data Analysis Techniques

Exploratory analysis was conducted to examine EV adoption patterns and relationships among forecasting variables. Model performance was evaluated using Mean Absolute Error (MAE), Root Mean Square Error (RMSE), and R^2 score. A leakage-aware time-series validation technique was used with historical validation periods, and the final model performance was assessed with an unseen 2025 holdout dataset. A feature importance analysis was also conducted to discover the key parameters driving EV adoption predictions.

RESULTS AND DISCUSSION

Dataset and EV Adoption Trend Analysis

The analysis revealed that the forecasting model developed was based on a master panel of 416 country-year observations for 26 economies, for the period 2010-2025. Of these observations, 297 observations had values for the officially defined EV sales share targets, and the other EV sales share targets were omitted to prevent an artificial expansion of the data set. The final forecasting framework produced 266 leakage-safe (one-year ahead) supervised samples across the 26 economies. The EV share of new car sales trajectories for the chosen emerging economies are shown in Figure 1 from 2010 to 2025. The figure shows that there are significant variations in the pattern of EV uptake across countries, with some economies having significant growth, and others having relatively slower uptake patterns. This is because these changes remind us of the need to take historical patterns of adoption and country specific variables into account when predicting the market for EVs.

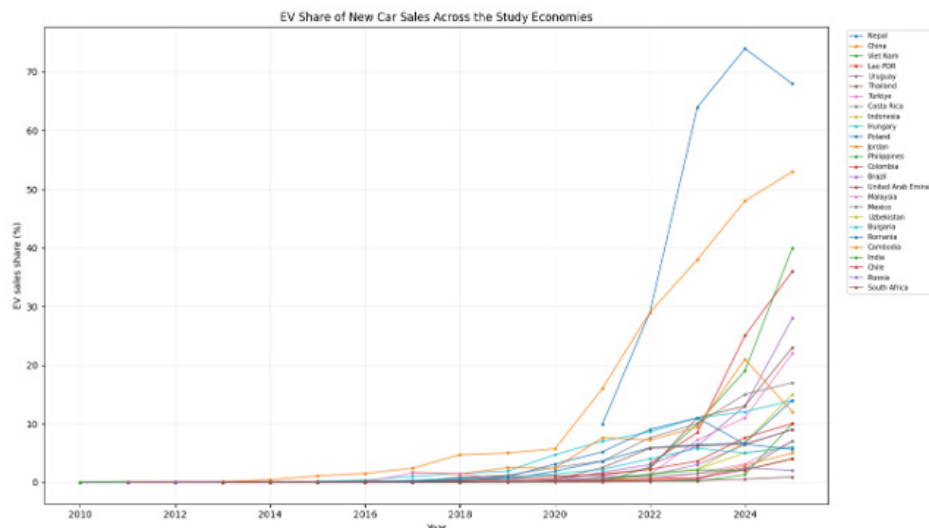


Figure 1: EV Share of New Car Sales Across the Study Economies (2010–2025)

Forecasting Model Performance

The forecasting performance of various machine-learning models was assessed using a leakage-aware rolling-origin validation technique. The development review considered prediction years ranging from 2021 to 2024, with each forecasting period based only on information available prior to the prediction year. The models compared were baseline forecasting techniques, linear regression, ridge regression, xgboost regression, gradient boosting regression, and the suggested calibrated ensemble model.

Figure 2 shows a rolling-origin backtest comparison based on RMSE values for various forecasting models. The results demonstrated that nonlinear ensemble-based techniques outperformed classic regression approaches in terms of predicting capabilities. The final forecasting framework combined calibrated XGBoost and Gradient Boosting models, with calibration performed solely on pre-2025 out-of-fold predictions to avoid future information leaking.

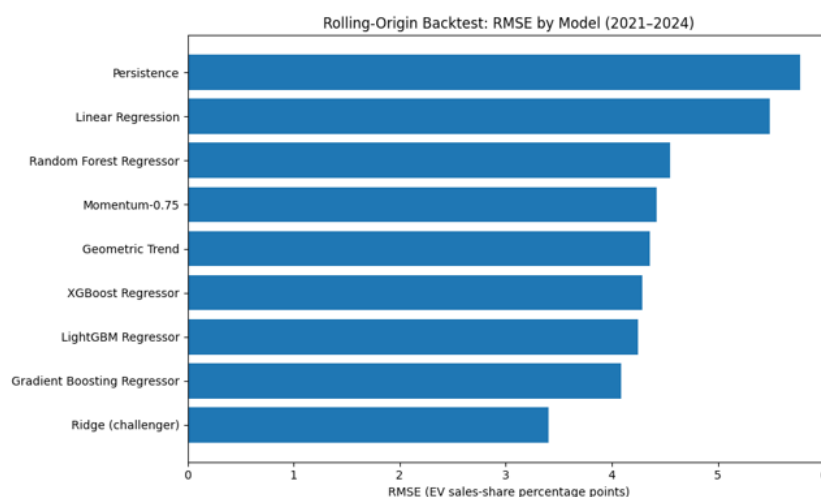


Figure 2: Rolling-Origin Backtest: RMSE Comparison of Forecasting Models (2021–2024)

Final Holdout Evaluation and Prediction Analysis

The final model performance was assessed using an unseen 2025 holdout dataset that included all 26 economies. During the independent test period, the calibrated XGBoost and Gradient Boosting ensemble model demonstrated excellent predicting ability. The final evaluation findings are shown in Table 1.

The difference was accounted for by the value of the

model that was used to forecast. The prediction error was within a tolerable range for forecasting the cross country EV market, with the RMSE value at 5.0773 percentage points. It is clear from Figure 3 that the actual and projected EV adoption remains constant throughout the holdout period of 2025 years. The results show that in the selected economies, the expected values were close to what was seen on the ground for EV uptake.

Table 1: Performance of the Calibrated XGB+GBR Ensemble Model on 2025 Holdout Data

Metric	Value
MAE	3.7198
RMSE	5.0773
R ²	0.9010
MAPE	36.8323%
sMAPE	31.7089%

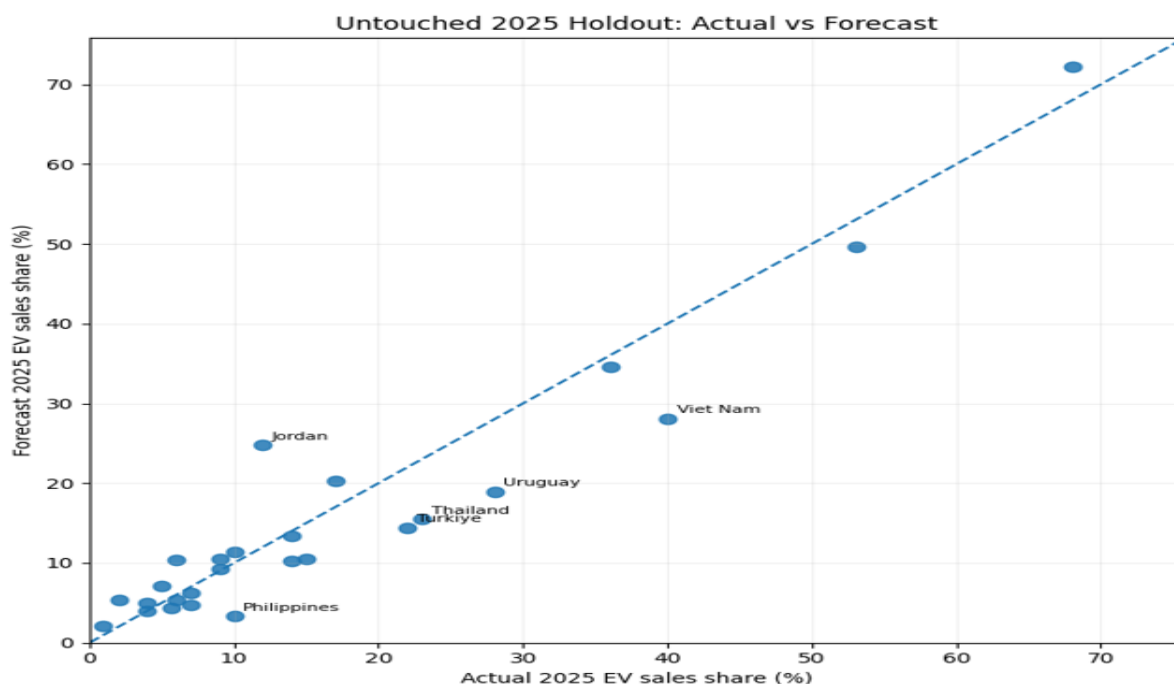


Figure 3: Country-Level Comparison of Actual and Forecasted EV Adoption Share in 2025

The country-level comparison of the actual and projected EV adoption share for the 2025 holdout economies is shown in Figure 3. The graphic illustrates how the calibrated XGB+GBR ensemble model may account for differences in EV adoption rates among various emerging economies.

Feature Importance Analysis

[illegible]

other factors mentioned above, including previous market development, readiness of infrastructure, economic capability, and supportive policy environments.

Future EV Adoption Forecasting

The created approach was then used to forecast EV uptake for 2026. The 2026 forecasting characteristics were developed using just information accessible through 2025, guaranteeing that no future market information was used in the prediction process. Prediction uncertainty was evaluated using a time-dependent calibration method based on prior forecasting errors. The estimated 90% prediction interval has an uncertainty radius of about ± 8.95 percentage points. Figure 5 shows the 2026 EV adoption predictions for the selected economies, with 90% prediction intervals. The visualization compares anticipated 2026 EV adoption levels to observed 2025 values, revealing likely future market transition patterns.

DISCUSSION

The outcomes of this study show that machine learning-based forecasting may accurately capture the complex patterns related with electric vehicle (EV) uptake in emerging economies. The suggested framework's

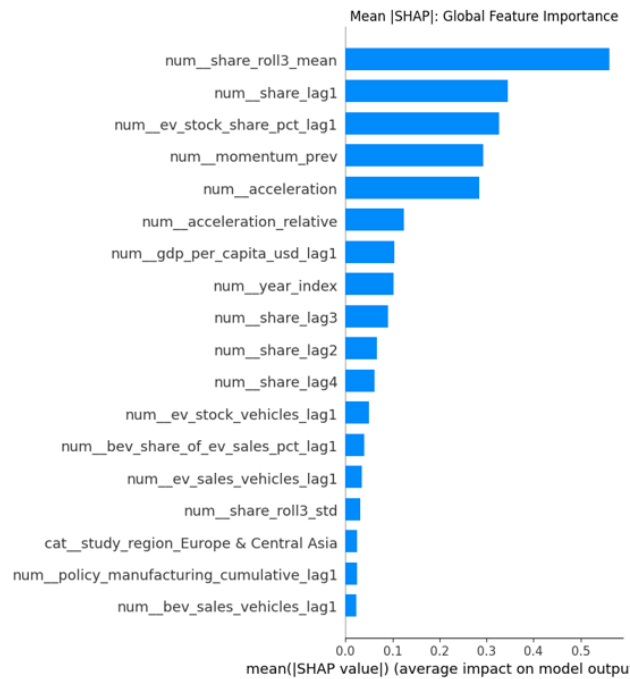


Figure 4: SHAP-Based Feature Importance Analysis of EV Adoption Forecasting Model

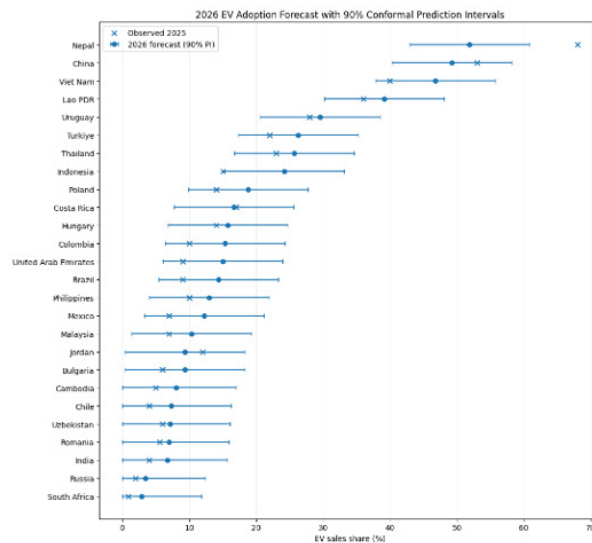


Figure 5: 2026 EV Adoption Forecast with 90% Prediction Interval

good predictive performance suggests that combining historical adoption trends with economic, infrastructure, and market-related aspects might improve forecasting accuracy. Similar data-driven approaches have proven that advanced machine learning models, such as artificial neural networks and hybrid forecasting frameworks, are successful in capturing nonlinear linkages in the energy and technology markets (Li *et al.*, 2023). The findings also emphasize the necessity of charging infrastructure and energy system readiness as important drivers of EV market growth. Previous research has identified high car costs and limited charging infrastructure as important hurdles to widespread EV adoption, emphasizing the necessity for coordinated infrastructure development and supportive policy (Hafeez *et al.*, 2023). As a result,

forecasting models that include infrastructure-related variables can provide more accurate insights into potential EV adoption paths. Furthermore, the findings highlight the growing importance of artificial intelligence and machine learning in sustainable transportation planning. Recent research indicates that AI-based techniques can evaluate large-scale mobility data, forecast transportation trends, and optimize sustainable mobility systems (Rouky *et al.*, 2025). Financial limits, technology constraints, legal concerns, and market preparation all have an impact on adoption patterns in emerging economies. These considerations must be considered while constructing viable forecasting frameworks for developing regions (Hmamed *et al.*, 2026). Overall, this study builds on past research by offering a comprehensive

forecasting approach that considers many EV adoption variables rather than focusing on individual factors. The combination of machine learning with various socioeconomic and infrastructure characteristics might help policymakers and industry stakeholders establish evidence-based strategies for speeding sustainable EV adoption in emerging nations.

Findings

1. This study was able to create a machine-learning framework to accurately predict the EV adoption level in the emerging economies.

2. The comparative analysis revealed that the ensemble model XGBoost (with 81.59%) and Gradient Boosting (with 81.71%) were the best forecasters among the models considered.

3. The selected ensemble model's performance on the unseen holdout data set of 2025 resulted in an MAE of 3.7198, RMSE of 5.0773 and an R^2 of 0.9010.

4. Historical EV adoption, charging infrastructure, economic conditions, vehicle price factors, and policy-related indicators were identified as features in 4. The features identified for historical EV adoption, charging infrastructure, economic conditions, vehicle price factors, and policy-related indicators were used to forecast EV adoption.

5. The forecasting model generated information that can be used in the planning of sustainable transportation and future EV market assessment.

Recommendations

1. Machine-learning-based forecasting is recommended to be used to gauge future EV adoption trends in emerging economies.

2. As the main forecasting method in the current framework, the calibrated XGBoost and Gradient Boosting ensemble should be taken into account.

3. A single performance measure is not adequate to evaluate the forecasting models of EVs; multiple regression metrics should be used instead.

4. When examining the future development of the EV market, the following factors should be taken into account: 4. Historical adoption, charging infrastructure, economic conditions, vehicle prices and policy-related factors.

5. The data-driven EV forecasts shall serve as evidence to support sustainable transport planning and EV transition strategies for policy makers and other stakeholders.

Limitations

This study has several limitations that should be considered.

1. The analysis was carried out using a dataset that covered 26 emerging economies from 2010 to 2025; thus, the findings may not fully reflect EV adoption patterns in other worldwide markets.

2. Some contributing aspects, such as customer

behavior, social acceptance, charging accessibility at the local level, and unforeseen market disruptions, were excluded from the forecasting methodology due to data availability constraints.

3. This study's policy intensity index is based on research and may not accurately reflect the complexities of government policy implementation and effectiveness.

CONCLUSION

This study used machine learning techniques to create a long-term market forecasting framework for electric car uptake in emerging economies. The suggested framework used historical EV adoption trends, charging infrastructure, economic indicators, vehicle market determinants, and policy-related variables to forecast future EV market growth. Several forecasting models were tested, and the calibrated Boost plus Gradient Boosting ensemble model outperformed the others on the previously unseen 2025 holdout dataset. The model has a R^2 value of 0.9010, showing it can explain a significant amount of variability in EV adoption rates among emerging economies. The feature analysis revealed that historical adoption trends, infrastructure availability, economic conditions, car affordability, and policy assistance all have a significant impact on the EV market transition. Overall, the findings show that machine-learning-based forecasting has the potential to help with sustainable transportation planning decisions. To increase forecasting reliability and practical applicability, future research should include additional behavioral, regional, and market-specific characteristics, as well as evaluate the framework using larger datasets from a wider range of nations.

REFERENCES

- Dixit, S. K., & Singh, A. K. (2022). Predicting Electric Vehicle (EV) Buyers in India: A Machine Learning Approach. *The Review of Socionetwork Strategies*, 16(2), 221–238. <https://doi.org/10.1007/s12626-022-00109-9>
- Khusanboev, I., Yodgorov, I., & Karimov, B. (2023). Advancing Electric Vehicle Adoption: Insights from Predictive Analytics and Market Trends in Sustainable Transportation. *Proceedings of the 7th International Conference on Future Networks and Distributed Systems*, 314–320. <https://doi.org/10.1145/3644713.3644754>
- Kozlovskiy, S., Kulinich, T., Duszyński, M., Popovskiy, T., Dluhopolska, T., Kornatka, A., & Popovskiy, Y. (2025). Forecasting Demand for Eco-Friendly Vehicles Using Machine Learning Technologies in the Era of Management 5.0. *Sustainability*, 17(10), 4429. <https://doi.org/10.3390/su17104429>
- Kumar, S., Singh, V., & Goel, R. (2024). Strategic Forecasting for Electric Vehicle Sales: A Cutting Edge Holistic Model Leveraging Key Factors and Machine Learning Technique. *Transportation in Developing Economies*, 10(2), 23. <https://doi.org/10.1007/s40890-024-00213-1>
- Mehta, M. H., Patel, V., & Desai, J. P. (2026). Integrating

- machine learning and natural language processing for electric vehicle purchase intention prediction: A novel framework for emerging markets. *Development and Sustainability in Economics and Finance*, 9, 100116. <https://doi.org/10.1016/j.dsef.2026.100116>
- Nsan, N., Obi, C., & Etuk, E. (2025). Bridging Policy, Infrastructure, and Innovation: A Causal and Predictive Analysis of Electric Vehicle Integration Across Africa, China, and the EU. *Sustainability*, 17(12), 5449. <https://doi.org/10.3390/su17125449>
- Sanjib Kumar Shil, Muhammad Shoyaibur Rahman Chowdhury, Nikhil Rao Tannier, Md Tanvir Rahman Tarafder, Rabeya Akter, Nisha Gurung, & Mir Mohtasam Hossain Sizan. (2024). Forecasting Electric Vehicle Adoption in the USA Using Machine Learning Models. *Journal of Computer Science and Technology Studies*, 6(5), 61–74. <https://doi.org/10.32996/jcsts.2024.6.5.6>
- Sagr, A. E.-S., Saraya, M. S., & El-Kenawy, E.-S. M. (2025). Enhancing CO2 emissions prediction for electric vehicles using Greylag Goose Optimization and machine learning. *Scientific Reports*, 15(1), 16612. <https://doi.org/10.1038/s41598-025-99472-0>
- Reza, S. A., Hasan, M. S., Amjad, M. H. H., Islam, M. S., Rabbi, M. M. K., Hossain, A., Shovon, M. S. S., & Jakir, T. (2025). Predicting Energy Consumption Patterns with Advanced Machine Learning Techniques for Sustainable Urban Development. *Journal of Computer Science and Technology Studies*, 7(1), 265–282. <https://doi.org/10.32996/jcsts.2025.7.1.20>
- Kabir, M. A., Master of Science in Marketing Analytics & Insights; Wright State University, Ohio, USA, Ahmed, F., & Master of Science in Marketing Analytics & Insights, Wright State University, Ohio, Usa. (2025). Strategic Us Energy Market Insights: A Data-Driven Analysis Of U.S. Fuel Consumption, Pricing Trends, And The Rise Of Electric Vehicles. *American Journal of Interdisciplinary Studies*, 06(01), 174–207. <https://doi.org/10.63125/6bka3w37>
- Cordero, D. M., Villavicencio, M. F., Luna, K. A., & Castillo, Y. (2026). Intention to adopt electric transportation services by university students in emerging countries. *PLOS One*, 21(1), e0341736. <https://doi.org/10.1371/journal.pone.0341736>
- Sobiech-Grabka, K., Stankowska, A., & Jerzak, K. (2022). Determinants of Electric Cars Purchase Intention in Poland: Personal Attitudes v. Economic Arguments. *Energies*, 15(9), 3078. <https://doi.org/10.3390/en15093078>
- Rahman, M. (2025). *IoT-Enabled Smart Charging Systems for Electric Vehicles*. <https://doi.org/10.36227/techrxiv.176049766.60280824/v1>
- Nassar, Y., & Khaleel, M. (2024). *Sustainable Development and the Surge in Electricity Demand Across Emerging Economies*. <https://ijeos.org/index.php/ijeos/index>
- Almuwallad, M. (2026). AI-Driven Resilient Reverse Logistics Network for Electric Vehicle Battery Circular Economy: A Deep Reinforcement Learning Approach with Multi-Objective Optimization Under Disruption Uncertainty. *Energies*, 19(3), 738. <https://doi.org/10.3390/en19030738>
- Bin Abu Sofian, A. D. A., Lim, H. R., Siti Halimatul Munawaroh, H., Ma, Z., Chew, K. W., & Show, P. L. (2024). Machine learning and the renewable energy revolution: Exploring solar and wind energy solutions for a sustainable future including innovations in energy storage. *Sustainable Development*, 32(4), 3953–3978. <https://doi.org/10.1002/sd.2885>
- Zaino, R., Ahmed, V., Alhammadi, A. M., & Alghoush, M. (2024). Electric Vehicle Adoption: A Comprehensive Systematic Review of Technological, Environmental, Organizational and Policy Impacts. *World Electric Vehicle Journal*, 15(8), 375. <https://doi.org/10.3390/wevj15080375>
- Salman, S., Karim, Md. R., Morshed, S. M., Rahman, R., Tushar, S. R., Liza, S. A., & Chowdhury, N. R. (2025). Mapping industry 4.0 strategies for sustainable logistics: Insights from the electronic industry in emerging markets. *International Journal of System Assurance Engineering and Management*, 16(6), 2246–2264. <https://doi.org/10.1007/s13198-025-02798-1>
- Khan, M. R., Islam, M. T., Islam, K. S., & Hossain, A. (2024). Closing The Productivity Gap In Electric Vehicle Manufacturing: Challenges And Solutions. *Innovatech Engineering Journal*, 1(01), 223–243. <https://doi.org/10.70937/itej.v1i01.21>
- De Silva, K. P. N. T., Shehan, H. A., Jayawardhane, A. S., Premarathne, A. P. S., Krishara, J., & Wijendra, D. R. (2025). AI-Driven Vehicle Valuation and Market Trend Analysis for Sri Lanka's Automotive Sector. *2025 IEEE International Conference on Automatic Control and Intelligent Systems (I2CACIS)*, 461–466. <https://doi.org/10.1109/I2CACIS65476.2025.11101629>
- Akbari, M., & Hopkins, J. L. (2022). Digital technologies as enablers of supply chain sustainability in an emerging economy. *Operations Management Research*, 15(3–4), 689–710. <https://doi.org/10.1007/s12063-021-00226-8>
- Ahmed, S. (2026). *Renewable electricity data and policy* [Dataset]. Mendeley Data. <https://doi.org/10.17632/NB6V979284.1>
- Ghobadpour, A., Monsalve, G., Cardenas, A., & Mousazadeh, H. (2022). Off-Road Electric Vehicles and Autonomous Robots in Agricultural Sector: Trends, Challenges, and Opportunities. *Vehicles*, 4(3), 843–864. <https://doi.org/10.3390/vehicles4030047>
- Mhlanga, D. (2021). Artificial Intelligence in the Industry 4.0, and Its Impact on Poverty, Innovation, Infrastructure Development, and the Sustainable Development Goals: Lessons from Emerging Economies? *Sustainability*, 13(11), 5788. <https://doi.org/10.3390/su13115788>
- Pozo-Burgos, E. J., Alpala, L. O., & Heredia-Campaña, A. L. (2026). Electric Mobility Transition, Intelligent Digital Platforms, and Grid-Vehicle Integration Models: A Systematic Review. *World Electric Vehicle*

- Journal*, 17(3), 123. <https://doi.org/10.3390/wevj17030123>
- Singh, S. K., Alhassan, M., Wang, B., Wan Alwi, S. R., Abdul Manan, Z., Woon, K. S., & Lim, J. S. (2026). Forecasting Malaysia's energy consumption dynamics: A sectoral analysis using hybrid RF-ANN modeling and shared socioeconomic pathways. *Energy*, 347, 140196. <https://doi.org/10.1016/j.energy.2026.140196>
- Hafeez, A., Alammari, R., & Iqbal, A. (2023). Utilization of EV Charging Station in Demand Side Management Using Deep Learning Method. *IEEE Access*, 11, 8747–8760. <https://doi.org/10.1109/ACCESS.2023.3238667>
- Hmamed, H., Cherrafi, A., Shokri, A., Garza-Reyes, J. A., & Foster, M. (2026). Barriers to Low-Carbon Technology Adoption: Insights From the Automotive Manufacturing Sector in Emerging Economies. *Business Strategy and the Environment*, 35(3), 4422–4443. <https://doi.org/10.1002/bse.70337>
- Li, X., Sengupta, T., Si Mohammed, K., & Jamaani, F. (2023). Forecasting the lithium mineral resources prices in China: Evidence with Facebook Prophet (Fb-P) and Artificial Neural Networks (ANN) methods. *Resources Policy*, 82, 103580. <https://doi.org/10.1016/j.resourpol.2023.103580>
- Rouky, N., Benmoussa, O., Fri, M., Abourraja, M. N., & Ben-Bouazza, F-E. (2025). Artificial Intelligence Applications for Smart and Sustainable Mobility as a Service Concept: A Systematic Literature Review. *Future Transportation*, 5(3), 122. <https://doi.org/10.3390/futuretransp5030122>