An In-depth Examination of Parameters Contributing to the Success of Electric Vehicle Business Models: A Comprehensive Database Review and Key Findings

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Abstract

The automotive industry is witnessing a transformative shift toward electric vehicles (EVs) to address global CO2 emissions. Despite technological advancements and increasing consumer interest, the EV market faces challenges in scaling as anticipated. This study delves into datasets on EV market share in the United States to understand how infrastructure and policies influence EV adoption. Its goal is to identify key variables essential for a robust EV business model and guide infrastructure and policy decisions. Using Multiple Linear Regression (MLR), this research reveals influential predictors of EV-related metrics. High R-squared values underscore the significance of factors like trip counts, cost disparities, fuel-related aspects, and median income in driving EV adoption rates and registrations. These findings highlight the intricate relationship between diverse factors and EV metrics, emphasizing the need for comprehensive analyses when forecasting EV-related dynamics. The study aims to provide actionable insights for businesses, policymakers, and researchers to foster the growth of the EV industry. Future research avenues should incorporate customer feedback, expand datasets chronologically, and explore the roles of EV producers to deepen understanding of EV adoption dynamics.

Introduction

In response to the pressing global imperatives of reducing CO_2 emissions, the automotive industry is undergoing a profound transformation, marked by the introduction and commercialization of electric vehicles (EVs) (Secinaro et al., 2020). Both established automotive giants and entrepreneurial newcomers have recognized this shift and are actively developing hybrid and electric vehicles in response (Umar et al., 2021). Governmental and non-governmental incentives further bolster the prominence of EVs in the market (Yang & Tan, 2019). Heightened environmental concerns are spurring consumer interest in electric vehicles, and the convergence of technological progress, public subsidies, and rising consumer enthusiasm is poised to revolutionize the transportation landscape, transitioning it toward electricity-based systems from conventional internal combustion engines (ICEs). However, despite these encouraging attributes and favorable conditions, the electric vehicle market has not been scaling up to the extent envisioned by government and manufacturer strategies (Ziegler & Abdelkafi, 2022).

The economic feasibility of EVs is closely tied to the efficacy of the business models underpinning their adoption. The entrance of EVs into the market promises a new paradigm in vehicular offerings, yet it faces formidable challenges when competing for market share alongside established ICE vehicles (Ziegler & Abdelkafi, 2022). While considerable approaches have been made, the pace of progress has been rather moderate when measured against the ambitious initiatives designed to promote EVs (Breetz & Salon, 2018; Conejero et al., 2014; Dijk et al., 2016). Although there has been significant technological advancement, the EV market grapples with the absence of innovative business models essential for successfully commercializing this transformative technology. The profitability of business models traditionally designed for ICE vehicles often proves inadequate for the unique characteristics of EVs, such as their limited driving range, extended charging times, and higher acquisition costs (Secinaro et al., 2020, 2022; Ziegler & Abdelkafi, 2022). Consequently, the commercialization of EVs necessitates the development of distinctive business models tailored to their specific requirements.

In academia and policymaking, there is a growing interest in exploring the multifaceted dimensions of the electric vehicle (EV) business model to ensure its effective market penetration. It is widely acknowledged that meticulous planning of charging infrastructure, which is intricately interlinked with the pace of EV diffusion, is of paramount importance, particularly in light of the inherent constraints associated with the EVs' limited driving range (Danielis et al., 2020; Yang & Tan, 2019; Zhang et al., 2018). Variables such as purchase price, fuel efficiency, and driving range have garnered significant attention (Danielis et al., 2020; Ziegler & Abdelkafi, 2022). Attributes like battery serviceability and charging speed have been recognized as instrumental in shaping consumer inclinations toward EV adoption (Dorcec et al., 2019). Scholars have also explored the notion of market segmentation, differentiating between public and private EV transport systems, ride-sharing alternatives, and battery leasing options, as pivotal strategies for fostering the EV business model. While government incentives are instrumental in the nascent phases of EV market establishment, it is imperative to acknowledge their inadequacy as a long-term solution (Yang & Tan, 2019; Ziegler & Abdelkafi, 2022). These recommendations, grounded predominantly in current market trend analyses, necessitate empirical validation, underlining the urgency of delineating priorities pertaining to immediate versus long-term infrastructure developments requisite for the success of the EV business model (Secinaro et al., 2020, 2022; Ziegler & Abdelkafi, 2022). This suggests the necessity to adopt a holistic approach to analyze the current situation of the aforementioned parameters and analyze their impact on Ev's current market diffusion.

In response to these needs, this project seeks to explore existing datasets on electric vehicle (EV) market share, examining how different infrastructural elements and current policies influence the adoption of EVs. With a specific focus on the United States' geographic context, the objective is to identify critical variables that could establish the foundation for a thriving EV business model. This initial inquiry will create a structured framework that shapes infrastructure development and policymaking in the early stages of crafting an EV-friendly business model. The outcomes of this research are poised to provide valuable insights beneficial to businesses, policymakers, and researchers, enabling informed decision-making to nurture the growth of the electric vehicle industry. Ultimately, the project aims to deliver empirically backed insights into the key factors that propel the success of an EV business model, offering guidance for crucial infrastructure and policy development.

Methodology

To achieve the objective of this project, a structured methodology has been devised. It commenced with the collection of essential data, followed by processing and the creation of a comprehensive master datasheet. Subsequently, a thorough analysis of the data patterns was conducted using descriptive statistics. For inferential statistics, data preprocessing and necessary transformations were executed, and parameter tuning techniques were applied to identify optimal parameters for modeling purposes. The project then utilized Linear Regression modeling to derive predictive insights from the collected datasets, addressing various parameters. The specifics of each step are elaborated upon in the subsequent sections.

Data Collection

In reviewing the existing literature on the electric vehicle (EV) business model, certain influential parameters impacting EV diffusion have been identified. Within the scope of this project, a targeted selection was made, focusing on charging station distribution, electric vehicle registrations, household demographics (including income and travel tendencies), and total ownership costs. Data for these specific parameters were sourced based on state-wise market distribution across the US. Table 1 outlines the origins of the datasets, while comprehensive details for each dataset are available in the Appendix under "Database Details."

Table 1 Parameters and associated datasets

Parameters	Database URL
Charging station distribution	https://www.kaggle.com/datasets/prasertk/electric-vehicle-charging-stations-in-usa
Electronic vehicle registration	https://afdc.energy.gov/data/10962 https://electrek.co/2022/08/24/current-ev-registrations-in-the-us-how-does-your-state-stack-up/
Household	https://worldpopulationreview.com/state-rankings/households-by-state
Household income	https://www.statista.com/statistics/233170/median-household-income-in-the-united-states-by-state/
Total costs of Ownership	https://www.self.inc/info/electric-cars-vs-gas-cars-cost/#maintenance-cost
Household travel tendency	https://www.bts.gov/statistical-products/surveys/vehicle-miles-traveled-and-vehicle-trips-state

Data Processing

The collected datasets were thoroughly analyzed and processed to extract vital insights into how infrastructure and policies across different states are contributing to the diffusion of EVs in the US market. The processing involved several steps: removing redundant columns and rows, encoding state names into their respective state-codes, tallying specific variable values for each state, computing new variable values from column inputs, and finally, merging the processed datasets. This processing resulted in a comprehensive master datasheet containing essential data from all 50 states, represented in 50 rows. In the yielded dataset, there were 34 columns containing values for both independent and dependent variables across the states. These columns encompass a range of metrics including Average Mileage, Trip Counts, Total Costs (with and without purchase price), Taxes, Fuel, Insurance, Household Metrics, EV Registrations, Charging Station Counts, and Probability of EV Ownership per Household. These columns were meticulously examined and categorized into groups based on their roles as independent or dependent variables. Table 2 delineates these columns based on their variable associations. Notably, the "State" column contains string-type data, serving as a sample identifier, while the remaining columns predominantly hold either float or integer data types. A detailed breakdown of these variables is provided in the Appendix under the section 'Variable Details'.

Table 2 Variable association

Variable	Associated columns
Independent Variable	Average Mileage, Average trip counts, Average Mileage per trips, Total Cost without purchase price of EV, Total Cost with purchase price of EV, Taxes, Fuel, Insurance, Total cost of Non EV without purchase price, , Total cost of Non EV with purchase price, Non-EV Taxes, Non-EV Fuel, Non EV Insurance, Non EV vs EV difference in Total cost without purchase price, Non EV vs EV difference in Total cost with purchase price, Non EV vs EV difference in Taxes, Non EV vs EV difference in Fuel, Non EV vs EV difference in Insurance, Median Income, Total Households,
Dependent variable	Count of EV registration (2022), Growth percentage, Probability of having EVs per household

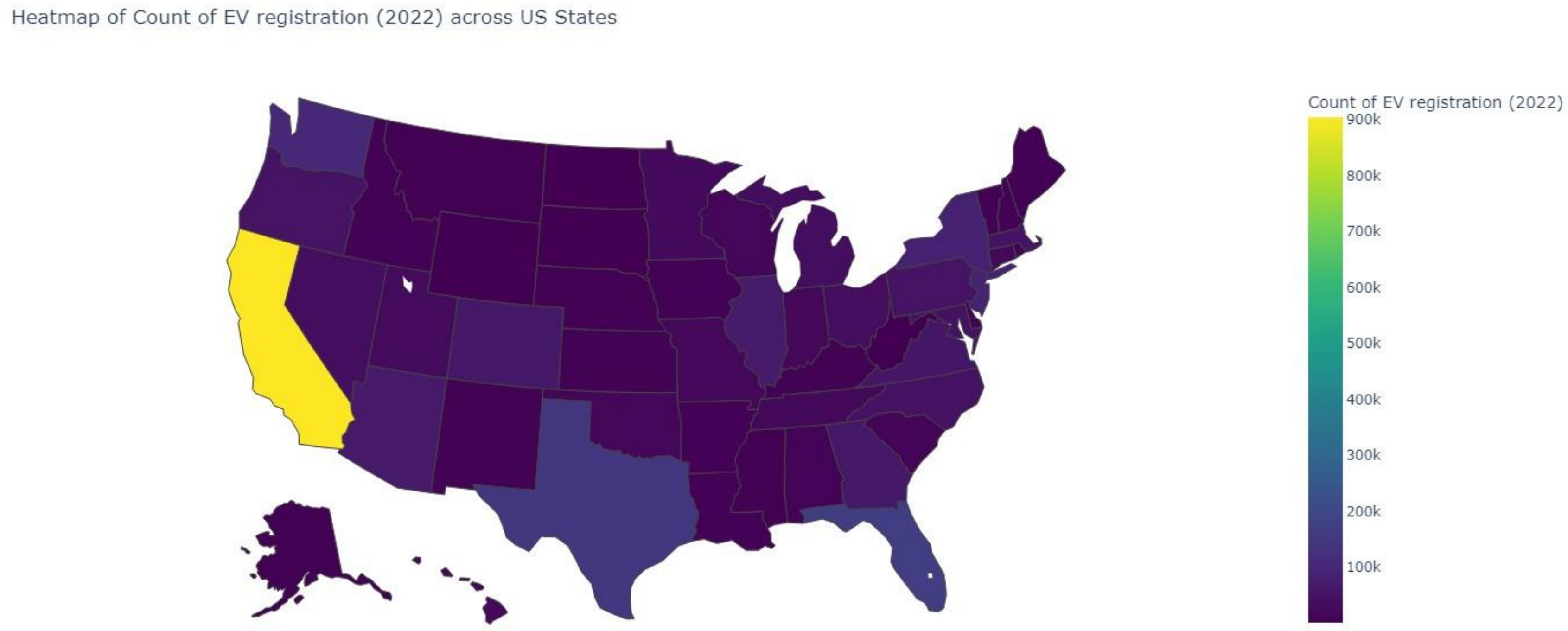
Statistical Approach

The resulting comprehensive data sheet was utilized for both descriptive and inferential data analyses. Dependent variables were employed in generating data visualizations through heatmaps, assigning pertinent values to corresponding states. This approach summarized the current diffusion of the EV market across various states in the US, showcasing the disparities in market penetration. Subsequently, descriptive and inferential statistics were applied. data normalization achieved through z-score normalization. In analyzing the trend in the data, focusing on the impact of independent variables on the dependent ones, feature selection was performed using information gained to explore their associations. Correlation matrices were depicted via heatmaps, and to mitigate collinearity's impact the variance inflation factor (VIF) was approached.

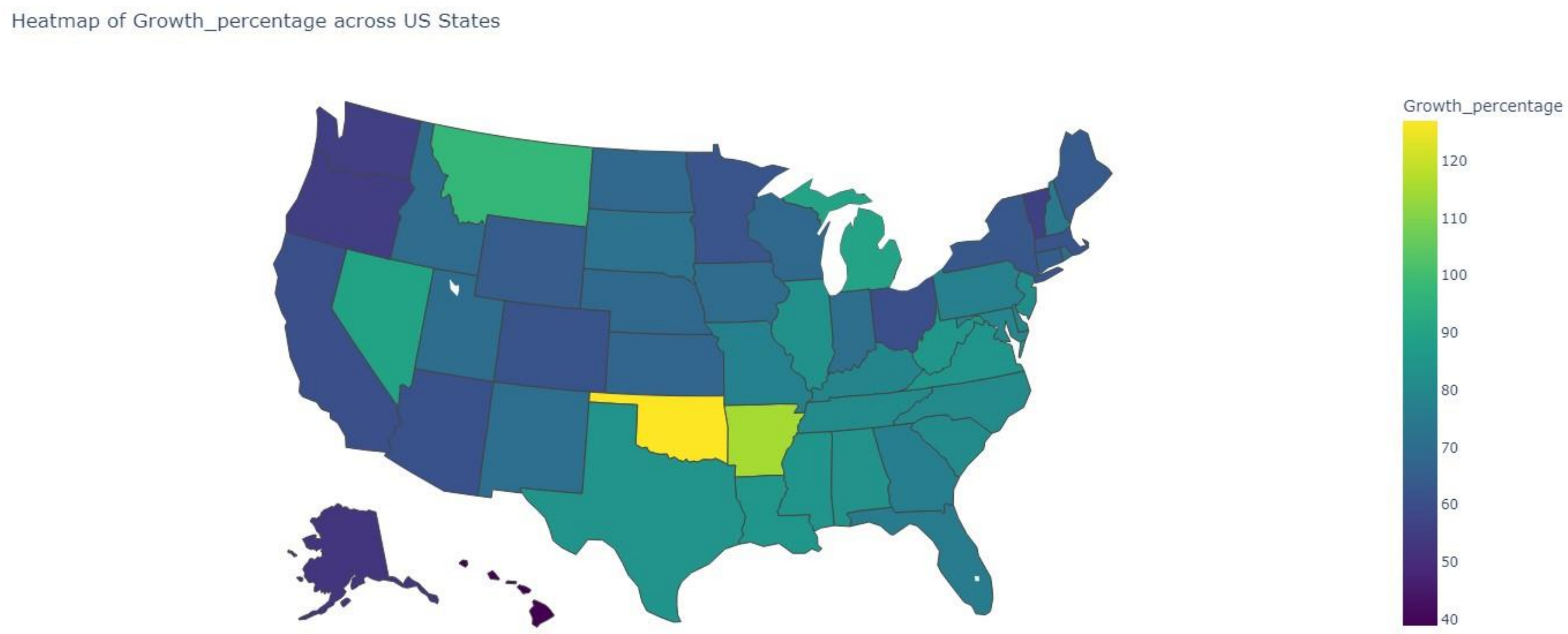
Variables were selected for modeling based on an acceptable VIF value of <5.0, aiming to reduce the potential for inflated Eigenvalues during predictive modeling. In the predictive modeling phase, stepwise multivariate linear regression was employed, dropping independent variables from the modeling based on significance levels > 0.05. This approach was aimed to ensure a robust and precise predictive statistical model for the EV market dynamics.

Results and Discussion

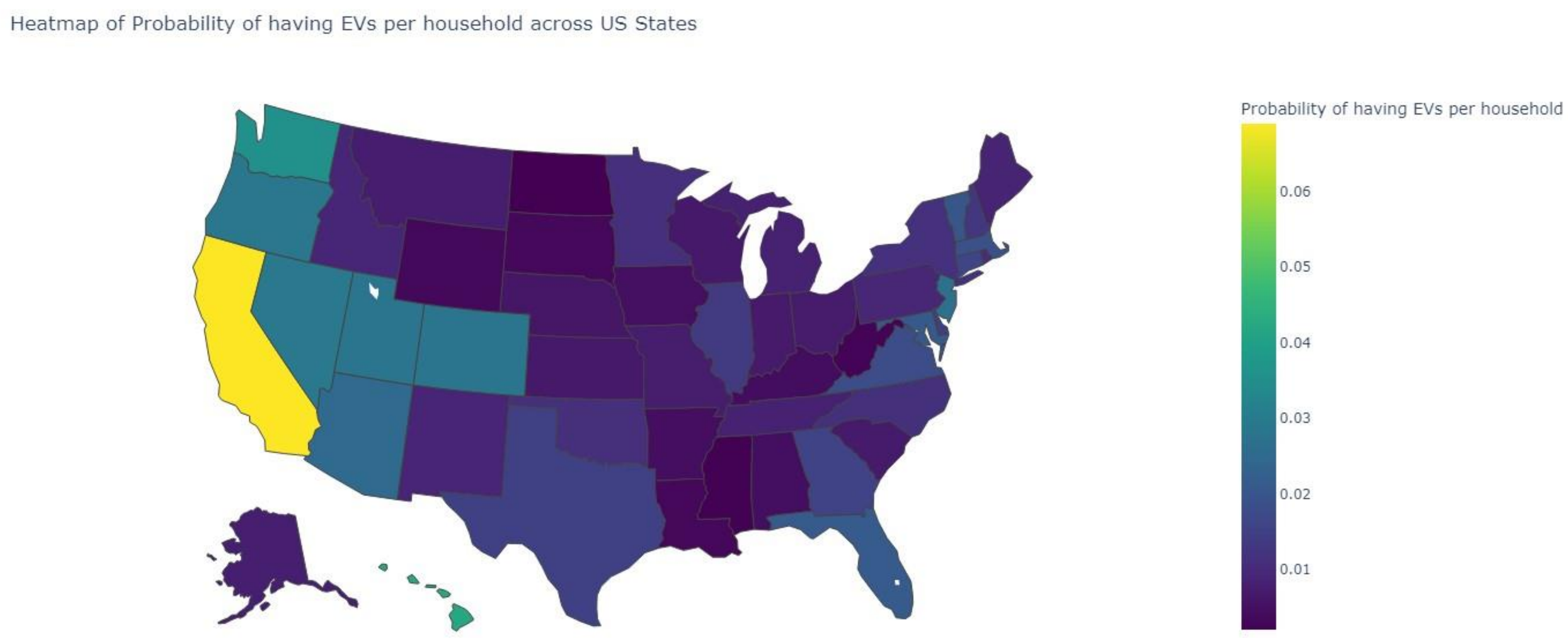
Figure 1 presented heatmaps illustrating (a) the count of EV registrations in 2022, (b) the growth percentage, and (c) the probability of households having EVs across US states. The heatmaps reveal that, in comparison to California, other states exhibit considerably lower EV registration. Notably, California, Florida, Washington, Texas, and Oregon lead in higher registered EV counts. Households along the West Coast and neighboring states demonstrate a greater propensity for adopting EVs, with California, Washington, Nevada, and Oregon leading in this aspect. When considering the growth percentage of EV registrations, states like Oklahoma, Arizona, Montana, and Nevada show higher growth rates, while California indicates a slower growth, suggesting a potential saturation in the EV market. Nevertheless, some states like Michigan, Illinois, and West Virginia exhibit gradual yet noticeable growth in their EV markets. Following the heatmap insights, indicating varied EV market diffusion rates across states, further examination of infrastructure and policy differences among states is crucial to understand their impact on market diffusion.



(a)



(b)



(c)

Figure 1 Heatmaps illustrate (a) the count of EV registrations in 2022, (b) the growth percentage, and (c) the probability of households having EVs across US states.

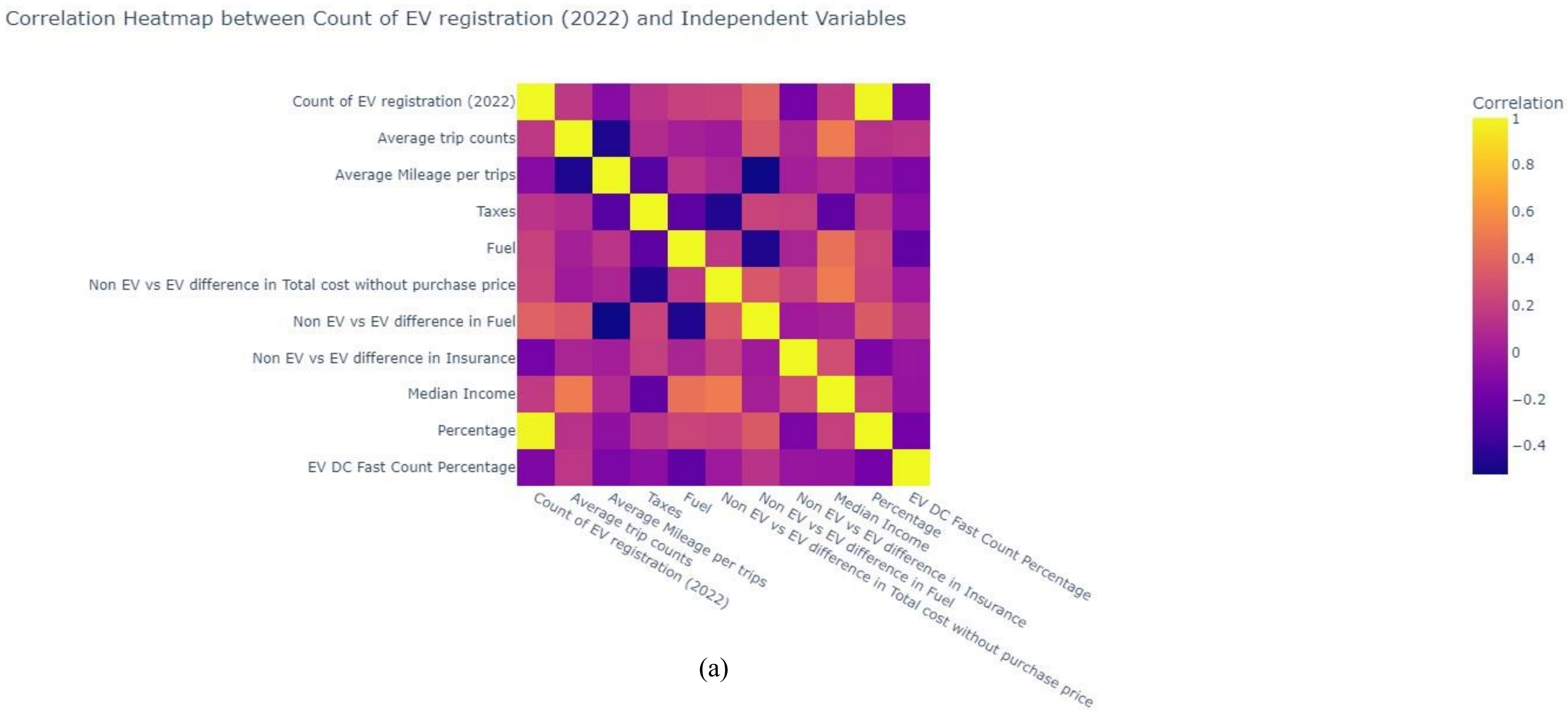
To comprehend the diverse impacts of variables on EV adoption, feature selection using information gain was employed. Table 3 displayed the information gain values of independent variables concerning the three distinct dependent variables. For the count of EV registrations in 2022, variables like 'Total Count', 'Percentage', 'Non-EV vs EV difference in Total cost', and 'Total Cost with purchase price of EV' emerged as pivotal. Concerning growth percentage, 'Average Mileage per trips', 'Total Cost without/with purchase price of EV', 'Non-EV vs EV difference in Total cost', and 'Median Income' showcased significant impact. Similarly, factors such as 'Average Mileage per trips', 'Total Cost without/with purchase price of EV', 'Non-EV vs EV difference in Total cost', 'Taxes', and 'EV Level1 EVSE Percentage' played substantial roles in predicting household EV adoption probabilities. These findings underscore the critical roles of cost dynamics, vehicle mileage, and specific financial disparities between EVs and non-EVs in shaping EV adoption rates, growth trends, and the likelihood of EV ownership within households. Notably, 'Average Mileage per trips', 'Non EV vs EV difference in Total cost without purchase price', 'Average trip counts', 'Percentage', 'Non EV vs EV difference in Total cost with purchase price', 'Non EV vs EV difference in Fuel', 'Total Count', 'Total Cost without purchase price of EV', 'Median Income', 'Total Cost with purchase price of EV', 'Fuel', and 'Taxes' emerged as the most influential factors across these variables. However, there's a notable possibility of high interrelation among the independent variables themselves.

Table 3 Information Gain values of independent variables

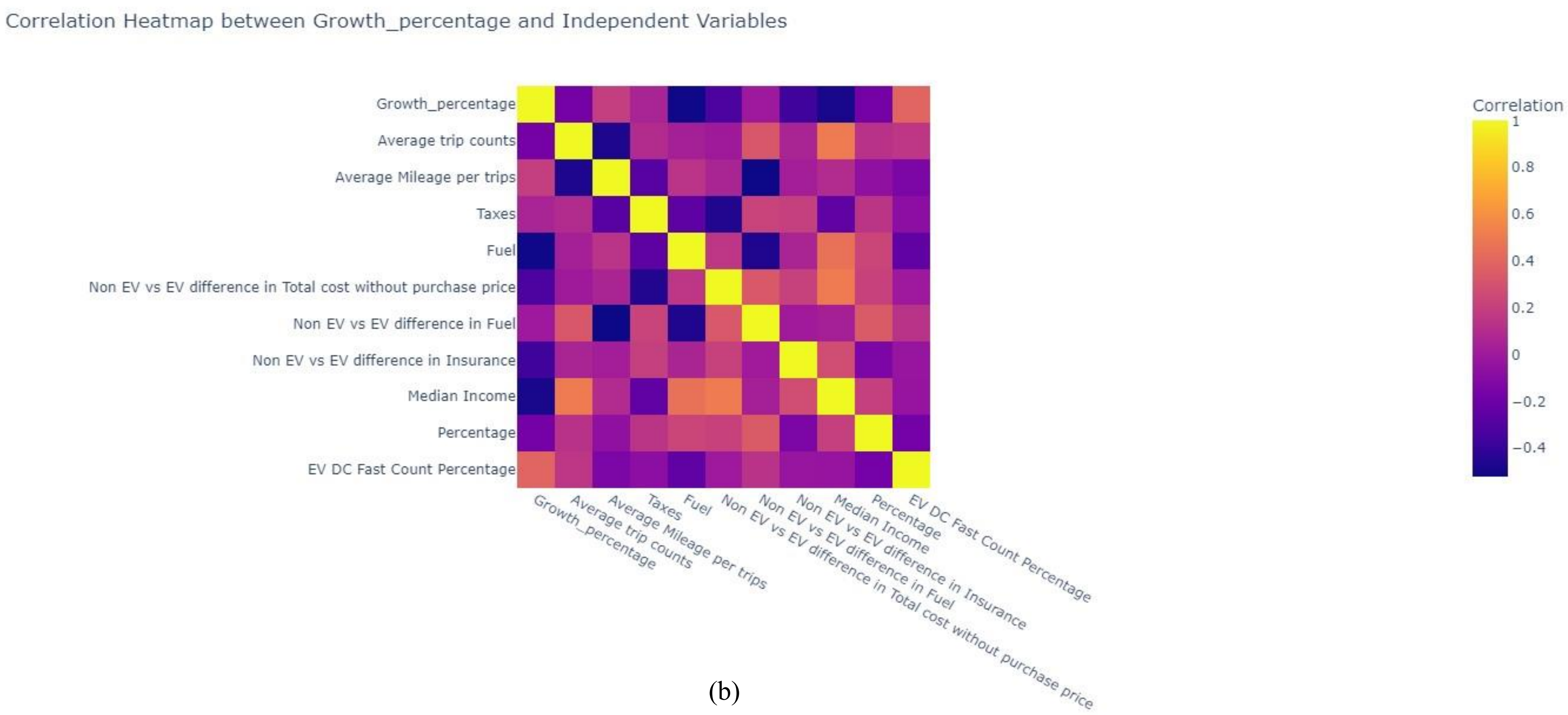
Independent variables	Count of EV registration (2022)	Growth percentage	Probability of having EVs per household
Average Mileage	0.04379	0.01316	0.04352
Average trip counts	0.03041	0.07505	0.03963
Average Mileage per trips	0.09016	0.23646	0.39239
Total Cost without purchase price of EV	0.10185	0.15161	0.12008
Total Cost with purchase price of EV	0.11335	0.16688	0.13273
Taxes	0.02567	0.01715	0.16423
Fuel	0.04271	0.15523	0.04650
Insurance	0.0	0.08543	0.0
Non-EV vs EV difference in Total cost without a purchase price	0.14539	0.20619	0.20619
Non-EV vs EV difference in Total cost with purchase price	0.15586	0.20434	0.20434
Non-EV vs EV difference in Taxes	0.0	0.0	0.03520
Non-EV vs EV difference in Fuel	0.07304	0.046638	0.10818

Non-EV vs EV difference in Insurance	0.02020	0.07713	0.0
Median Income	0.04809	0.21876	0.14772
Total Count	1.07625	0.06748	0.32622
Percentage	1.07625	0.06748	0.32622
EV Level1 EVSE Percentage	0.01759	0.01500	0.17910
EV Level2 EVSE Percentage	0.04973	0.15488	0.0
EV DC Fast Count Percentage	0.0	0.0	0.0

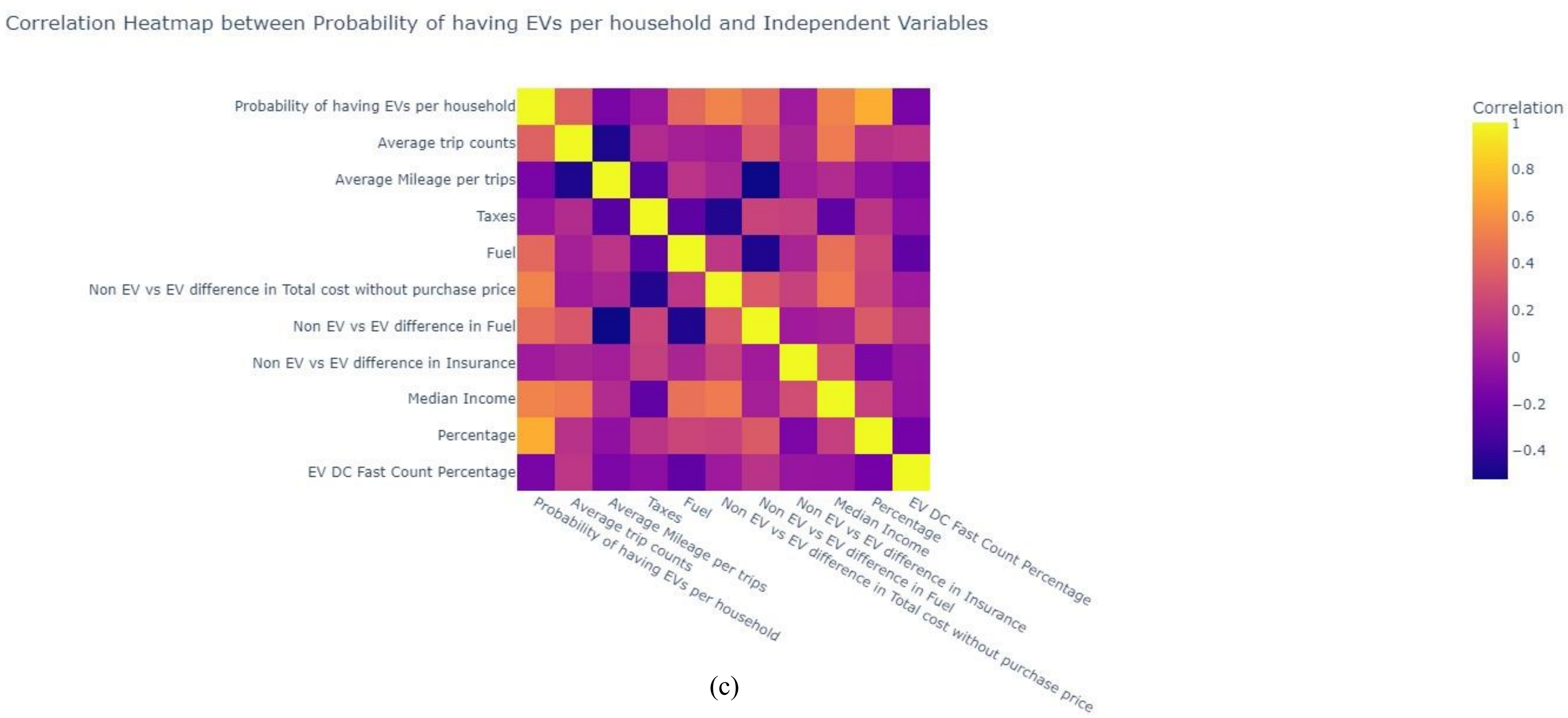
Following the information gain analysis, the exploration extended to a correlation heatmap analysis aiming to reveal relationships between influential independent variables and the dependent ones. Figure 2 depicted heatmaps showcasing correlation matrices for the three dependent variables, unraveling potential interdependencies and interactions among these factors. This visualization provided insights into their co-variation and potential mutual influence. By examining these correlations, it facilitated the refinement of variable selection for predictive modeling, granting a deeper understanding of their collective impact on the dependent variables. Notably, pairs like (median income - Non-EV vs EV difference in total cost without purchase price), (average trip count - median income), and (Fuel - median income) demonstrated strong correlations (>0.4), indicating potential associations with higher living costs relative to increased median household income. However, such strong intercorrelation among independent variables could complicate predictive modeling accuracy, emphasizing the need to mitigate intercorrelation among these variables.


Correlation Heatmap between Count of EV registration (2022) and Independent Variables
Count of EV registration (2022)
Average trip counts
Average Mileage per trips
Taxes
Fuel
Non EV vs EV difference in Total cost without purchase price
Non EV vs EV difference in Fuel
Non EV vs EV difference in Insurance
Median Income
Percentage
EV DC Fast Count Percentage
Correlation
1
0.8
0.6
0.4
0.2
0
−0.2
−0.4

(a)


Correlation Heatmap between Growth_percentage and Independent Variables
Growth_percentage
Average trip counts
Average Mileage per trips
Taxes
Fuel
Non EV vs EV difference in Total cost without purchase price
Non EV vs EV difference in Fuel
Non EV vs EV difference in Insurance
Median Income
Percentage
EV DC Fast Count Percentage
Correlation
1
0.8
0.6
0.4
0.2
0
−0.2
−0.4

(b)


Correlation Heatmap between Probability of having EVs per household and Independent Variables
Probability of having EVs per household
Average trip counts
Average Mileage per trips
Taxes
Fuel
Non EV vs EV difference in Total cost without purchase price
Non EV vs EV difference in Fuel
Non EV vs EV difference in Insurance
Median Income
Percentage
EV DC Fast Count Percentage
Correlation
1
0.8
0.6
0.4
0.2
0
−0.2
−0.4

(c)

Following the correlation heatmap analysis, the next step involved Variance Inflation Factor (VIF) analysis. VIF analysis aims to assess multicollinearity among independent variables, particularly identifying instances where predictor variables are highly correlated with each other. High multicollinearity can inflate the standard errors of coefficients in regression models, leading to unreliable interpretations of variable effects and potentially misleading results. Therefore, conducting VIF analysis helps in identifying and mitigating multicollinearity, ensuring the reliability and stability of the predictive model built using these variables. In this analysis, independent variables with VIF values exceeding 5 were dropped from the model. This was necessary as VIF values exceeding 5 indicate a high level of multicollinearity, which could adversely affect the accuracy and reliability of the predictive model by introducing instability and bias in the estimates of coefficients. Removing these variables with high VIF values helps in improving the robustness and trustworthiness of the subsequent predictive modeling. Table 4 charted the associated VIF values of the selected independent variables for further modeling. Dropped variables are: Total Count, EV Level1 EVSE Percentage, Total Cost without purchase price of EV, Non-EV vs EV difference in Total cost with purchase price, Insurance, Average Mileage, Total Cost with purchase price of EV, EV Level2 EVSE Percentage, Non EV vs EV difference in Taxes.

Table 4 VIF values of selected independent variables

Features	VIF
EV DC Fast Count Percentage	1.170173
Non-EV vs EV difference in Insurance	1.700288
Percentage	1.923264
Average Mileage per trips	2.395079
Fuel	2.830533
Average trip counts	2.900389
Median Income	3.815981
Non-EV vs EV difference in Total cost without purchase price	3.970373
Non EV vs EV difference in Fuel	3.995650
Taxes	4.609854

Following the selection of independent variables, Multiple Linear Regression (MLR) modeling was applied. The VIF analysis played a crucial role in identifying and eliminating highly collinear variables, ensuring the model's stability and mitigating the risk of multicollinearity-induced inaccuracies. MLR, known for its reliability, not only handles multiple factors but also enables the construction of a predictive model that delineates how each independent variable influences the dependent variable. Its strength lies in its ability to validate assumptions, evaluate model performance, and provide insights into the individual impact of each predictor. Consequently, MLR establishes a robust framework for predictive analytics, offering a comprehensible avenue to interpret complex relationships. Specific details of the MLR models are outlined in Table 5. The details of the models have been added in the appendix MLR detail section.

Table 5 MLR models

Dependent Variable	Parameters	Coefficient	Significance	R^2
Count of EV registration	Average Trip counts	0.0860	0.002	0.979
	Non-EV vs EV difference in Total cost without purchase price	0.0610	0.027	
	Median income	-0.0967	0.003	
	Percentage	0.9820	0.000	
Growth Percentage	Average mileage per trips	0.2052	0.001	0.609
	Fuel	0.4088	0.004	
	Non-EV vs EV difference in insurance	0.2818	0.008	
	Median income	0.3177	0.017	
	EV DC fast count Percentage	0.4285	0.001	
Probability of having EVs per Household	Average trip counts	0.2052	0.003	0.845
	Fuel	0.4088	0.000	
	Non-EV vs EV difference in total cost without purchase price	0.2818	0.000	
	Non-EV vs EV difference in Fuel	0.3177	0.002	
	Percentage	0.4285	0.000	

The Multiple Linear Regression (MLR) analyses for the three dependent variables offer compelling potential inferences regarding the influential predictors of EV-related metrics. The high R-squared values in the models predicting count of EV registrations in 2022 and the probability of households adopting EVs (0.979 and 0.845, respectively) suggest that factors like trip counts, cost disparities between EVs and non-EVs, fuel-related aspects, and median income play pivotal roles in determining EV adoption rates and registration numbers. Conversely, the model for growth percentage (R-squared of 0.609) indicates that while mileage per trip, fuel-related factors, insurance cost differences, and EV DC Fast Count Percentage significantly influence growth rates, other unaccounted variables might also contribute to growth trends. These insights emphasize the intricate relationship between diverse factors and EV metrics, suggesting a need for comprehensive analysis and consideration of multifaceted influences when evaluating and forecasting EV-related dynamics.

Conclusion

This project endeavors to explore existing datasets concerning the electric vehicle (EV) market share, particularly examining how infrastructural elements and current policies shape EV adoption. Focused on the geographic context of the United States, the goal is to identify crucial variables pivotal in establishing a robust foundation for a thriving EV business model. This research serves as a structured framework influencing infrastructure development and policymaking, guiding the creation of an EV-friendly ecosystem. The anticipated outcomes aim to furnish valuable insights benefiting businesses, policymakers, and researchers, facilitating informed decision-making pivotal in nurturing the electric vehicle industry's growth. Through empirically backed analyses, this endeavor seeks to uncover key factors underpinning the success of an EV business model, providing guidance for essential infrastructure and policy development. The models derived from Multiple Linear Regression analyses reveal compelling insights into influential predictors of EV-related metrics. High R-squared values in predicting EV registrations and household EV adoption rates underscore the significance of trip counts, cost disparities, fuel-related aspects, and median income in driving EV adoption. Conversely, the model for growth percentage suggests the impact of mileage per trip, fuel-related factors, insurance cost differences, and EV DC Fast Count Percentage, stressing the complexity of factors influencing growth trends. These findings highlight the need for comprehensive analyses and considerations of multifaceted influences when evaluating and forecasting EV-related dynamics, emphasizing the interconnectedness of diverse variables in shaping the EV market landscape.

Limitations and Future Studies

To further operationalize the models and deepen the inferences, several additional avenues require exploration in future studies. Incorporating customer feedback data would provide invaluable insights into consumer perceptions and preferences, shaping the understanding of EV adoption dynamics. Furthermore, integrating a comprehensive chronological dataset spanning from 2023 to 2025 would enable a more nuanced analysis of evolving trends and patterns in the EV market over time. Additionally, an examination of the producers' role is crucial, encompassing details about the facilities offered by EV manufacturers, battery output, and related factors. Understanding these aspects would contribute significantly to comprehending how various features and offerings impact consumer behavior and market dynamics within the electric vehicle industry.

Author Contribution

Oluwatoyin Oniroko- Literature Review, data preparation, Model planning, writing; Ishmam Zahin Chowdhury- Conceptualization, Model planning, Predictive modeling, writing. Both authors have contributed to the project.

Appendix

Database Details

Database-1

Source-

https://www.kaggle.com/datasets/prasertk/electric-vehicle-charging-stations-in-usa

Columns-

Fuel Type Code, Station Name, Street Address, Intersection Directions, City, State, ZIP, Plus4, Station Phone, Status Code, Expected Date, Groups With Access Code, Access Days Time, Cards Accepted, BD Blends,NG Fill Type Code, NG PSI, EV Level1 EVSE Num, EV Level2 EVSE Num, EV DC Fast Count, EV Other Info, EV Network, EV Network Web, Geocode Status, Latitude, Longitude, Date Last Confirmed, ID, Updated At, Owner Type Code, Federal Agency ID, Federal Agency Name, Open Date, Hydrogen Status Link, NG Vehicle Class, LPG Primary, E85 Blender Pump, EV Connector Types, Country, Intersection Directions (French), Access Days Time (French), BD Blends (French), Groups With Access Code (French), Hydrogen Is Retail, Access Code, Access Detail Code, Federal Agency Code, Facility Type, CNG Dispenser Num, CNG On-Site Renewable Source, CNG Total Compression Capacity, CNG Storage Capacity, LNG On-Site Renewable Source, E85 Other Ethanol Blends, EV Pricing, EV Pricing (French), LPG Nozzle Types, Hydrogen Pressures, Hydrogen Standards, CNG Fill Type Code, CNG PSI, CNG Vehicle Class, LNG Vehicle Class, EV On-Site Renewable Source, Restricted Access

Accessibility- Free to download.

Database-2

Source-

https://afdc.energy.gov/data/10962

and

https://electrek.co/2022/08/24/current-ev-registrations-in-the-us-how-does-your-state-stack-up/

Columns-

State, Count of EV registrations (2020), Percent of total EVs (2020), Count of EV registrations (2021), Percent of total EVs (2021), YOY Growth,

and

State, Registration Count

Accessibility- Free to download.

Database-3

Source-

https://worldpopulationreview.com/state-rankings/households-by-state

Columns-

Fips, state, densityMi, pop2023, pop2022, pop2020, pop2019, pop2010, growthRate, growth, growthSince2010, TotalHouseholdsand

Accessibility- Free to download.

Database-4

Source-

https://www.statista.com/statistics/233170/median-household-income-in-the-united-states-by-state/

Columns-

State, Median household income (2022)

Accessibility- Free to download after signing in

Database-5

Source-

https://www.self.inc/info/electric-cars-vs-gas-cars-cost/#maintenance-cost

Columns-

State, Total cost of Non EV without purchase price, State, Total cost of Non EV with purchase price, State, Non-EV Taxes, State, Non-EV Fuel, State, Non_EV Insurance, State, Total Cost without purchase price of EV, State, Total Cost with purchase price of EV, State, Taxes, State, Fuel, State, Insurance

Accessibility- Have to procure the data from the interactive map. Generated datasheet “Total cost of ownership for MSIS programming”

Database-6

Source-

https://www.bts.gov/statistical-products/surveys/vehicle-miles-traveled-and-vehicle-trips-state

Columns-

State, Vehicle miles traveled (Urban, Suburban, Rural), Vehicle trips (Urban, Suburban, Rural)

Accessibility- Free to download

[Note: dataset zip file have been attached]

Variable Details

1. Average Mileage- average mile travelled by per household per day.
2. Average trip counts- average count of trips made by per household per day.
3. Average Mileage per trips- average mileage/ average trip counts
4. Total Cost without purchase price of Electric vehicle (EV)- Annual cost of ownership of EV (includes tax, fuel, insurance)
5. Total Cost with purchase price of EV- Annual cost of ownership of EV (includes purchase price, tax, fuel, insurance)
6. Taxes- Annual tax paid
7. Fuel- Annual Fuel cost
8. Insurance- Annual insurance paid.
9. Non-EV vs EV difference in Total cost without a purchase price- Difference between annual cost of ownership of Non-EV and EV (includes tax, fuel, insurance)
10. Non-EV vs EV difference in Total cost with purchase price- Difference between annual cost of ownership of Non-EV and EV (includes purchase price, tax, fuel, insurance)
11. Non-EV vs EV difference in Taxes- Difference between annual tax paid for Non-EV and EV
12. Non-EV vs EV difference in Fuel- Difference between annual fuel cost for Non-EV and EV
13. Non-EV vs EV difference in Insurance- Difference between annual insurance paid for Non-EV and EV
14. Median Income- Household median income
15. Total Count- Total number of charging stations across the U.S.
16. Percentage- Charging station percentage based on state wise distribution.
17. EV Level1 EVSE Percentage- percentage of slow charging facility based on total charging station availability.

18. EV Level2 EVSE Percentage- percentage of fast-level charging facility based on total charging station availability.

19. EV DC Fast Count Percentage- percentage of fast charging facility based on total charging station availability.

Coding

Libraries Used-

1. pandas
2. US
3. plotly
4. sklearn
5. statmodels

[Note: Zip files have been attached]

MLR details

```
===== Count of EV registration (2022) =====
                                   OLS Regression Results
==========================================================================================
Dep. Variable:     Count of EV registration (2022)   R-squared:                       0.979
Model:                                         OLS   Adj. R-squared:                  0.977
Method:                              Least Squares   F-statistic:                     532.3
Date:                             Tue, 12 Dec 2023   Prob (F-statistic):           2.95e-37
Time:                                     09:43:53   Log-Likelihood:                 25.998
No. Observations:                               50   AIC:                            -42.00
Df Residuals:                                   45   BIC:                            -32.44
Df Model:                                        4
Covariance Type:                         nonrobust
==================================================================================================================================
                                                        coef    std err          t      P>|t|      [0.025      0.975]
----------------------------------------------------------------------------------------------------------------------------------
const                                              7.633e-17      0.021   3.56e-15      1.000      -0.043       0.043
Average trip counts                                   0.0860      0.026      3.262      0.002       0.033       0.139
Non EV vs EV difference in Total cost without purchase price    0.0610      0.027      2.292      0.027       0.007       0.115
Median Income                                        -0.0967      0.030     -3.178      0.003      -0.158      -0.035
Percentage                                            0.9820      0.022     44.288      0.000       0.937       1.027
==============================================================================
Omnibus:                       19.584   Durbin-Watson:                   1.986
Prob(Omnibus):                  0.000   Jarque-Bera (JB):               31.352
Skew:                          -1.222   Prob(JB):                     1.56e-07
Kurtosis:                       6.013   Cond. No.                         2.51
==============================================================================

Notes:
[1] Standard Errors assume that the covariance matrix of the errors is correctly specified.
```

```
===== Growth_percentage =====
                            OLS Regression Results
==============================================================================
Dep. Variable:      Growth_percentage   R-squared:                       0.609
Model:                            OLS   Adj. R-squared:                  0.564
Method:                 Least Squares   F-statistic:                     13.68
Date:                Tue, 12 Dec 2023   Prob (F-statistic):           4.56e-08
Time:                        09:43:53   Log-Likelihood:                -47.499
No. Observations:                  50   AIC:                             107.0
Df Residuals:                      44   BIC:                             118.5
Df Model:                           5
Covariance Type:            nonrobust
=========================================================================================================
                                          coef    std err          t      P>|t|      [0.025      0.975]
---------------------------------------------------------------------------------------------------------
const                               -3.469e-17      0.094  -3.68e-16      1.000      -0.190       0.190
Average Mileage per trips               0.3269      0.096      3.405      0.001       0.133       0.520
Fuel                                   -0.3345      0.111     -3.025      0.004      -0.557      -0.112
Non EV vs EV difference in Insurance   -0.2736      0.098     -2.778      0.008      -0.472      -0.075
Median Income                          -0.2763      0.111     -2.489      0.017      -0.500      -0.053
EV DC Fast Count Percentage             0.3425      0.099      3.474      0.001       0.144       0.541
==============================================================================
Omnibus:                       16.087   Durbin-Watson:                   1.954
Prob(Omnibus):                  0.000   Jarque-Bera (JB):               22.079
Skew:                           1.078   Prob(JB):                     1.61e-05
Kurtosis:                       5.440   Cond. No.                         1.92
==============================================================================
```

```
Notes:
[1] Standard Errors assume that the covariance matrix of the errors is correctly specified.
```

```
===== Probability of having EVs per household =====
                                       OLS Regression Results
===================================================================================================
Dep. Variable:     Probability of having EVs per household   R-squared:                       0.845
Model:                                                 OLS   Adj. R-squared:                  0.827
Method:                                      Least Squares   F-statistic:                     47.94
Date:                                     Tue, 12 Dec 2023   Prob (F-statistic):           1.03e-16
Time:                                             09:43:53   Log-Likelihood:                -24.354
No. Observations:                                       50   AIC:                             60.71
Df Residuals:                                           44   BIC:                             72.18
Df Model:                                                5
Covariance Type:                                 nonrobust
===========================================================================================================================
                                                            coef    std err          t      P>|t|      [0.025      0.975]
---------------------------------------------------------------------------------------------------------------------------
const                                                  1.006e-16      0.059   1.69e-15      1.000      -0.120       0.120
Average trip counts                                       0.2052      0.066      3.095      0.003       0.072       0.339
Fuel                                                      0.4088      0.086      4.772      0.000       0.236       0.581
Non EV vs EV difference in Total cost without purchase price   0.2818      0.070      4.045      0.000       0.141       0.422
Non EV vs EV difference in Fuel                           0.3177      0.097      3.283      0.002       0.123       0.513
Percentage                                                0.4285      0.072      5.919      0.000       0.283       0.574
==============================================================================
Omnibus:                        0.256   Durbin-Watson:                   2.051
Prob(Omnibus):                  0.880   Jarque-Bera (JB):                0.445
Skew:                          -0.095   Prob(JB):                        0.801
Kurtosis:                       2.579   Cond. No.                         2.98
==============================================================================
```

```
Notes:
[1] Standard Errors assume that the covariance matrix of the errors is correctly specified.
```

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