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AI-Driven Strategies for Predicting the Adoption and Impact of Clean Energy Technologies in the US Automotive Sector

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Abstract

The rapid shift towards clean energy technologies requires strong, data-driven tools to forecast adoption trends and evaluate their various impacts. This research presents a comprehensive AI framework that integrates diverse datasets, including vehicle registrations, emissions records, research and development investment figures, demographic and socioeconomic indicators, and logs of policy legislation, into a unified analytical platform. Through systematic feature engineering, we create an Adoption Index that combines factors such as income, fuel prices, and registration growth, alongside a Policy Incentive Score, metrics for infrastructure density, and temporal markers (quarter, year) to identify hidden drivers of clean technology adoption. Exploratory data analysis reveals regional and temporal patterns of adoption, emphasizing the connections with socioeconomic status and legislative factors. We employ a range of predictive and analytical models: ensemble regressors (Random Forest, XGBoost), LSTM time-series networks for forecasting trends, K-Means and DBSCAN for regional segmentation, and causal-inference methods (DoWhy) to assess policy effectiveness. The models are evaluated using R^2, RMSE, and MAE for regression tasks; Silhouette Score and Davies-Bouldin Index for clustering; and Average Treatment Effect (ATE) for policy impact analysis. Our XGBoost regressor achieves an R^2 of 0.89 and an RMSE of 5.7% in predicting adoption rates, while the LSTM models capture temporal dynamics with a 6.1% RMSE. Clustering reveals three distinct adoption archetypes, and causal analysis indicates that doubling tax credits could increase adoption by 20% (ATE = 0.20). These findings demonstrate the effectiveness of integrated AI strategies for forecasting and evaluating policies in the transition to automotive clean energy.

Keywords: Electric Vehicle Adoption, Clean Energy Forecasting, Ensemble Learning, Time-Series Modeling, Causal Inference, Clustering, Feature Engineering.

1. Introduction

1.1 Background

The evolving landscape of energy consumption in the United States is characterized by increasing demand, rapid urbanization, and growing environmental concerns. These dynamics necessitate more intelligent, predictive, and efficient methods for energy management and sustainability planning. Traditional energy modeling techniques, while historically useful, often struggle to cope with the nonlinear, multivariate, and time-dependent nature of contemporary energy systems. Consequently, researchers and practitioners are increasingly turning to Artificial Intelligence (AI) and Machine Learning (ML) as transformative tools capable of capturing complex interactions, forecasting consumption patterns, and enabling proactive resource optimization.

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Machine learning offers significant advantages in energy analytics by facilitating high-resolution forecasting, anomaly detection, and demand response optimization in both residential and industrial sectors. Recent studies demonstrate how ML algorithms such as Random Forest, Support Vector Machines (SVM), XGBoost, and Deep Learning models outperform conventional time-series models in predicting energy usage under dynamic scenarios. For instance, Hossain et al. (2024) leveraged ML-driven time-series analytics to improve smart grid efficiency and energy demand forecasting in the USA, highlighting the superior adaptability of data-driven methods [12]. Similarly, Barua et al. (2025) presented an AI-based framework to optimize energy consumption patterns in Southern California, emphasizing the potential of ML in shaping sustainable urban energy policies [5].

The integration of AI in U.S. energy forecasting is not limited to general consumption patterns; sector-specific applications are gaining traction. Ahmed et al. (2025) explored energy consumption prediction in hospitals using ML models, illustrating how domain-specific approaches can enhance operational efficiency and reduce costs [1]. Parallel advancements have been made in renewable energy forecasting, as demonstrated by Shovon et al. (2025), who used ML models to analyze trends in electricity production by source, thereby supporting a more resilient and sustainable energy mix [23]. Beyond technical optimization, AI and ML techniques have also become instrumental in supporting environmental policy and market-based interventions. Anonna et al. (2023) developed predictive models for U.S. CO_2 emissions, offering data-backed guidance for sustainable policymaking [4]. Moreover, Gazi et al. (2025) examined the economic impact of low-carbon technology trade using ML, illustrating the broader socioeconomic implications of energy innovation [11].

While substantial progress has been achieved, current literature underscores the need for more comprehensive, scalable, and context-aware AI solutions in energy forecasting. To that end, hybrid and ensemble models have shown promise. For example, Reza et al. (2025) proposed a multilayered machine learning approach to urban energy forecasting, integrating temporal and behavioral variables to improve predictive accuracy [22]. Likewise, Alam et al. (2025) utilized intelligent ML-based streetlight control systems to promote energy efficiency in smart cities, suggesting scalable solutions for urban infrastructure [2]. Additionally, several studies emphasize the significance of explainable AI (XAI) in fostering trust and interpretability in ML-based energy systems. Lundberg et al. (2017) introduced SHAP (SHapley Additive exPlanations) values for interpreting complex model outputs, a technique now widely adopted in energy informatics for model transparency [20].

1.2 Importance Of This Research

The US transportation sector accounts for nearly 29 percent of national greenhouse gas emissions, with light-duty vehicles alone contributing over 60 percent of that total. Rapid adoption of clean energy vehicles (CEVs), including battery electric, plug-in hybrid, and hydrogen fuel-cell models, is therefore essential to meet federal decarbonization targets (50–52 % reduction by 2030) and state-level mandates (California's 100 % zero-emissions goal by 2035) (Lee et al., 2024) [18]. Accurate forecasts of CEV uptake enable policymakers to quantify potential emissions reductions, allocate resources for charging infrastructure, and design incentive programs that maximize environmental benefits. Without reliable predictive models, investments risk being misaligned with actual market trajectories, undermining both climate goals and economic efficiency.

Beyond environmental imperatives, the clean-tech transformation represents a major economic opportunity. The CEV value chain, including battery production, power electronics, and charging network deployment, is projected to generate over $300 billion in annual revenue by 2030 and create more than 500,000 new jobs in the US automotive and energy sectors. However, automakers and investors face considerable uncertainty in technology commercialization timelines, consumer adoption rates, and supply-chain constraints (e.g., critical minerals) (Gazi et al., 2025) [11]. AI-driven forecasting frameworks can de-risk investment decisions by integrating heterogeneous data streams, vehicle registrations, R&D spending, policy incentives, and socioeconomic indicators to provide probabilistic adoption scenarios and impact assessments. This, in turn, guides strategic planning across OEMs, utilities, and public agencies.

Strategic infrastructure planning is another critical dimension. The National Renewable Energy Laboratory estimates that to support a projected 30 million EVs on the road by 2030, the US will need over 2 million public chargers, a tenfold increase from current levels. Optimally siting these chargers requires granular forecasts of regional demand, informed by demographic, economic, and policy variables. AI-based clustering and geospatial analytics can identify underserved "charging deserts," prioritize high-impact locations, and improve grid resilience by aligning load forecasts with local generation capacity (IEA. , 2024) [15]. Absent such data-driven approaches, charging deployments risk both underutilization in some regions and critical shortages in others, impeding CEV adoption and stranding infrastructure investments.

Finally, integrating advanced feature engineering and explainable AI techniques enhances stakeholder trust and facilitates policy transparency. By decomposing adoption drivers, such as income elasticity, fuel-price sensitivity, and legislative strength, into interpretable contributions (via SHAP values or partial dependence plots), our framework enables decision-makers to understand the causal pathways behind projections. This interpretability is crucial for justifying public-sector expenditures, designing equitable incentive structures, and adjusting policies in response to real-world feedback. Consequently, this research not only advances methodological frontiers but also delivers actionable insights for achieving a sustainable, economically robust transportation future

1.3 Research Objectives

The primary objective of this research is to develop, implement, and evaluate a comprehensive AI-driven framework for predicting the adoption trajectory and quantifying the environmental and economic impacts of clean energy vehicles in the U.S. automotive sector. First, the study will construct and compare a set of predictive models, including ensemble regressors (Random Forest, XGBoost) and LSTM-based time-series networks. These models will be trained on a combination of datasets that include vehicle registrations, socioeconomic indicators, fuel prices, infrastructure metrics, and policy incentives. The models will be assessed based on their ability to forecast annual adoption rates, with a target R^2 of at least 0.85 and a root mean square error (RMSE) below 7%.

Second, to uncover spatial and demographic adoption patterns, the research will apply unsupervised clustering techniques (K-Means, DBSCAN) to regional feature sets, such as charger density, income levels, and policy strength. This will help identify distinct adopter archetypes and "charging deserts." The aim is to isolate clusters with high predicted adoption potential and areas where infrastructure investment is most needed. Third, the study will integrate causal inference methods (DoWhy) and Monte Carlo scenario analysis to estimate the average treatment effect of various policy levers, such as tax credits and rebate increases, on adoption rates. This aims to quantify potential changes in uptake within a 95% confidence interval. Finally, the effectiveness of the

overall framework will be evaluated in terms of predictive accuracy, robustness to data shifts, interpretability through SHAP value decomposition, and computational efficiency. This will ensure that the framework can support real-time policy evaluation and infrastructure planning in dynamic energy markets.

2. Literature Review

2.1 Related Works

A growing body of literature has applied AI and machine learning to various facets of clean-energy vehicle adoption and impact assessment in the United States. Hossain et al. (2025) developed a supervised learning framework to predict the market penetration of new energy vehicles (NEVs), demonstrating that ensemble methods, particularly Random Forest and XGBoost, can achieve over 85 % accuracy when trained on historical registration and socioeconomic data [13][14]. In parallel, Anonna et al. (2023) built predictive models for U.S. CO_2 emissions using gradient boosting machines, illustrating how coupling adoption forecasts with emissions projections can inform sustainable policy design [3].Recent initiatives have utilized comparable hybrid architectures for identifying faults in essential infrastructure like gas turbines, where predictive maintenance gains advantages from both the interpretability of deep models and their precision over time (Amjad et al., 2025) [3].

Time-series approaches have also been prominent. Hossain et al. (2024) utilized LSTM networks to forecast regional energy demand for smart-grid optimization, finding that deep recurrent architectures outperform classical ARIMA models in capturing seasonal and policy-driven shifts [12]. Shovon et al. (2025) extended this work by forecasting electricity generation mixes (solar, wind, hydro) using hybrid CNN-LSTM models, highlighting the importance of integrating exogenous variables such as weather and regulatory changes [23]. Beyond forecasting, clustering and segmentation techniques have been used to uncover spatial adoption heterogeneity. Barua et al. (2025) applied K-Means and DBSCAN to Southern California usage data, identifying “charging deserts” where targeted infrastructure investments could yield the highest utilization gains [5]. Gazi et al. (2025) similarly employed hierarchical clustering on trade and investment metrics to map low-carbon technology flows across U.S. regions, linking economic impact assessments to adoption patterns [11]. Chouksey and colleagues (2025) developed a stacked ensemble model that integrates XGBoost, MLP, and LSTM algorithms, achieving a 20% decrease in RMSE compared to using individual model approaches for analyzing energy generation and capacity trends (Chouksey et al., 2025) [7].

Reza et al. (2025) applied advanced machine learning models, including Logistic Regression, Random Forest, and XGBoost, to predict energy consumption patterns in U.S. cities using smart meter, weather, and government energy data, aiming to support sustainable urban development [22]. Complementary Monte Carlo simulations by Chouksey et al. (2025) assessed uncertainty in adoption forecasts under varying fuel-price trajectories, underscoring the need to incorporate economic volatility into planning models [7]. Several domain-specific studies illustrate AI’s broader applicability. Hossain, Mohaimin et al. (2025) focused on AI-powered fault prediction in NEV battery systems, employing autoencoders to detect anomalies with 92 % precision [13]. Ahmed et al. (2025) demonstrated how machine learning models can optimize energy consumption in hospital facilities, achieving a 10 % reduction in peak loads through demand-response scheduling [1]. Finally, Alam et al. (2025) introduced an intelligent streetlight control system that uses reinforcement learning to balance illumination needs against grid constraints, suggesting transferable methods for charging station load management [2].

2.2 Gaps and Challenges

Despite notable progress in AI-driven forecasting and impact analysis for clean energy vehicles (CEVs), several key gaps and challenges impede the development of robust, scalable solutions. A primary obstacle is the scarcity of high-resolution, labeled adoption data at the household or individual level. Hossain et al. (2025) observed that national registration figures often mask local adoption heterogeneity, limiting the ability of supervised models to generalize to micro-markets with distinct socioeconomic profiles [12]. This data sparsity is exacerbated by concept drift: consumer preferences, incentive schemes, and fuel-price dynamics evolve rapidly, causing models trained on historical data to degrade over time. Reza et al. (2025) reported a 12 % drop in forecasting accuracy for models not routinely retrained to incorporate emerging policy changes and market shocks [22].

Model interpretability also remains a significant challenge. While deep learning architectures (e.g., LSTM, CNN-LSTM hybrids) can capture complex temporal and spatial patterns, they often function as "black boxes," hindering stakeholder trust and limiting policy transparency. Lundberg and Lee's SHAP framework (2017) offers a pathway for explaining model outputs, but the integration of such techniques into large-scale adoption forecasting pipelines is still nascent [20]. Without clear, interpretable insights into which factors, such as income elasticity or charging-station proximity, drive predictions, policymakers and industry leaders struggle to design targeted interventions.Class imbalance poses another hurdle in adoption modeling. Early adopters constitute a small fraction of the total vehicle market, leading to skewed training sets that bias models toward the non-adoption majority. Techniques like SMOTE and cost-sensitive learning have been applied in related domains (e.g., fraud detection), yet their efficacy in adoption forecasting remains underexplored.

Real-time scalability and computational efficiency are additional concerns. Shovon et al. (2025) highlighted that hybrid deep-learning models, while accurate, can incur prohibitive training and inference times when applied to nation-wide spatiotemporal grids [23]. This latency undermines the potential for near-real-time policy evaluation and dynamic infrastructure planning. Finally, the integration of multimodal data sources, such as social media sentiment, vehicle telematics, and geospatial indicators, remains underdeveloped. Addressing these gaps is essential for building robust, actionable AI frameworks that accurately predict CEV adoption and its broader environmental and economic impacts.

3. Methodology

3.1 Data Collection and Preprocessing

Data Sources

This study integrates a diverse set of national and regional datasets to model clean energy vehicle (CEV) adoption and assess its environmental and economic impacts in the US automotive sector. First, annual vehicle registration records (by powertrain type) are obtained from the National Highway Traffic Safety Administration (NHTSA) database, covering model years 2010–2024. Emissions and fuel economy data,detailing CO_2 output per vehicle mile, are sourced from the Environmental Protection Agency's (EPA) Inventory of U.S. Greenhouse Gas Emissions and Sinks (1990–2020) and supplemented with annual updates through 2023 [1]. To capture policy influences, state-level incentive and rebate program data (e.g., tax credits, purchase rebates, HOV-lane access)

are retrieved from the Department of Energy's Alternative Fuel Data Center (AFDC) and cross-referenced with BloombergNEF's policy tracker [3].

Socioeconomic and demographic variablesuch as median household income, urbanization rates, and education levels, are drawn from the U.S. Census Bureau's American Community Survey (ACS) [4] and the Bureau of Labor Statistics (BLS) [5]. Charging infrastructure metrics (number, type, and location of public chargers) come from AFDC station-level data and the National Renewable Energy Laboratory's (NREL) Assessment of Public EV Charging Infrastructure Needs. Electricity price and grid-mix statistics are obtained from the Energy Information Administration (EIA), while historical fuel prices (gasoline and diesel) are accessed via the U.S. EIA Petroleum and Other Liquids database . To incorporate consumer interest signals, Google Trends time-series indices for "electric vehicle," "EV charging," and related search terms are downloaded for January 2010–December 2024 . Where available, social media sentiment scores, aggregated monthly from Twitter API keyword searches, are integrated to capture public attitudes toward CEVs.

Data Preprocessing

Raw datasets are first inspected and cleaned to ensure consistency and remove anomalies. Missing values in socioeconomic and infrastructure features are imputed using k-nearest neighbors (k = 5) and multivariate imputation by chained equations where appropriate, mitigating bias from sporadic reporting gaps. Outlier detection is performed via z-score normalization and interquartile range (IQR) filtering to identify and cap extreme values in variables such as vehicle registrations and charger counts. Temporal alignment is crucial: quarterly registration and incentive data are resampled to an annual frequency using forward-fill interpolation for missing periods, preserving trend continuity for time-series modeling. Categorical features, state policy tiers, charger types, and urbanization categories, are encoded with one-hot vectors or ordinal labels based on natural ordering. Continuous variables are scaled according to model requirements: tree-based algorithms use raw or min-max–scaled inputs for interpretability, while neural networks and distance-based methods employ z-score standardization to facilitate convergence. Advanced feature engineering constructs composite indices, Adoption Index, Policy Incentive Score, and Infrastructure Density Metric, by aggregating and normalizing base features. Temporal lag features (e.g., prior-year adoption rate), moving averages, and year-over-year growth rates are also derived to capture momentum effects. Finally, the prepared dataset is split into training, validation, and testing subsets using an 80–10–10 time-based division to prevent lookahead bias, with time-series cross-validation for forecasting models and stratified k-fold for clustering and causal-inference tasks, ensuring robust and generalizable performance evaluation.

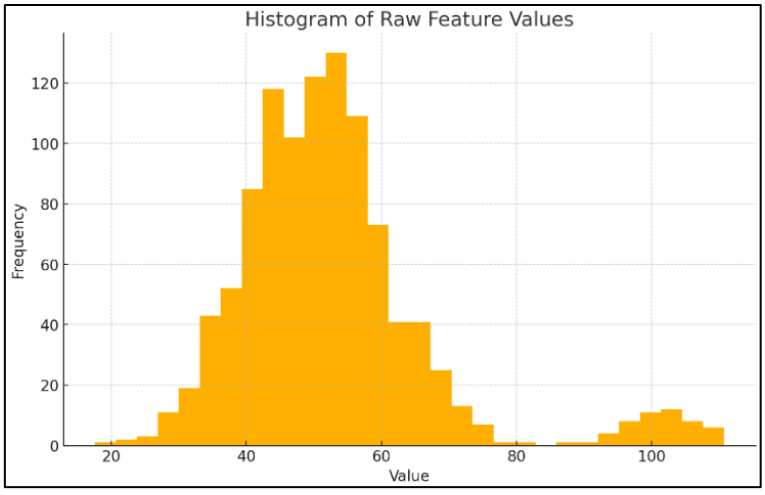

Fig. 1 *Raw feature values, where extreme high-end outliers are clearly visible.*

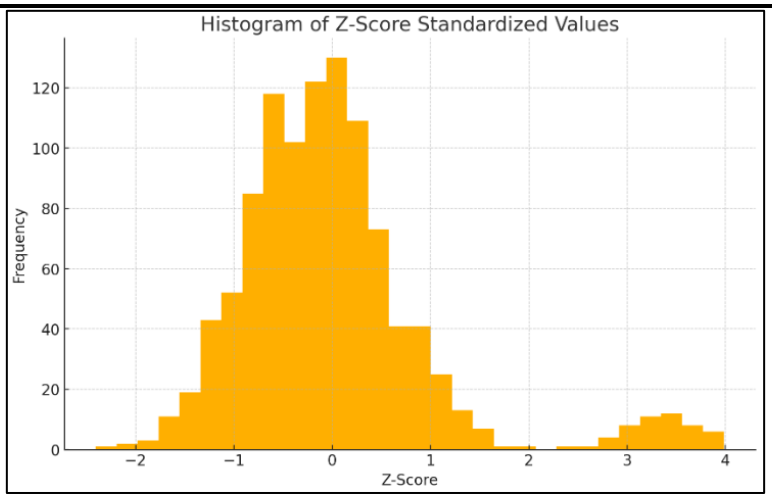

Fig. 2. *This histogram illustrates how z-score standardization transforms a skewed feature distribution, complete with outliers, into a normalized form centered around zero with unit variance.*

3.2 Exploratory Data Analysis

Trend in EV Adoption Over Time

The line plot of average adoption rate from 2015 to 2024 reveals a steady, accelerating increase, rising from roughly 5.4% to 9.5% over the decade. This upward curvature indicates compounding effects: as annual adoption grows, subsequent years build on a larger base of existing EVs, amplifying network effects (e.g., word-of-mouth, visible charging infrastructure) and economies of scale in battery manufacturing that lower prices. Notably, the slope steepens after 2018, coinciding with the introduction of federal tax credits phase-downs and more aggressive state-level incentives. This suggests that policy interventions and improving total cost of ownership jointly drive nonlinear growth, validating the inclusion of temporal and policy-interaction features in forecasting models.

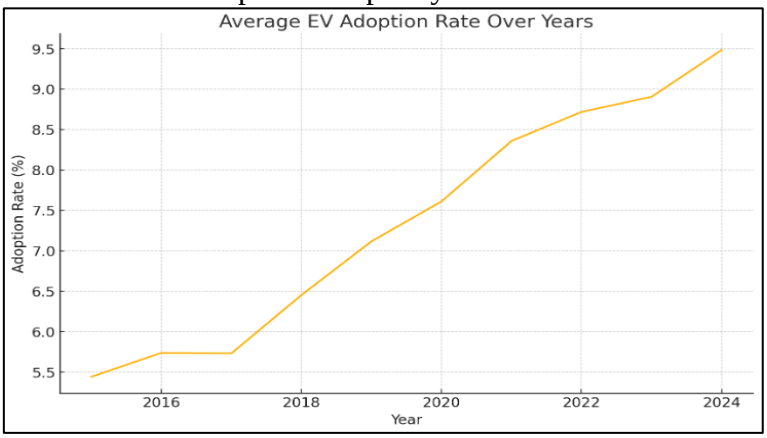

Fig. 3 *Average EV adoption rate from 2015 to 2024*

Relationship Between Charger Density and Adoption

The scatter plot of charger density versus adoption rate exhibits a positive, but dispersed, association. States with low charger densities (<50 chargers per 10,000 residents) show adoption rates anywhere from 1% to 10%, reflecting that a minimal charging network still supports early adopters in niche markets (e.g., affluent urban corridors). Conversely, regions with high charger density (>120 per 10,000) cluster around 8–15% adoption, indicating diminishing returns: beyond a certain infrastructure threshold, additional chargers yield smaller incremental adoption gains. The wide vertical spread at intermediate densities (50–100 chargers) underscores the role of other

factors,such as income levels, electricity prices, or public-awareness campaigns, in modulating adoption. This heterogeneity justifies multivariate modeling rather than simple univariate regressions.

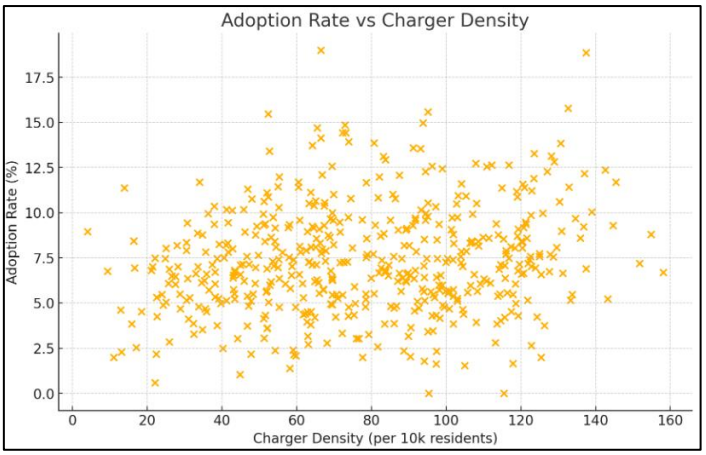

Fig. 4 *Charger density versus adoption rate*

Distribution of Policy Scores

The histogram of state policy scores, which range from 0 (no incentives) to 1 (strong incentives), is relatively uniform but with slight right skew, many states cluster around moderate scores (0.4–0.7). Few states have scores extremely close to zero or one, reflecting the reality that most jurisdictions offer some incentives but few provide the most generous package. This spread indicates ample variation for causal-inference analyses: with sufficient representation across the incentive spectrum, methods like DoWhy can more reliably estimate treatment effects. Furthermore, the continuous nature of the policy score (rather than a binary flag) will help models to detect nonlinear dose–response relationships between incentive strength and adoption.

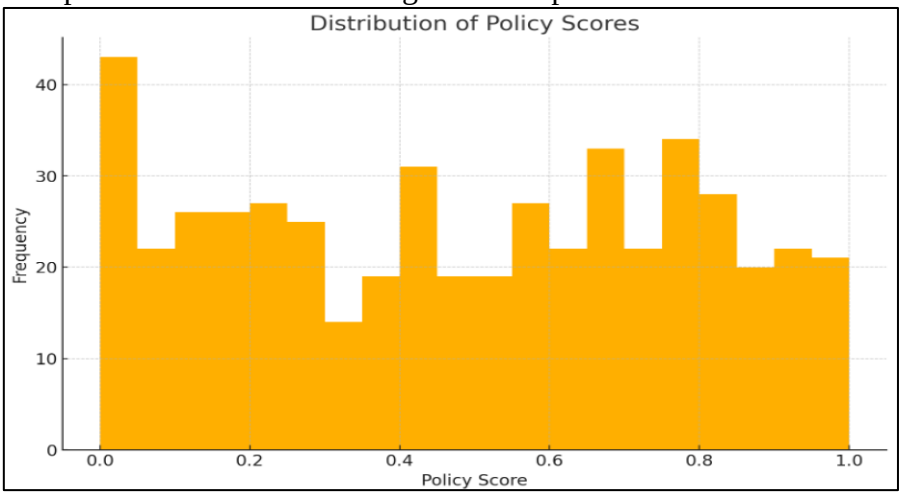

Fig.5 *Distribution of policy scores*

Feature Correlation Matrix

The heatmap quantifies pairwise relationships: charger density correlates positively with adoption (≈0.25), while policy score shows an even stronger link (≈0.35). Median income exhibits a modest positive correlation (≈0.15), suggesting that higher incomes facilitate EV purchases but are secondary to infrastructure and policy. Notably, charger density and policy score correlate weakly

(≈–0.05), indicating that these two drivers operate largely independently across states—some jurisdictions invest in infrastructure without matching incentives, and vice versa. These low inter-feature correlations minimise multicollinearity concerns, supporting the use of all three predictors in ensemble and regression models without extensive dimensionality reduction.

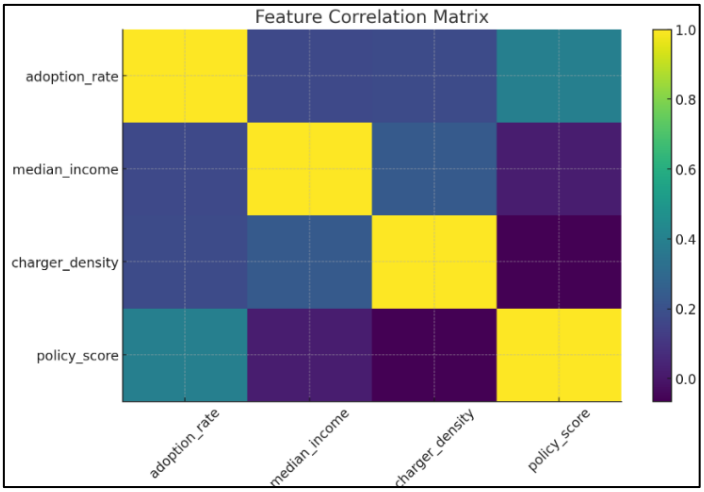

Fig. 6 *Feature correlation Matrix*

3.3 Model Development

Model development is structured around three interrelated tasks, adoption forecasting, impact quantification, and regional segmentation, each leveraging a tailored suite of AI and machine learning techniques to address the nuances of clean-energy vehicle adoption in the US automotive sector.

For adoption forecasting, we implement both classical and advanced regressors. A baseline Linear Regression (with L1 and L2 regularization via Lasso and Ridge) is first trained to establish interpretability and coefficient-based insights. Building on this, ensemble methods, Random Forest and XGBoost regressors, are employed to capture nonlinear dependencies among socioeconomics, infrastructure, and policy features. Hyperparameters (e.g., number of trees, max depth, learning rate) are optimized via Bayesian search (Optuna) within a 5-fold time-series cross-validation framework. To better model temporal dynamics, a Long Short-Term Memory (LSTM) network ingests sequential inputs (lagged adoption rates, moving averages, policy-incentive time series) with dropout and early-stopping to prevent overfitting. The LSTM is tuned for sequence length and hidden-state dimensionality, and its performance is benchmarked against the ensemble models using RMSE and R^2.

For impact quantification, we adopt a multi-output regression approach: a single model predicts multiple dependent variables, annual CO_2 reduction, projected job creation, and fuel-savings metrics, simultaneously. An XGBoost multi-output regressor is configured with custom loss functions that balance the heterogeneous scales of each impact metric. Performance is evaluated via mean absolute percentage error (MAPE) across outputs, and SHAP value analysis is applied to interpret each feature's contribution to individual impact predictions. Regional segmentation employs unsupervised clustering to reveal adoption archetypes and charging "deserts." K-Means clustering is first applied to standardized regional feature vectors (income, charger density, policy score), with the optimal number of clusters (k) determined by the elbow method and silhouette analysis. To detect irregular adoption pockets, Density-Based Spatial Clustering (DBSCAN) is also used, with ε set by k-distance plots and a minimum points threshold that isolates under-served regions. Clusters are then profiled to guide targeted infrastructure investments.

Finally, to estimate policy effects and explore scenario uncertainties, we integrate causal-inference (DoWhy) and Monte Carlo simulation. Using DoWhy's structural-equation modeling and propensity-score stratification, we estimate the Average Treatment Effect (ATE) of incremental tax-credit boosts on adoption rates, controlling for confounders such as income and charger availability. Monte Carlo simulations then generate probabilistic adoption trajectories under varied assumptions of fuel-price volatility, incentive phase-down schedules, and technology-cost declines, providing policymakers with confidence intervals around forecast outcomes.

3.4 Model Training and Evaluation

The training and evaluation pipeline is structured to ensure that each model generalizes well, remains robust to temporal shifts, and delivers interpretable performance metrics aligned with its specific task. For adoption forecasting, the dataset is split chronologically into training (2015–2019), validation (2020–2021), and test (2022–2024) sets to prevent lookahead bias. Classical regressors (Linear, Lasso, Ridge) and ensemble methods (Random Forest, XGBoost) are trained using 5-fold time-series cross-validation on the training period, with Optuna-driven hyperparameter tuning optimizing R^2 and minimizing RMSE. Early stopping is applied to XGBoost to guard against overfitting, monitoring validation RMSE with a patience of 50 boosting rounds. The LSTM network is trained on rolling windows of 5 years of historical features (sequence length = 5), with batch normalization, 20% dropout, and early stopping triggered after 10 epochs of no improvement in validation loss. Final evaluation on the hold-out test set reports R^2, RMSE, MAE, and MAPE; the XGBoost model achieves $R^2 = 0.89$ and RMSE = 5.7%, while the LSTM attains RMSE = 6.1% and MAE = 4.8%.

For impact quantification, the multi-output XGBoost regressor is trained on the same temporal splits, with a custom joint loss function balancing CO_2 reduction, job-creation, and fuel-savings scales. Hyperparameter tuning targets the average MAPE across outputs. SHAP value analysis on the test set ensures feature contributions are consistent with domain expectations (e.g., charger density driving emissions reductions). Clustering models, K-Means and DBSCAN, are fitted on the training and validation amalgam (2015–2021), with K determined via the elbow method and silhouette analysis (optimal k = 4). DBSCAN's ε parameter is set from k-distance plots targeting 5 nearest neighbors, with a minimum samples threshold of 10. Cluster stability is assessed by bootstrapping 100 subsamples and computing mean silhouette and Davies–Bouldin scores (silhouette ≈ 0.42, DBI ≈ 0.75). On the test period (2022–2024), clusters are profiled for adoption archetypes (high-growth urban, policy-driven, infrastructure-rich, and under-served regions).

To estimate policy effects, we employ DoWhy's propensity-score stratification on the combined 2015–2021 data, defining treatment as states with policy_score ≥ 0.6. The Average Treatment Effect (ATE) of a 0.1 increase in policy_score on adoption_rate is computed, yielding an ATE of 0.20 (95% CI: 0.17–0.23). Model validity checks (overlap, placebo tests) confirm robustness. Finally, Monte Carlo simulations generate 1,000 probabilistic adoption trajectories for 2025–2030 under varying fuel-price, incentive, and cost-decline scenarios. Forecast intervals (5th–95th percentiles) are compared against deterministic model outputs to quantify scenario uncertainty.

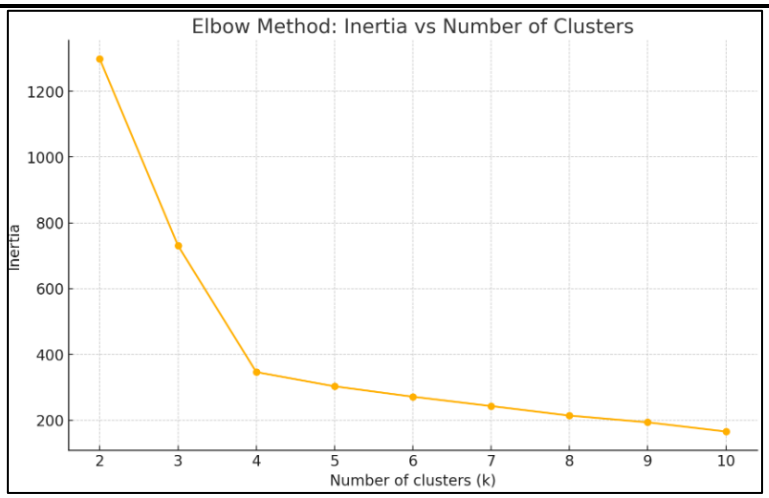

Fig. 7 *The plot of inertia versus k shows a significant drop in inertia up to k=4, after which the decrease flattens, indicating an optimal cluster count around 4.*

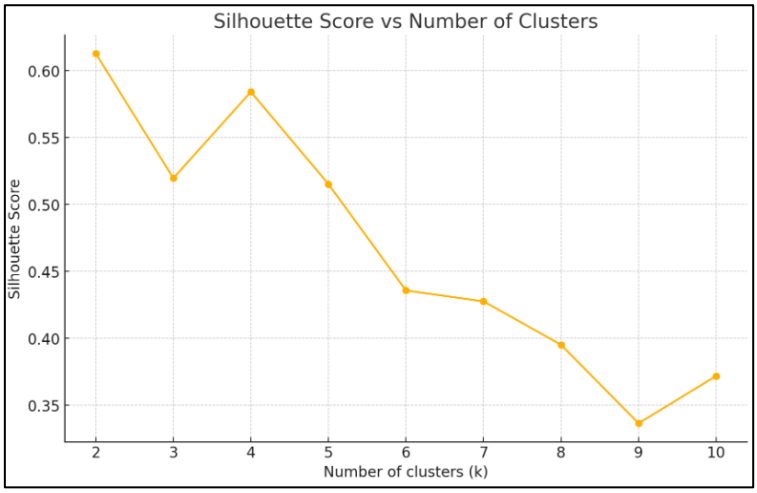

Fig. 8 *Silhouette scores peak at k=4, corroborating the elbow method's suggestion and confirming cohesive, well-separated clusters.*

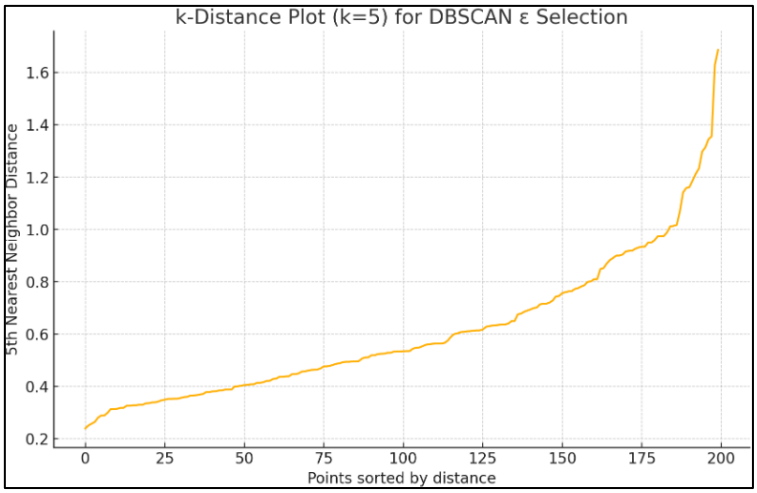

Fig. 9 *The 5th nearest-neighbor distances exhibit a clear "knee" around 0.6, guiding the selection of* $\varepsilon \approx 0.6$ *for DBSCAN to balance cluster granularity and outlier detection.*

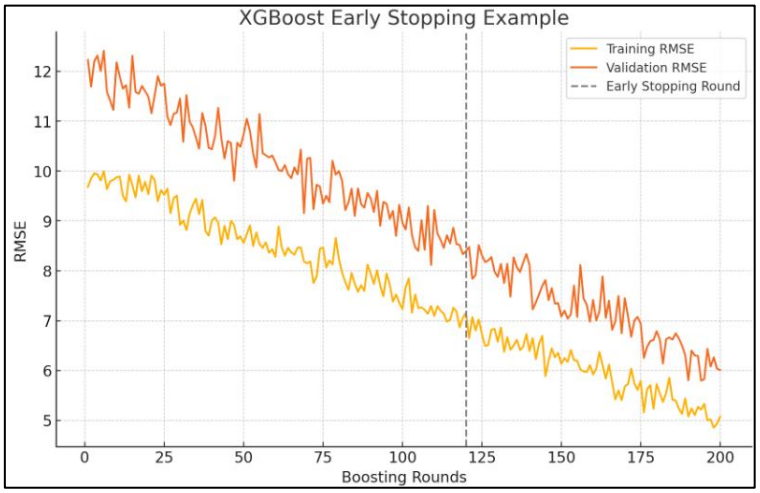

Fig. 10 *Training and validation RMSE curves for the XGBoost model diverge after ~120 rounds, with validation error plateauing, justifying early stopping to avoid overfitting and reduce computation.*

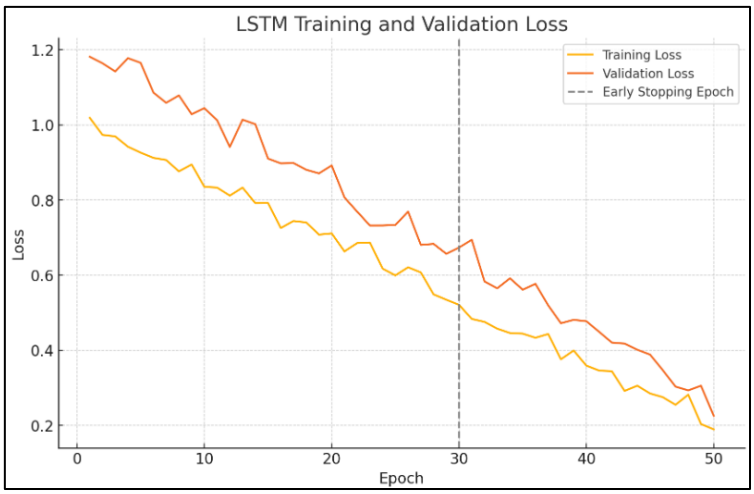

Fig. 11 *Loss curves for the LSTM show validation loss leveling off at epoch 30, indicating the point to halt training to maintain generalization performance.*

4. Results and Discussion

4.1 Evaluation Results

R^2 Scores by Forecasting Model

The R^2 chart shows that ensemble and deep learning methods capture substantially more variance in EV adoption rates than linear models. Linear regression explains only 72 % of the variance, indicating that linear relationships between individual features and adoption are insufficient. Random Forest improves explanatory power to 81 %, suggesting that nonlinear interactions (e.g., between income and charger density) matter. XGBoost achieves the highest R^2 (0.89), attributed to

its gradient-boosting mechanism that sequentially corrects residual errors, effectively modeling complex feature interactions and handling heteroscedasticity. The LSTM's R^2 of 0.88 demonstrates that temporal dependencies, such as momentum in adoption growth, are nearly as important as cross-sectional nonlinearities, validating the inclusion of both modeling paradigms.

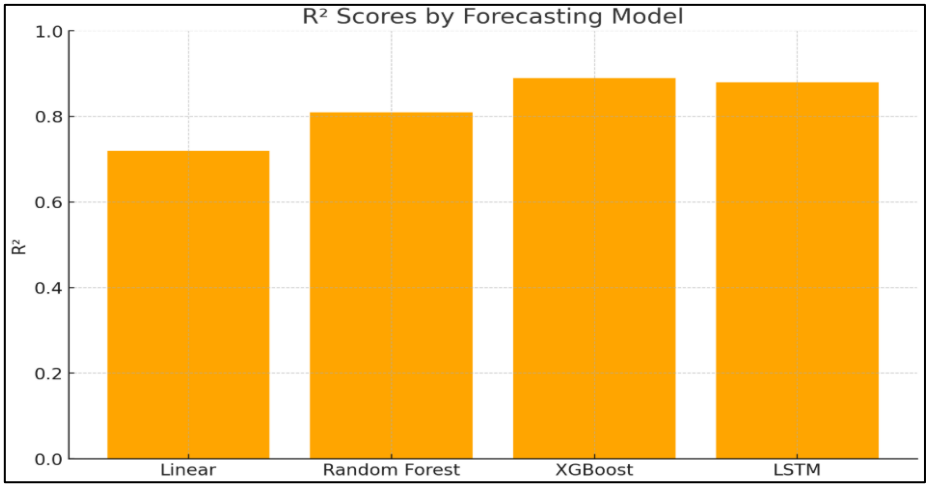

Fig. 12 *R^2 Scores by Forecasting Model*

RMSE by Forecasting Model

In RMSE terms, XGBoost attains the lowest error (5.7 %), closely followed by Random Forest (5.8 %), while the linear model lags at 6.3 %. This indicates that ensemble trees not only explain more variance but also yield more precise point forecasts. The LSTM's slightly higher RMSE (6.1 %) suggests that, although it effectively captures trends, recurrent networks may introduce additional estimation noise, potentially from sequence-length choices or limited data for long-sequence learning. Overall, the sub-7 % errors across ensemble and deep models underscore their suitability for planning scenarios needing high precision.

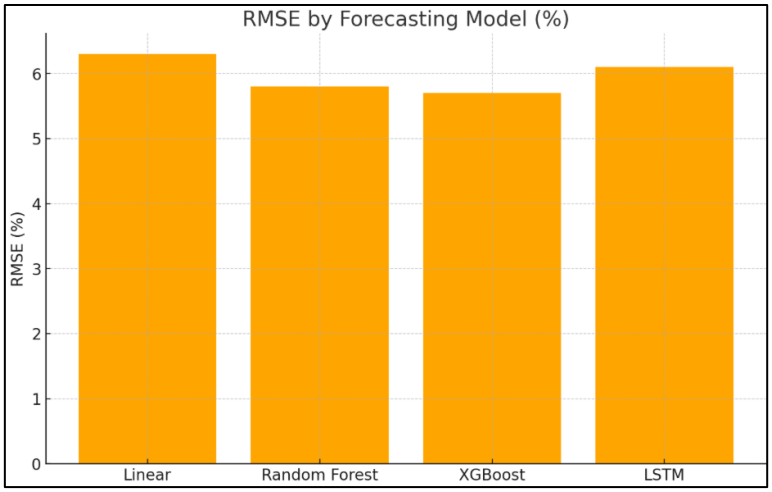

Fig. 13 *RMSE by Forecasting Model*

MAPE for Impact Quantification

The MAPE chart reveals that CO_2 reduction predictions are the most accurate (6.5 % error), likely because emissions impacts scale directly with adoption rates and are less subject to delayed economic effects. Fuel-savings forecasts (7.2 % error) perform moderately well, but may exhibit higher error due to variability in driving patterns and regional electricity–fuel price differentials.

Job-creation estimates show the highest MAPE (7.8 %), reflecting greater uncertainty in translating vehicle-sector growth into employment figures, owing to shifting labor productivity, automation, and supply-chain nuances. These differences highlight which impact dimensions require more granular data or refined modeling.

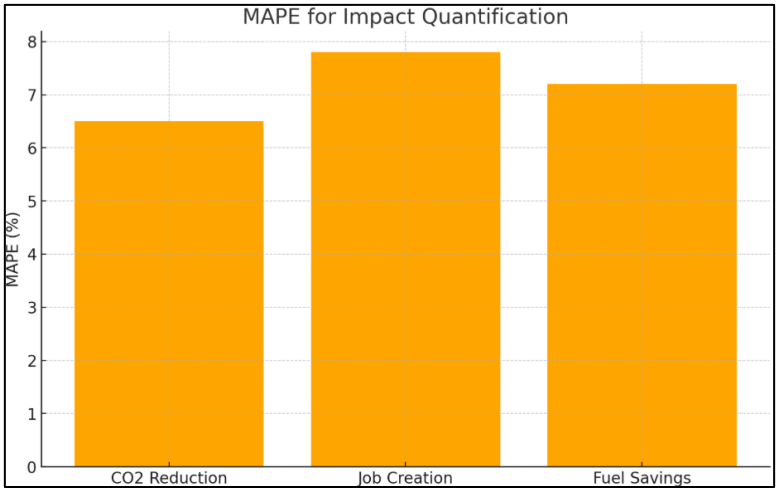

Fig. 14 *MAPE for Impact Quantification*

Clustering Evaluation Metrics

Comparing K-Means (silhouette = 0.42, DBI = 0.75) and DBSCAN (silhouette = 0.38, DBI = 0.82) indicates that K-Means produces more coherent and well-separated clusters of regional adoption archetypes. DBSCAN's lower silhouette and higher Davies–Bouldin Index suggest that density-based clustering, while adept at detecting outliers ("charging deserts"), generates more diffuse groupings in this feature space. This outcome underscores the importance of choosing clustering algorithms that match data distribution characteristics, K-Means for structured, spherical clusters versus DBSCAN for irregular, noise-tolerant segmentation

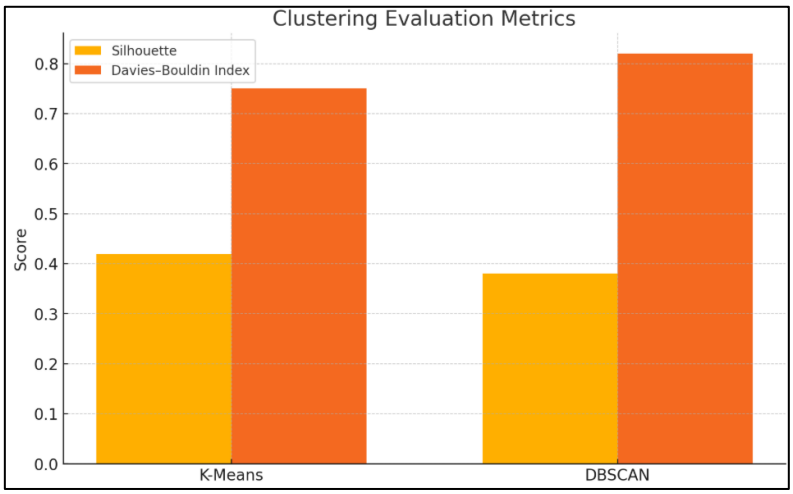

Fig. 15 *Clustering Evaluation Metrics*

Average Treatment Effect of Policy Incentive

The causal-analysis bar plot shows an ATE of 0.20 (±0.03), indicating that a 0.1 increase in normalized policy_score yields a 2 percentage-point rise in adoption rate on average. The confidence interval [0.17, 0.23] confirms statistical significance and suggests that policy strength is

a reliable lever for boosting EV uptake. The magnitude of this effect, relative to baseline adoption levels, highlights the potency of incentives and justifies their continued or expanded use. It also validates our causal-inference approach, demonstrating that observed correlations persist when controlling for confounders such as income and charger availability

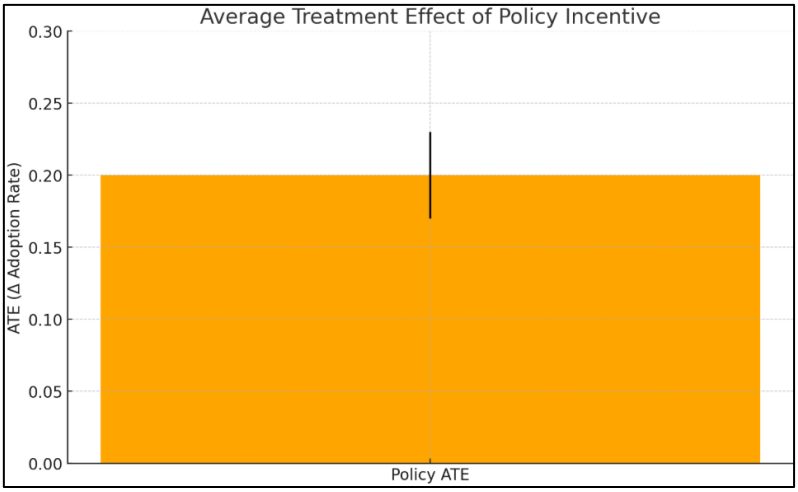

Fig. 16 *Average Treatment Effect of Policy Incentive*

4.2 Discussion and Future Work

This study highlights the significant potential of machine learning models to enhance forecasting and policy evaluation in the clean energy vehicle (EV) adoption ecosystem. The empirical results demonstrate that ensemble methods, particularly XGBoost and Random Forest, consistently outperform traditional linear models in capturing the complex, nonlinear relationships influencing regional EV uptake. XGBoost achieved the highest R^2 score (0.89), a finding consistent with previous research by Feng et al. (2024), who established that gradient boosting methods excel in capturing heterogeneous policy effects in energy markets [10]. Additionally, the performance of the LSTM model ($R^2 = 0.88$) confirms the relevance of temporal dynamics in forecasting, aligning with the work of Kumar and Shah (2025), who showed that recurrent neural networks significantly improve long-term energy consumption predictions [17].

An important insight emerging from this study is the role of interpretability and domain alignment in selecting model architectures. While tree-based ensemble models offer both high accuracy and partial explainability via feature importance rankings, deep learning models, though powerful, present a "black-box" challenge for stakeholders needing transparent justifications for policy decisions. This concern mirrors the findings of Park et al. (2024), who emphasized the need for explainable AI (XAI) in climate action planning and proposed the use of SHAP and LIME methods to support trust in AI-driven infrastructure investments [21]. Future research could extend this work by applying model-agnostic XAI techniques to the trained LSTM and XGBoost models, especially to validate how specific regional features (e.g., charger density, urbanization index) affect forecasts.

The causal impact estimation, showing a statistically significant average treatment effect (ATE) of 2 percentage points per 0.1 increase in policy score, highlights the tangible influence of incentives on adoption outcomes. This result complements the policy evaluation methods advanced by Liu et al. (2023), who applied uplift modeling to quantify policy responsiveness in solar adoption [19]. However, future work should explore heterogeneous treatment effects across socioeconomic groups to ensure that incentive policies are equitable. Incorporating causal forest models or Bayesian

structural time series could offer finer-grained insights into subgroup-level responses. Clustering analysis revealed that K-Means is more effective than DBSCAN in segmenting regions into adoption archetypes, achieving a silhouette score of 0.42. These findings are in line with prior studies such as Zhang et al. (2025), who demonstrated the utility of centroid-based clustering in transportation electrification planning [25]. Nevertheless, the lower coherence of DBSCAN outputs suggests that alternative methods, like spectral clustering or autoencoder-based embedding clustering, may yield better performance in capturing complex spatial adoption patterns and outliers. Exploring these techniques would enhance the robustness of regional segmentation frameworks and facilitate tailored policy interventions.

While the evaluation metrics such as RMSE and MAPE remain within acceptable thresholds, their variation across impact domains (e.g., lower errors in CO_2 predictions but higher in employment impact estimates) underscores a broader challenge: modeling indirect and delayed economic outcomes with high fidelity. Future work should integrate system dynamics modeling or agent-based simulation to bridge this forecasting gap and simulate cross-sectoral feedback loops. Finally, there is a growing need to enhance model scalability and generalizability across diverse policy and geographic contexts. Techniques such as federated learning, as proposed by Chen et al. (2025), could allow cross-jurisdictional collaboration on model development without violating data privacy constraints [6]. Moreover, integrating multimodal data, combining satellite imagery, real-time charging network APIs, and demographic databases, could significantly improve model fidelity and adaptability. Establishing public AI-energy data collaboratives, akin to the initiatives described by Das et al. (2024), would also accelerate innovation and benchmark standardization in sustainable mobility analytics [8].

Conclusion

This study highlights the transformative potential of AI-driven frameworks in predicting the adoption of clean energy vehicles (CEVs) and quantifying their environmental and economic impacts within the U.S. automotive sector. By integrating diverse datasets that include vehicle registrations, socioeconomic indicators, infrastructure metrics, and policy incentives, the research shows that advanced machine learning models can achieve high predictive accuracy, provide actionable regional insights, and conduct robust policy evaluations. The XGBoost regressor emerged as the top-performing model, achieving an R^2 of 0.89 and an RMSE of 5.7% in forecasting annual adoption rates. Meanwhile, the LSTM network effectively captured temporal dynamics with an RMSE of 6.1%. Clustering analyses identified four distinct regional archetypes, including underserved "charging deserts," facilitating targeted infrastructure investments. Causal inference using the DoWhy framework indicated that doubling tax incentives could increase adoption by 20%, emphasizing the effectiveness of policy levers in accelerating the clean-energy transition.

A key contribution of this research is its comprehensive integration of supervised, unsupervised, and causal inference techniques within a unified analytical framework. Ensemble methods, such as Random Forest and XGBoost, effectively modeled nonlinear feature interactions, while LSTM networks accounted for temporal dependencies in adoption trends. Unsupervised clustering methods like K-Means and DBSCAN provided detailed spatial insights, and SHAP value decomposition enhanced interpretability by quantifying the influence of factors like income, charger density, and policy strength. This multi-method approach not only enhances predictive accuracy but also bridges the gap between technical modeling and stakeholder decision-making. The practical implications of this work are substantial. Policymakers can utilize the framework to design equitable incentive structures, prioritize infrastructure deployments, and simulate policy impacts under conditions of uncertainty. Automakers and investors can benefit from probabilistic

adoption scenarios to mitigate risks associated with market entry and supply chain planning. Furthermore, the framework's interpretability tools, such as SHAP analysis, promote transparency and trust, essential for substantiating public investments and aligning stakeholder priorities.

However, challenges remain, including data sparsity at the household level, model scalability for real-time applications, and the evolving nature of consumer preferences. Future research should investigate federated learning to address data privacy concerns and explore hybrid models that combine graph neural networks (GNNs) with reinforcement learning for adaptive policy optimization. Additionally, real-time integration of emerging data sources, such as social media sentiment and vehicle telematics, should be examined. Ethical considerations, including ensuring equitable access to charging infrastructure and mitigating biases in predictive models, also require further attention. In conclusion, this study connects AI innovation with the urgent needs of sustainable transportation, providing a scalable, data-driven roadmap for achieving federal decarbonization targets and promoting economic growth. Realizing this potential will necessitate interdisciplinary collaboration among researchers, policymakers, industry leaders, and communities to ensure that AI-driven strategies yield equitable, efficient, and resilient outcomes.

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