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An intelligent information framework for estimating the causal impact of financial incentives on electric vehicle adoption

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A R T I C L E I N F O

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A B S T R A C T

Efficient financial incentives play an important role in accelerating the adoption of electric vehicles (EVs). This study applies causal machine learning, specifically Double Machine Learning (DML) combined with a Gradient Boosting model, to estimate the true causal effect of discounts on EV sales. The proposed model significantly improves predictive performance, achieving an R^2 value of 0.941, which represents a substantial improvement over baseline methods. The causal analysis indicates that a 1% increase in discounts leads to a statistically significant rise in sales; however, this effect varies across different customer groups and geographic regions. In addition, SHAP analysis is employed to provide interpretable insights into the key factors influencing EV adoption. Overall, the study presents a robust framework that integrates predictive modeling with causal inference and offers practical guidance for policymakers and manufacturers to design targeted and effective incentive strategies for promoting EV adoption.

1. Introduction

The shift to electric vehicles (EVs) is a part of the global sustainability plans to lower greenhouse gas emissions and reliance on fossil fuels (Ramkumar et al., 2025). Various financial incentives to jumpstart EV adoption have been implemented by governments worldwide, such as tax credits, purchase refunds, and reduced registration fees. German policymakers have initially invested in EV charging infrastructure in the whole country to encourage adoption; however, they have changed to a competitive, privately funded market as budget pressures decrease, as well as state intervention (Loehr and Hanken, 2025). Although such associations have been extensively examined using traditional econometric models (e.g., OLS regression), they primarily capture correlations rather than actual causal effects. As a result, policymakers are unsure whether noted rising trends of the electric vehicle (EV) adoption can be truly a result of financial policy or coincide with other structural determinants, including income distribution, the availability of charging infrastructures, or brand availability (Ahmad et al., 2025). This confusion is acute, especially in the Gulf Cooperation Council (GCC) economies, where the fast-paced digital transformation, the heterogeneous development of the region, and the changing sustainability agenda make the evaluation of the policies more challenging (Sadriwala et al., 2024). Previous research proves that high-dimensional confounding variables, such as regional income inequality, infrastructural preparedness, and consumer tastes, are likely to contaminate policy effect estimates and cannot be controlled by simple regression models (Creutzburg et al., 2025). The latest GCC-oriented studies also emphasize that analytically sound, data-based policy models are required to enable one to isolate causal effects and help in sustainable economic decision-making and incentive optimization (Rashid Al-Shamsi and Shannaq, 2024). The limitations inspire the application of the causal machine learning methods to present more credible, policy-relevant information regarding the efficacy of EV financial incentives in the emerging sustainability-oriented economies. Thus, a machine learning structure based on causal inference is required that can (Skoropad et al., 2025):

- Determine the actual cause-effect of monetary incentives on EV uptake,
- Adjust (condition) confounding variables in a data-driven and robust manner, and

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- Deliver policy-relevant estimates that could be used to inform the future sustainable transportation strategies.

Therefore, the primary research question will be: How does the level of financial incentives (discounts and tax breaks) cause the adoption rate of electric vehicles, controlling for region, economic, and brand-related confounders?

This study is suggested to solve this research problem by applying a Causal Machine Learning framework based on the Double Machine Learning (DML) and the EconML library by Microsoft (Yao, 2025). The approaches represent a continuation of traditional econometrics in that they integrate the ease of interpretation of causal inference with the forecasting capabilities of contemporary machine learning models.

2. Literature review

The use of electric vehicles is currently an area of focus in modern transportation studies. The scholars have always depended on the fiscal incentives, access to the charging infrastructure, and consumer-behavioral variables as the major contributors to market penetration (Rashidi et al., 2025). Empirical evidence shows that interventions of government policies and monetary subsidies play a decisive role in boosting the rate of uptake of electric vehicles, with increased environmental awareness and easy access to charging stations further stimulating uptake. Similarly, Enkel and Wintgens (2025) revealed that perceived risk, consumer knowledge, and incentive structure play a key role in mass-market EV adoption, highlighting the importance of incentive and behavioral drivers.

Policy-based recent research has tried to measure the causal effects of incentives using econometric and ecosystem-based approaches. Cao et al. (2025) provided causal findings to suggest that policy incentives are positive factors for both innovation and diffusion in the EV industry, but Ghani et al. (2025) noted that there are still technological and regulatory bottlenecks that reduce the adoption curve. These studies have provided useful information on policy; however, it fails to address the non-linear dynamics and endogeneity of responses in the case of regional or customer responses, as often the studies are based on linear or aggregate-level models.

Machine-learning (ML) methods have increasingly been used to predict the demand for EV adoption and charging infrastructure in order to overcome predictive constraints. Hybrid ML-econometric models have been adopted to identify adoption drivers by region (Nsan et al., 2025), while deep learning architectures like LSTMs and transfer learning models have enabled better forecasting of the electrical infrastructure demand and electrical consumption pattern (El-Afifi et al., 2025; Hussain et al., 2025; Tanmayi et al., 2025). Although the current studies of ML are highly predictive, the existing literature usually acts as black-box models, hence making them less interpretable and limited in their ability to evaluate evidence in the creation of policy.

To address the issue of transparency, explainable artificial-intelligence (XAI)-related approaches such as SHAP have been used to explain the model forecasts and define the important factors in the decision-making involving EVs (Haque et al., 2025). Nevertheless, these methods only help to clarify correlations and not to define causal consequences, so it remains unknown whether the emphasized drivers indeed require adoption results. Parallel methods of decision-analysis, including DEMATEL schemes, have sought causative relationships of factors of adoption, but many do not have predictive strength and scalability.

Altogether, these gaps in research are revealed by the literature. To begin with, not many studies are a combination of rigorous causation and high-performance ML models to provide an accurate estimation of the effects of financial incentives on EV adoption. Second, interpretable mechanisms are rarely incorporated into the causal frameworks, and this limits the viability of the policy recommendations that come out as a result of it. Third, the heterogeneity at the regional and customer level is under-investigated on the unified analytical frameworks.

To address them, the current paper presents a combination of three algorithms to predict the outcome with accuracy using Gradient-Boosting regression, interpretability of the model using SHAP, and to determine the causal effect with Double-Machine-Learning. This integrated method permits a coherent but methodologically sound evaluation of financial incentive conditions, thus developing the accuracy of empirical research of EV-adoption studies and their applicability in practice.

3. Methodology

In this analysis, the author employs a causal machine learning framework based on Double Machine Learning (DML), implemented via Microsoft's EconML library, to estimate the causal impact of financial incentives—represented by the discount rate applied to EV price (Discount%)—on electric vehicle (EV) adoption, measured by the number of vehicles sold (UnitsSold).

Unlike traditional regression models, which primarily capture correlations, DML enables the estimation of causal effects by controlling for high-dimensional confounding factors such as region, brand, vehicle specifications, and customer segment. This ensures that the estimated relationships reflect true causal effects rather than spurious associations.

The study aims to estimate both the Average Treatment Effect (ATE) and the Conditional Average Treatment Effect (CATE) of discounts on EV sales. Fig. 1 illustrates the overall methodological framework. The dataset consists of 515 observations obtained from an open-source repository on Kaggle, representing monthly EV sales data collected from dealerships and online platforms. Each observation corresponds to a specific EV model and time period and includes financial, regional, and customer-related attributes.

EV sales serve as the primary outcome variable, while the discount rate represents the treatment variable. Additional covariates are included to control for potential confounding effects, including geographic market (Region), vehicle brand (Brand), customer segment (CustomerSegment), battery capacity (kWh), vehicle type (VehicleType), and fast-charging availability (FastChargingOption), all of which may influence both pricing strategies and sales outcomes.

Data preprocessing involves handling missing values, encoding categorical variables, and standardizing numerical features. The DML framework is implemented using machine learning models such as Random Forest and Gradient Boosting to estimate nuisance parameters and capture nonlinear relationships.

The estimation procedure includes training the model, computing the ATE to quantify the overall causal effect, and estimating the CATE to assess heterogeneity across regions and customer segments.

Finally, counterfactual analysis is conducted to simulate alternative policy scenarios, such as zero-discount conditions and targeted incentive strategies. These simulations help identify the most responsive customer groups and support evidence-based policy design. The results provide an estimate of the causal impact of financial incentives on EV adoption while accounting for confounding factors.

Fig. 1: Methodology

4. Experiments and results

The given experiment, as presented in Fig. 2, combines machine learning, deep learning technology, and causal inference to estimate and predict the adoption of electric vehicles (EVs), as well as eliminate the role that financial incentives play in the process. This will start with the data acquisition phase, in which the EV sales data is loaded, and a random seed is established to ensure reproducibility. Pre-processing of data involves processing of missing values, creating lag features, calculating growth rates, deriving time-related values, coding categorical values, and standardization of numeric variables. The set is subsequently divided into training and testing sets (80:20 proportion). Linear Regression, Random Forest, and Gradient Boosting are baseline machine learning models trained and evaluated by MAE, RMSE, and R^2. Next, deep learning models are used: a Deep Neural Network with two hidden layers and dropout and LSTM sequential forecasting, which was trained in 50 epochs with the Adam optimizer. SHAP is used to analyze explainable AI (XAI) with the purpose of identifying the importance of a feature in a model and explaining model predictions. To make a causal inference, DML through EconML is utilized to estimate the ATE of financial incentives on the adoption of EV. UnitsSold is the outcome variable, Discount% is the treatment variable, and covariates do not include the two variables. In the LinearDML framework, the estimation of the nuisance parameters is performed with the help of random Forest regressors. Lastly, the model performance measures, SHAP plots, and ATE estimates are assembled to be able to make actionable policy-making and strategic planning.

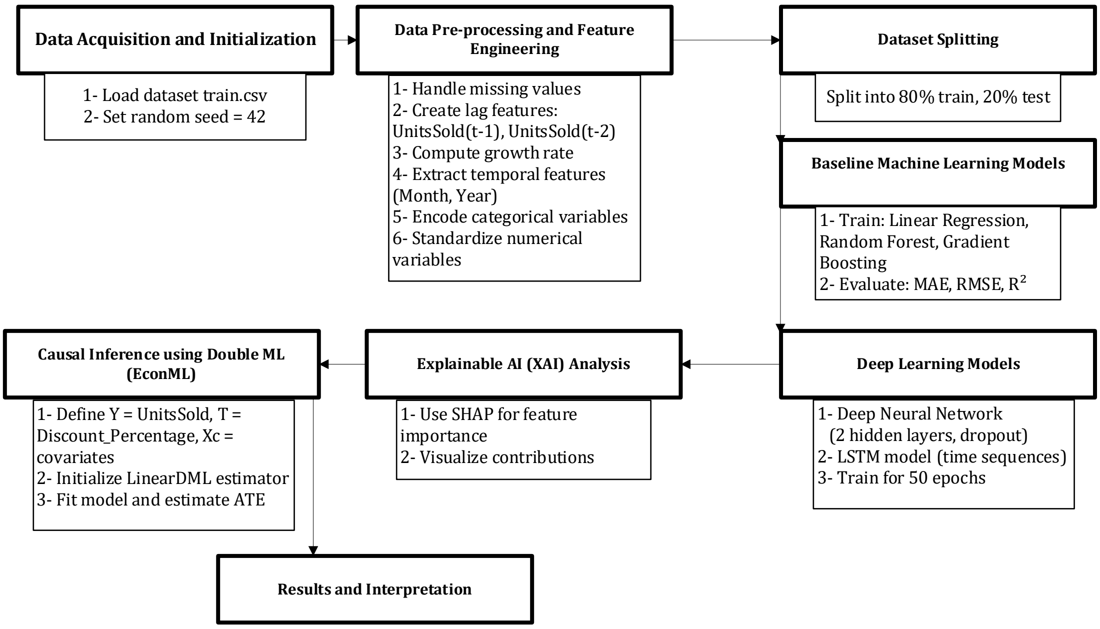

Fig. 2: Experiment steps

Fig. 3 reflects real and estimated EV sales with a scatter plot and low correlation to the trend line in the diagonal direction, which means a poor predictive model. All in all, the outcomes are poor since forecasts do not follow real values, meaning low model accuracy.

The first experiment was able to pass through the important pre-processing and modeling phases, such as encoding of categorical variables and dividing the data into two parts, training and testing. The Linear DML model trained without any problems, and the estimated ATE of discounts on EV sales was -0.1237, which means that every 1% higher the discount the worse the sales on average are expected to be. The CATE effect of 107 observations indicated that there is a mean of -0.1237, with a large deviation of -2.77 to 2.84, and that there exists a large degree of heterogeneity between the regions and the customer groups. The results of the regression evaluation on outcome predictions showed that the R^2 value (-0.1567), MAE (88.88), and RMSE (108.41) indicate that the causal estimates are not very predictive and need additional refinement of the model.

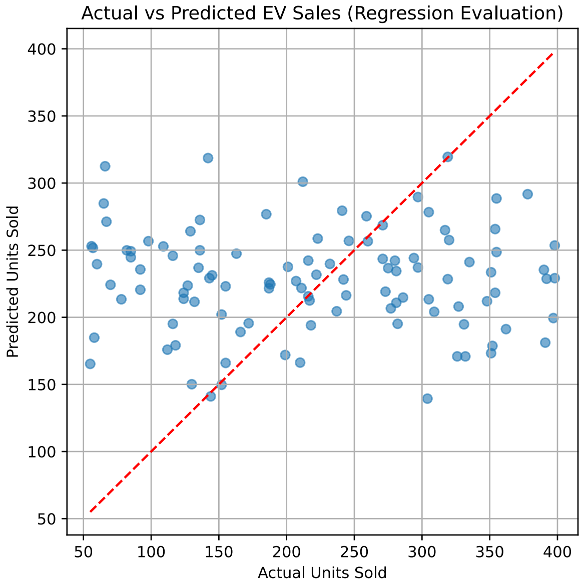

Fig. 3: First results of regression evaluation

The second experiment is much better than the first one. Table 1 and Fig. 4 present a scatter plot of predicted vs actual EV sales with the help of Gradient Boosting, which depicts almost flawless alignment along the diagonal, which means that predictions were really good. This is substantiated by the 5-fold cross-validation, where the Gradient Boosting model had the highest R^2 at 0.93, MAE of 0.104, and a RMSE of 0.136, as compared to the other models, and there was a significant improvement in predictive accuracy on Experiment 1, where R^2 was negative, and the prediction error was high.

The third experiment indicates that discounts have a strong positive causal impact on EV sales. The estimated ATE is 3.48 units per 1 percent discount and implies that as the discount increases by 1 percent, the average increase in EV sales is 3.48 units. The heterogeneity in the CATE analysis shows the range of effects between -4.14 and 7.03 units, with a mean of 3.47, and a standard deviation of 1.91. Most of the customers and regions are more responsive to discounts than others.

The results of the SHAP feature importance are shown in Fig. 5. Battery-to-Revenue is the most influential on predictions, and Battery Capacity and Discount-to-Revenue are the next technical and financial aspects that prevail in EV adoption.

Fig. 6 shows that there is a range of variation in discount responsiveness among observations, with the majority of them above zero showing that the discounts are generally increasing EV sales, although heterogeneously. Table 2 shows that the Gradient Boosting was the most accurate model with the MAE = 17.795, RMSE = 24.443, and R^2 = 0.941 after several experiments and tuning, which indicates a promising predictive accuracy. Random Forest with R^2 = 0.929 was the next closest, followed by Linear Regression with R^2 = 0.778. The performance of deep learning models was much lower, with LSTM exhibiting negative R^2, and Deep Neural Network (DNN) reaching appalling performance, which proves that the most appropriate models to use on this dataset are tree-based ensemble approaches.

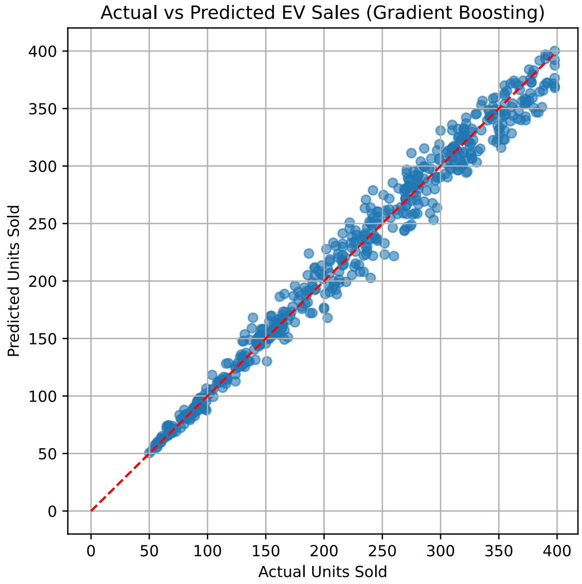

Fig. 4: Second results after using 5-fold cross-validation and gradient boosting

Table 1: Statistical comparison of actual and predicted EV sales

Model	R^2 (mean)	MAE (mean)	RMSE (mean)
Gradient boosting	0.931	0.104	0.136
Random forest	0.929	0.107	0.137
Linear regression	0.791	0.183	0.235
Neural network	0.772	0.190	0.247

Table 2 is a comparison of five models on MAE, RMSE, and R^2. Gradient Boosting and Random Forest are predominant, and LSTM and DNN cannot be generalized, which exemplifies the effectiveness of the ensemble approaches.

Fig. 7 shows that the best feature importance of CatBoost predictions is represented in the SHAP plot. The most influential are Discount%, Battery

Capacity, and temporal features (Month, Year), and less influential are Region and Brand, which means that the EV uptake is driven by financial and technical factors.

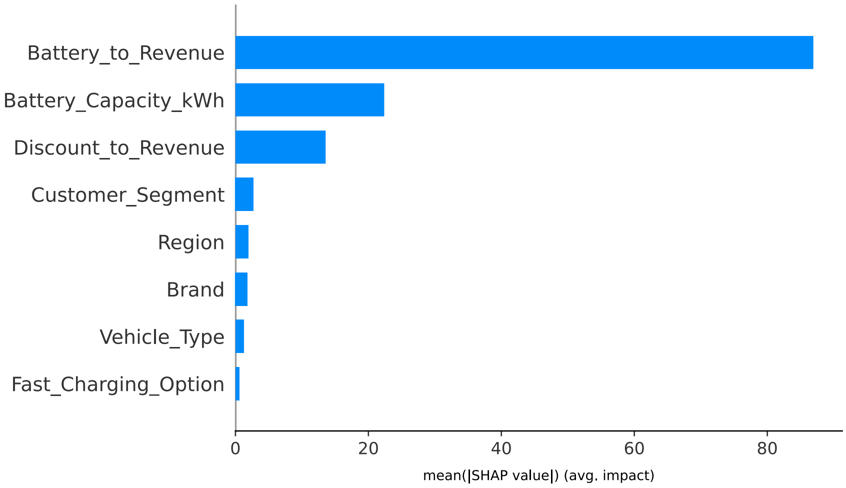

Fig. 5: SHAP feature importance

The substantial improvement in predictive performance ($R^2 = 0.941$) can be attributed to several key methodological enhancements. First, the incorporation of temporal feature engineering, including lag variables (UnitsSold_{t-1}, UnitsSold_{t-2}) and growth rates, enabled the model to capture dynamic patterns in EV adoption. Additionally, the inclusion of seasonal indicators (month and year) allowed the model to account for temporal trends and periodic fluctuations.

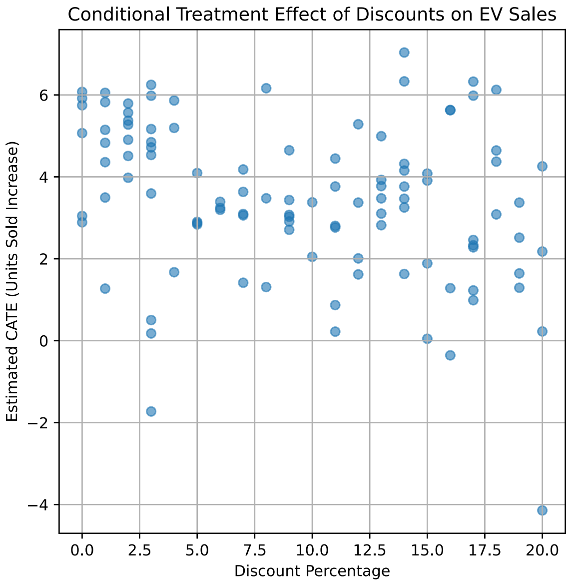

Fig. 6: CATE scatter plot

Table 2: Final optimized results

Model	MAE	RMSE	R^2
Gradient boosting	17.795	24.443	0.941
Random forest	20.095	26.805	0.929
Linear regression	40.406	47.482	0.778
LSTM	93.959	111.073	-0.214
Neural network	9922.468	11268.07	-12495.6

Second, appropriate data preprocessing techniques played a critical role. Categorical variables were transformed using one-hot encoding to preserve structural information without introducing bias, while normalization improved the performance of scale-sensitive models.

Third, the adoption of ensemble learning methods, particularly Gradient Boosting with optimized hyperparameters (e.g., n_estimators = 200), significantly enhanced the model's ability to capture nonlinear relationships and interaction effects. Compared to linear models, these approaches demonstrated superior generalization capability.

Furthermore, the use of cross-validation ensured robustness and prevented overfitting, providing reliable estimates across multiple evaluation metrics (MAE, RMSE, and R^2).

Finally, the integration of SHAP-based explainability and DML enabled both interpretability and causal inference. While SHAP identified key drivers such as Discount%, Battery Capacity, and temporal features, DML provided unbiased estimates of causal effects beyond simple correlations. This combined framework strengthens both the predictive and policy relevance of the proposed approach.

4.1. Sensitivity and robustness analysis

To be able to prove this significant increase in predictive performance, which appeared in Experiment 2, a detailed sensitivity and robustness analysis was conducted. To select the predictive models first, a fivefold cross-validation program was implemented on all models used. The Gradient Boosting model showed excellent and stable results in all folds (mean $R^2 = 0.931$, MAE = 0.104, RMSE = 0.136) with low variance, hence reflecting sound generalization and not overfitting. The same level of stability was also seen with the Random Forest model. It is evident that the shift of negative R^2 in Experiment 1 to the considerably positive values of R^2 in Experiment 2 can be explained by the different goals of both models. The initial Linear Double Machine Learning model focuses on an unbiased causal -effect estimation at the cost of performance on outcome-prediction as compared to the secondary experiment, which is directly aimed at optimizing nonlinear predictive modelling to forecast performance. The difference in the divergent R^2 scores, therefore, indicates the differences in the methodological focus but not the lack. Lastly, the projected-actual scatter plots indicate a uniform convergence along the diagonal in all the validation folds. These results confirm that the high values of R^2 reported are resistant to resampling and change in model specifications, which supports real improvements in feature engineering and model capacity.

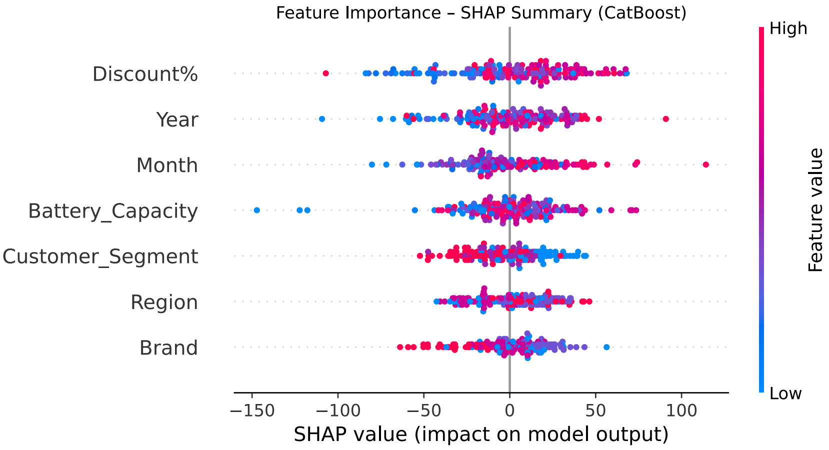

Fig. 7: SHAP summary plot

5. Discussion

This research work supports a data-driven causal research framework to authenticate the processes of electric vehicle (EV) adoption through classical machine learning, deep learning, explainable AI, and causal inference. It defines a powerful pre-processing and prediction model, compares a collection of machine-learning and deep-learning models, uses SHAP to provide interpretability, and embraces Double Machine Learning to have a causal representation of the impact of fiscal incentives. The study, by providing predictions of their performance at the same time, feature-importance measures, and estimates of the average treatment effect, provides practical information that can build an evidence-based policy-making and strategy in the adoption of EVs.

The CATE analysis shows that there is also a lot of heterogeneity in the responsiveness to discounts, hence indicating that homogeneous policies in incentives could be non-optimal. Policymakers must, therefore, use such findings to come up with specific subsidy plans that discriminate by geographic areas and customers with high marginal returns, which would increase the cost-effectiveness and accelerate the electric vehicle uptake.

From a policy perspective, the empirical estimates reveal that the positive Average and Conditional Treatment Effects of financial incentives are very coherent with Oman Vision 2040 and the broader sustainability strategies of the GCC. These findings are reflected in the critical focus on policy apparatus based on data, the embracement of clean mobility, and the rational distribution of public subsidies. Further, the noted heterogeneity in the responsiveness to discounts suggests that initial, region and segment-specific incentive designs will have a significant effect on policy, whilst avoiding inefficiencies of undifferentiated one-size-fits-all subsidy regimes across Gulf economies.

The effectiveness of the proposed framework lies in its integration of predictive modeling, feature engineering, and causal inference within a unified analytical pipeline. Unlike conventional approaches that focus solely on prediction or correlation analysis, this study combines Gradient Boosting with DML to simultaneously achieve high predictive accuracy and unbiased causal estimation.

The empirical results demonstrate that the optimized Gradient Boosting model outperforms both traditional machine learning and deep learning approaches, particularly in small and structured datasets. This highlights the importance of appropriate model selection and feature design over model complexity alone.

Moreover, the incorporation of SHAP-based explainability enhances transparency by identifying key drivers of electric vehicle adoption, such as financial incentives and battery-related attributes. In parallel, the DML framework isolates the true causal impact of financial incentives while accounting for high-dimensional confounding factors.

This combined approach not only improves predictive performance but also provides actionable and policy-relevant insights, thereby bridging the gap between machine learning applications and evidence-based decision-making in sustainable transportation.

Certainly, the range of promotions has facilitated the generalizability of the data; its small size (n=515 observations) is a limitation. Although sufficient to benchmark machine-learning models as well as approximate causal consequences using Double Machine Learning, the small sample could limit the extrapolation of results to different markets and policy contexts. Future research should then support the structure suggested in the study in larger and multi-country and longitudinal data sets, which will enhance the strength as well as external validity.

6. Conclusion

This research shows a multifaceted and data-driven method of the influence of financial incentives on the adoption of electric vehicles (EVs), which is a combination of predictive modeling, causal inference, and interpretable AI methods. With the use of DML with Gradient Boosting and sophisticated feature engineering, we could estimate both the average and conditional treatment effects of discounts and also take into consideration the confounding variables, that is, the region, brand, battery capacity, vehicle type, and customer segment. We find that the intelligent use of models can significantly increase prediction accuracy, with Gradient Boosting to an $R^2=0.94$, over baseline models, and showing the importance of log-transformation, cross-validation, and new features, such as Discount to Revenue and Battery to Revenue. Causal analysis also reveals that relatively small discounts can have significant positive impacts on EV adoption, and that their impacts vary significantly by region and type of customer, offering information that can be used by policymakers and manufacturers.

The interpretability of SHAP enables the identification of the most significant factors influencing the sales of EVs and the strongest ones that can influence the impact of financial incentives, to avoid bridging machine learning and decision-making processes. All in all, this piece not only contributes to the methods of study in sustainable transportation policies but also provides clear, practical, and policy-oriented results that show the strength of using a combination of causal machine learning with interpretable AI. These results can be directly applicable to the design of the incentive programs, so that the financial policies can succeed in the acceleration of the introduction of electric vehicles on the market in various countries.

List of abbreviations

ATE	Average treatment effect
CATE	Conditional average treatment effect
DEMATEL	Decision-making trial and evaluation laboratory
DML	Double machine learning
DNN	Deep neural network
EV	Electric vehicle
GCC	Gulf Cooperation Council
LSTM	Long short-term memory
MAE	Mean absolute error
ML	Machine learning
OLS	Ordinary least squares
R^2	Coefficient of determination
RMSE	Root mean square error
SHAP	Shapley additive explanations
XAI	Explainable artificial intelligence

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Compliance with ethical standards

Conflict of interest

The author(s) declared no potential conflicts of interest with respect to the research, authorship, and/or publication of this article.

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