Control Science and Engineering
2024; 8(1): 1-12
http://www.sciencepublishinggroup.com/j/cse
doi: 10.11648/j.cse.20240801.11
ISSN: 2994-7421 (Online)

Towards Achieving Energy Security: Data-Driven Analysis of Electric Vehicle Trends (1997-2024)

Jimoh Afeez Oyeshola[1, *], Muhammad Muktar Namadi[2], Sulaiman Afolabi[1], Teslim Oyewale Jimoh[3]

[1]Department of Informatics, University of Louisiana, Lafayette, USA

[2]Department of Chemistry, Nigerian Defence Academy, Kaduna, Nigeria

[3]IT Service Delivery Group, Habaripay GTCO, Lagos, Nigeria

Email address:

hafeezmemo@gmail.com (Jimoh Afeez Oyeshola)

[*]Corresponding author

To cite this article:

Jimoh Afeez Oyeshola, Muhammad Muktar Namadi, Sulaiman Afolabi, Teslim Oyewale Jimoh. (2024). Towards Achieving Energy Security: Data-Driven Analysis of Electric Vehicle Trends (1997-2024). *Control Science and Engineering*, *8*(1), 1-12. https://doi.org/10.11648/j.cse.20240801.11

Received: December 15, 2023; **Accepted**: December 29, 2023; **Published**: January 11, 2024

Abstract: The evolution of electric vehicles has emerged among the possible strategies towards achieving energy security. The amount of data produced is growing very fast, providing opportunities for information discovery through big data analysis. This study undertakes a comprehensive data analysis of electric vehicles produced from 1997 to 2024, exploring the development trends on data evaluation system that considers electric vehicle models, types (Battery Electric Vehicles - BEV, Plug-in Hybrid Electric Vehicles - PHEV, Clean Alternative Fuel Vehicle - CAFV Eligibility), electric vehicle range, and base Manufacturer Suggested Retail Price. Data analysis employs k-means as an unsupervised machine learning algorithm for dataset partitioning into clusters. Factor analysis and Principal Component Analysis (PCA) were also employed as supervised learning methods to explore patterns in the dataset without specific emphasis on underlying factors while retaining maximum variance. Further visualizations were carried out using scatterplots, correlation matrices, contingency tables, density plots, and box plots. This study was able to uncover dynamic directions and future industry trends in addressing significant challenges in sustainable development, the study recommends the use of datasets with increased observations spanning the period from 2020 to 2024 with emphasis on electric vehicle prices and their electric ranges. These are essential factors for a comprehensive understanding of the electric vehicle market.

Keywords: Electric Vehicles, Energy Security, Sustainable Development, Data Analysis, Industry Trends

1. Introduction

Global energy consumption has increased steadily over the last century as the world population has grown and more countries have become industrialized [1]. The advocacy for mitigating climate change in recent times has emphasized the reduction of overall greenhouse gas (GHG) emissions [2]. A significant aspect of this effort involves the gradual transition from traditional gas-powered automobiles to electric vehicles. Currently, we are witnessing extensive campaigns promoting electric vehicles. It is, therefore, imperative to conduct in-depth data analysis to substantiate these trends. In the pursuit of a sustainable and secure energy future, the automotive industry has witnessed a transformative shift towards electric vehicles (EVs). As the global community strives to address environmental concerns and reduce dependency on traditional fuel sources, electric vehicles have emerged as a pivotal solution. The development of alternative renewable energy continues to grow in recent times due to the fear of energy insecurity in the near future and environmental with sociopolitical issues associated with the use of fossil fuels [3]. Global climate change and air pollution are driving the demand for sustainable, low-carbon, and eco-friendly transportation [4-6]. In 2022, global energy-related CO_2 emissions reached 36.8 Gt, of which the transport sector contributed nearly 8 Gt, thereby accounting for 21.7 % [7]. In this context, scaling up the deployment of electric vehicles (EVs) has emerged as a feasible solution to the challenges posed by dispersive transport emissions. In 2022, the global stock of electric cars surpassed 26 million, marked by a record-high annual sale of over 10 million [8]. The top three regions for EV stock are China (13.8 million), Europe (7.8 million), and the United States (3 million) [9].

Zero emission and a smooth driving experience are the potential reasons why an electric vehicle is one of the popular choices for vehicle owners in recent times according to Majumder, in addition, the mechanical efficiency of an electric vehicle is between 60% and 70%, while the efficiency of a vehicle with an internal combustion engine is 18% to 22% [10]. Currently, major players in the automobile industry like Tesla and Porsche manufacture electric vehicles with lots of improvement, due to advancement in battery technology. This has led to the higher popularity of electric vehicles. In the United States, the annual cost of driving a petrol car can cost from 1500 USD to 2500 USD. While it costs about 500 USD for electric vehicles. The cost of maintenance is relatively cheap with highly efficient energy conversion. The transition to electric mobility represents a critical step towards reducing carbon emissions, mitigating climate change, and ensuring a resilient energy landscape [10]. Scholars have found factors in several parties (e.g., government, industry, and market), that influence the commercialization and development process of the EV industry, such as patent and prototype counts, research and development (R&D), fuel economy, subsidy policy, social impact, and keen interest of investment [11-14]. This study therefore aims to reveal the multifaceted dynamics characterizing the evolution of electric vehicles over nearly three decades by employing diverse statistical methods with a primary focus on achieving energy security. The methodologies employed encompass a comprehensive suite of statistical tools, including scatter plots for visualizing data patterns, correlation matrices to discern relationships between variables, contingency tables to explore categorical associations, box plots for outlier detection, and unsupervised learning techniques such as K-Means clustering, and supervised learning such as Principal Component Analysis (PCA), and Factor Analysis to uncover intricate patterns within the dataset. As we delve into the wealth of information encapsulated in the electric vehicle population data, the objective is not only to decipher trends but also to contribute valuable insights that can inform policy, industry practices, and consumer choices. By understanding the nuances of electric vehicle adoption, we aspire for a more sustainable and secure energy future.

2. Materials and Methods

2.1. Data

The data used for this research work was obtained from the United States government's open data website [15]. The dataset description was sourced from the same website. The original dataset comprises 150,482 observations with 17 columns. The original dataset was loaded into R, using the read.csv function. The head function was used to display the first 6 rows for each column is shown in Table 1.

Table 1. *Overview of the dataset used.*

…	Model year	Make	Electric Vehicle Type	Clean. Alternative. Fuel. Vehicle.. CAFV.. Eligibility	Electric Range	Base MSRP
…	2020	HYUNDAI	Battery Electric Vehicle (BEV)	Clean Alternative Fuel Vehicle Eligible	258	0
…	2022	JEEP	Plug-in Hybrid Electric Vehicle (PHEV)	Not eligible due to low battery range	25	0
…	2023	JEEP	Plug-in Hybrid Electric Vehicle (PHEV)	Not eligible due to low battery range	25	0
…	2018	TESLA	Battery Electric Vehicle (BEV)	Clean Alternative Fuel Vehicle Eligible	215	0
…	2018	BMW	Plug-in Hybrid Electric Vehicle (PHEV)	Clean Alternative Fuel Vehicle Eligible	97	0
…	2020	TESLA	Battery Electric Vehicle (BEV)	Clean Alternative Fuel Vehicle Eligible	266	0

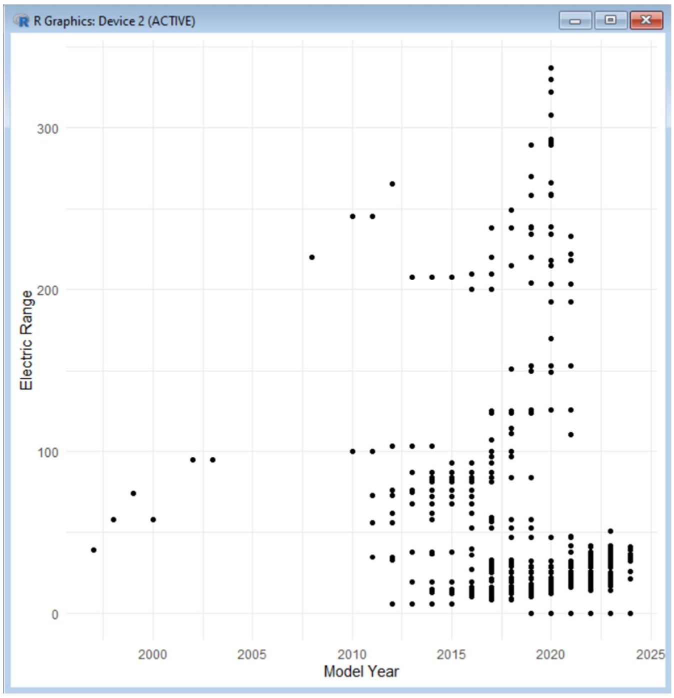
The str function was further used to view the structure of the dataset. This is to give an insight of the data types and the ones that require conversion. The datatypes shown in the original dataset structures infers that the data requires cleaning for proper analysis to be carried out. The summary() function show that the variables Postal. code, Legislative. District and X2020. Census. Tract has missing values. After removing the missing data, the number of observations reduced from 150,482 to 150,141. This shows that 0.23% of the data was removed, which is within the acceptable limit of missing data in a dataset.

2.2. Data Analysis

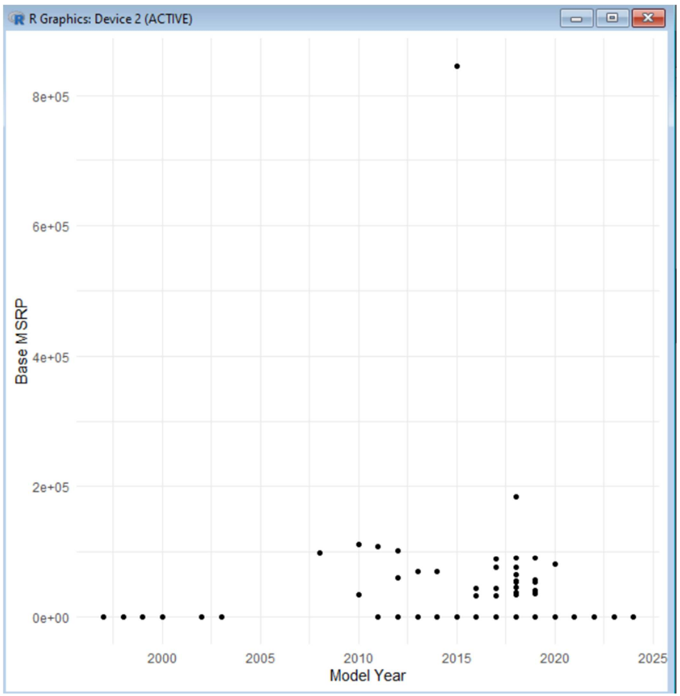
2.2.1. Scatterplots of Numeric Variables

Scatterplot was used to show correlation between the numeric variables. A positive correlation shows the points generally follow an upward trend, a negative correlation show points in a downward trend, no correlation show no clear pattern or trend in the scatter plot while mixed correlation show both positive and negative correlation at different ranges or intervals. Figure 1a-c shows the scatterplot for numeric variables in the dataset.

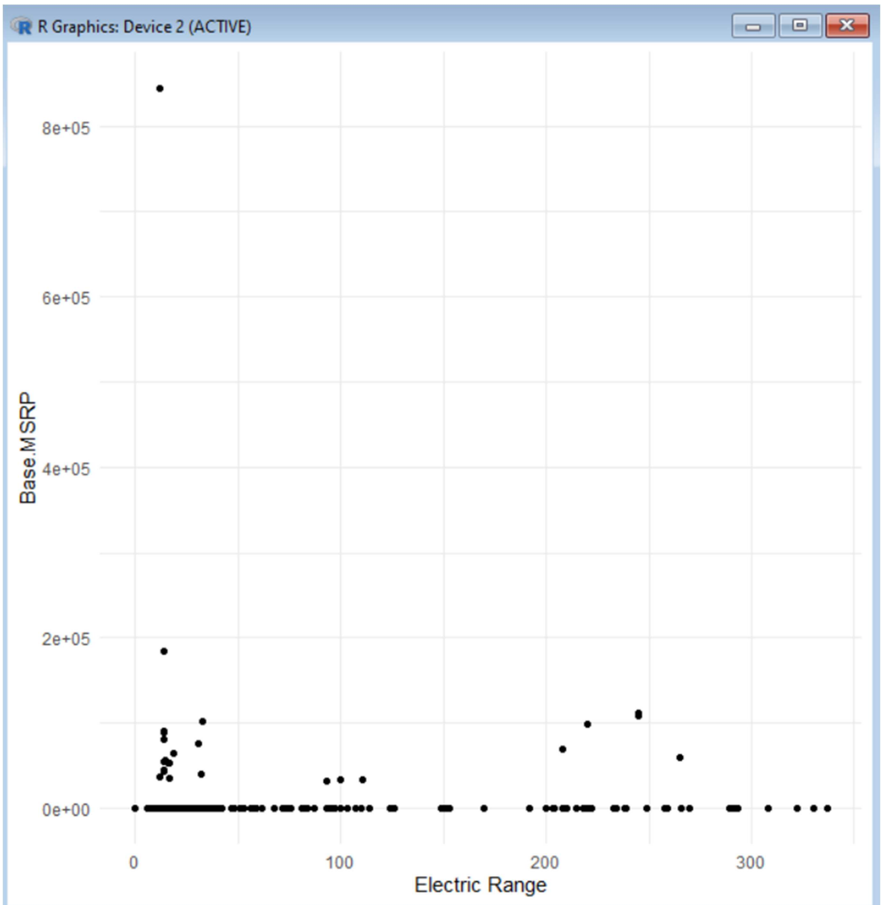
The scatter plot for Model Year vs. Electric Range show that there are both positive and negative correlations between the model year of an electric vehicle and its electric range. This could be as a result of the make of the electric vehicle or technology of battery used. The plot for Model Year vs. Base MSRP does not show significant correction but shows an outlier of a 2015 model electric vehicle with a very high retail price. The plot for Electric Range vs. Base MSRP does not show significant correlations between the variables, but an outlier as well. Faceting was further used to visually compare and contrast the scatter plots into groups of Electric Vehicle Type and Clean Alternative Fuel Vehicle Eligibility.



(a) Model Year vs. Electric Range



(b) Model Year vs. Base MSRP



(c) Electric Range vs. Base MSRP

Figure 1. *a-c: Scatterplot showing numeric variables.*

Figure 2. *a-b: Faceting of scatterplot into electric vehicle type and clean alternative fuel vehicle eligibility.*

2.2.2. Correlation Matrices for Numerical Variables

Correlation matrix was used to show linear relationships between pairs of numerical variables (Model Year, Electric Range and Retail Price). A positive correlation show that as one variable increases, the other tends to increase, while negative correlations indicate that as one variable increases, the other tends to decrease. The strength of the correlation is measured by the correlation coefficient, with values closer to 1 or -1 indicating a stronger relationship.

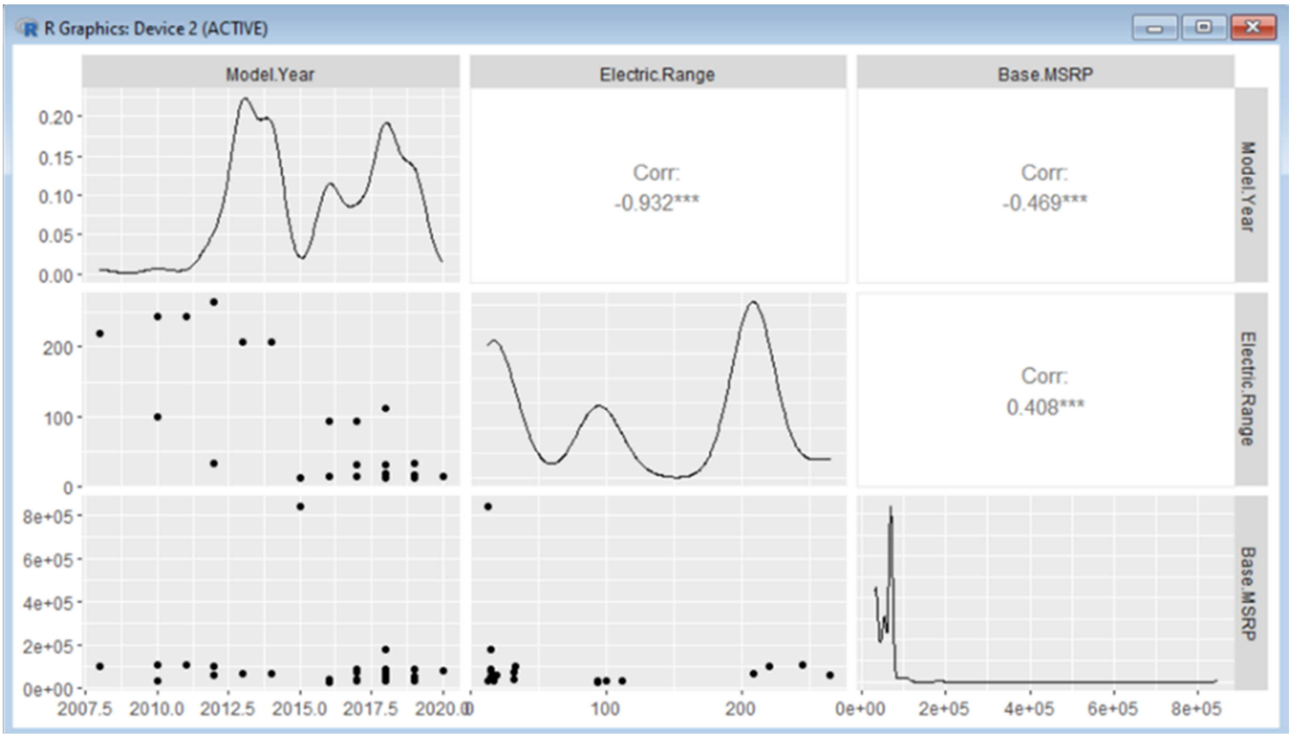


Figure 3. *Correlation Matrix for numerical variables.*

The results show that there is a positive correlation between "Base.MSRP" and "Electric.Range." The correlation coefficient is 0.408. This implies that retail price of electric vehicles positively correlates with its electric range in miles. This is because more expensive batteries would be used to achieve higher electric range of electric vehicles, thereby increasing the retail price of this vehicles. However, there is a negative correlation between "Base.MSRP" and "Model.Year." with correlation coefficient of approximately -0.469. And a much stronger negative correlation between "Electric.Range" and "Model.Year." with correlation coefficient of approximately -0.932. This suggests that the production year of electric vehicle models may not strongly correlate with their retail price and electric range. Various factors, including technological advancements, brand influence, and market strategies, contribute to this lack of correlation. For instance, a 2015 Porsche 918 Spyder electric vehicle may be more expensive than a 2022 Tesla Model Y, despite the Tesla offering greater electric range and additional features [16].

2.2.3. Contingency Tables

Contingency table was used to show the relationship between categorical variables: Electric Vehicle Type and Clean Alternative Fuel Vehicle (CAFV) Eligibility. The table function displays the frequency distribution of the Electric Vehicle Type column indicating that there are 116,585 Battery Electric Vehicle (BEV) and 33,556 Plug-in Hybrid Electric Vehicle (PHEV) in the dataset. The prop. table function was used to determine the proportion. The proportions of BEV (0.78) to PHEV (0.22) varied significantly. Pearson's χ^2 (chi-squared) test of independence was further used to determine if the electric vehicle type and eligibility of clean alternative fuel vehicle variables are independent or not.

H_0: *The variables are independent*

H_1: *The variables are dependent*

The null hypothesis (H_0) of the χ^2 test indicates that the variables are independent while the alternative hypothesis (H_1) indicates that they are dependent. The result obtained shows that the p-value (2.2×10^{-16}) is lower than 0.05. Hence, the null hypothesis is rejected. This implies that there is a relation between the electric vehicle type and the eligibility for clean alternative fuel.

2.2.4. Histograms and Density Plots

Histogram was used to visualize the frequency distribution for year of production of electric vehicles while, density plots was used to visualize the type of electric vehicles produced with respect to year of production. The eligibility for clean fuel was also visualized.

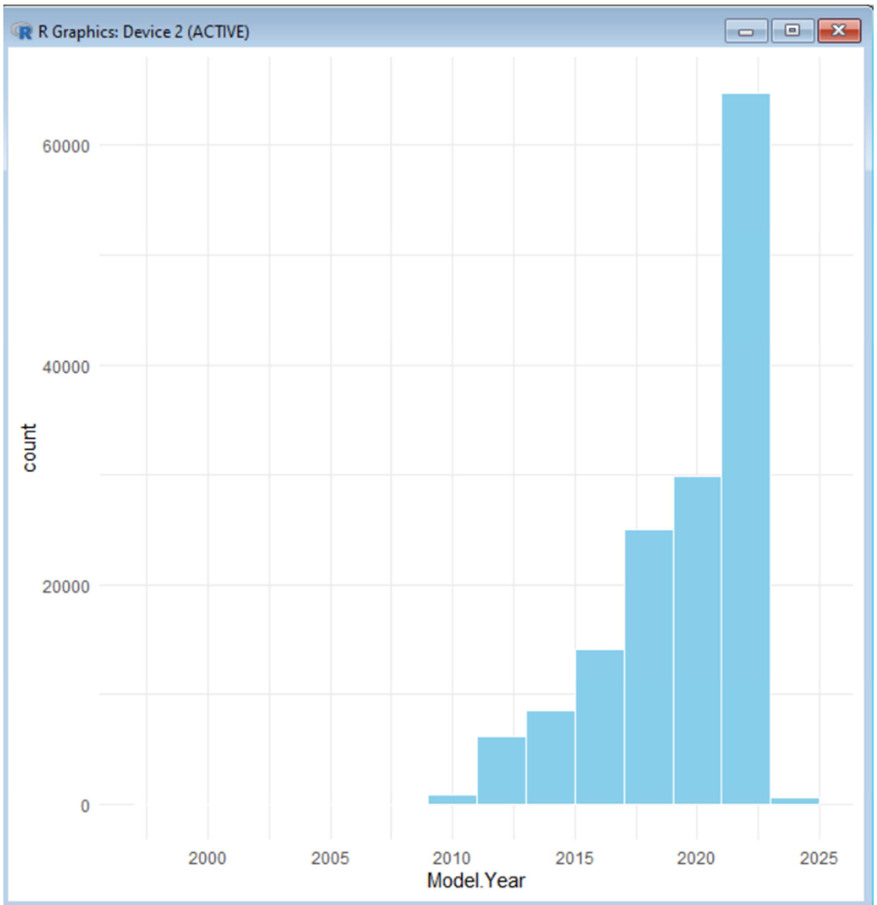


Figure 4. *Histogram showing years of production of electric vehicles.*

The results indicated a non-normal distribution, suggesting an asymmetric distribution with the data skewed to the right. This observation aligns with the current trend in the electric vehicle industry, which is experiencing growth over the years. The increasing production of electric vehicles is influenced by government policies gradually phasing out gas-powered automobiles. The industry is moving towards achieving zero carbon emissions by adopting sustainable sources of energy to power automobiles [17].

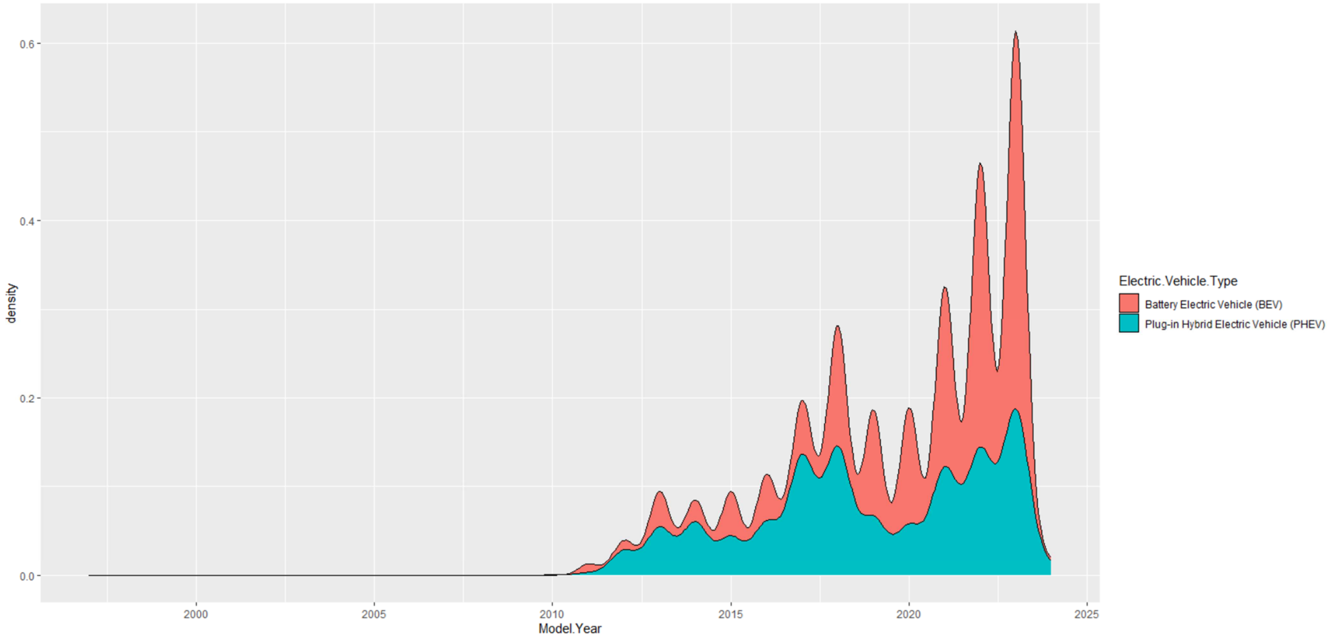


Figure 5. *Density Plot showing model year of electric vehicles produced with respect to electric vehicle type.*

Based on the findings from the density plot shown in figure 5, it is evident that most electric vehicles fall into the category of battery electric vehicles, outnumbering the presence of plug-in hybrid electric vehicles.

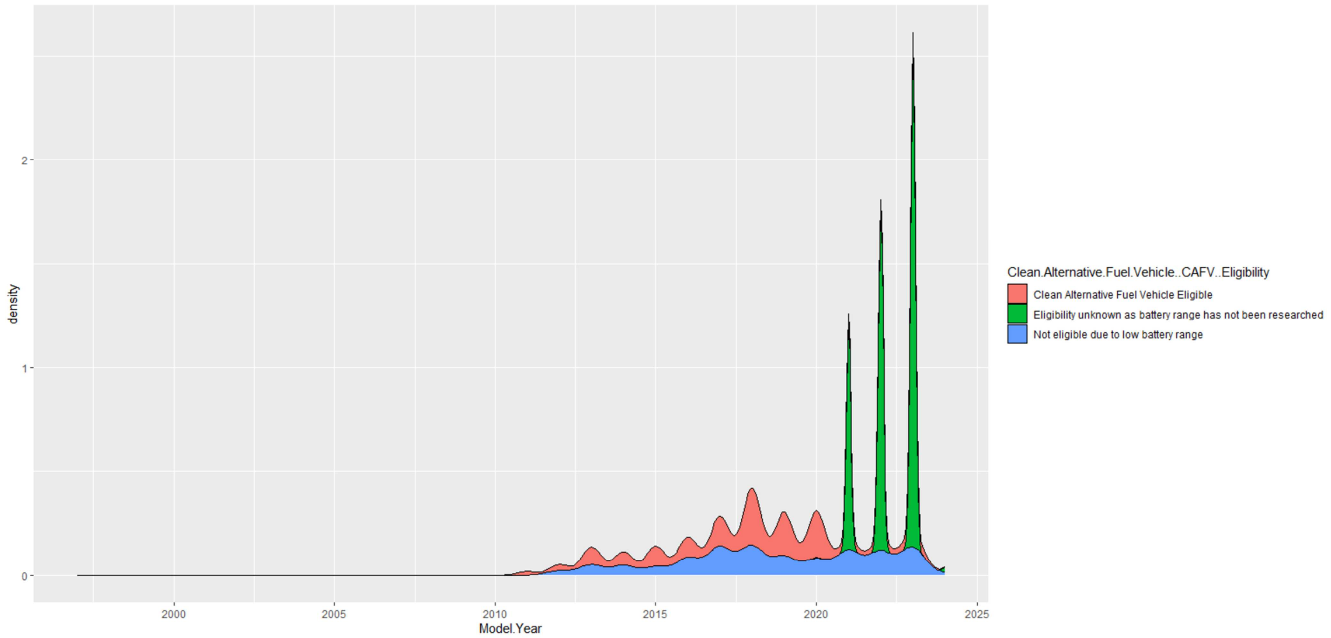


Figure 6. *Density Plot showing model year of electric vehicles produced with respect to clean alternative fuel vehicle eligibility.*

The result shown in figure 6 show that a considerable number of the electric vehicles qualify as clean alternative fuel vehicles. The spikes observed in the category of vehicles falling within the Model Year range of 2022 to 2024 and having unknown eligibility are primarily attributed to recently produced vehicles for which the battery range information has not been thoroughly researched.

2.2.5. Barplots

The barplot chart illustrates the top 20 manufacturers of electric vehicles and showed the evolution of electric vehicles from 2012 to 2023.

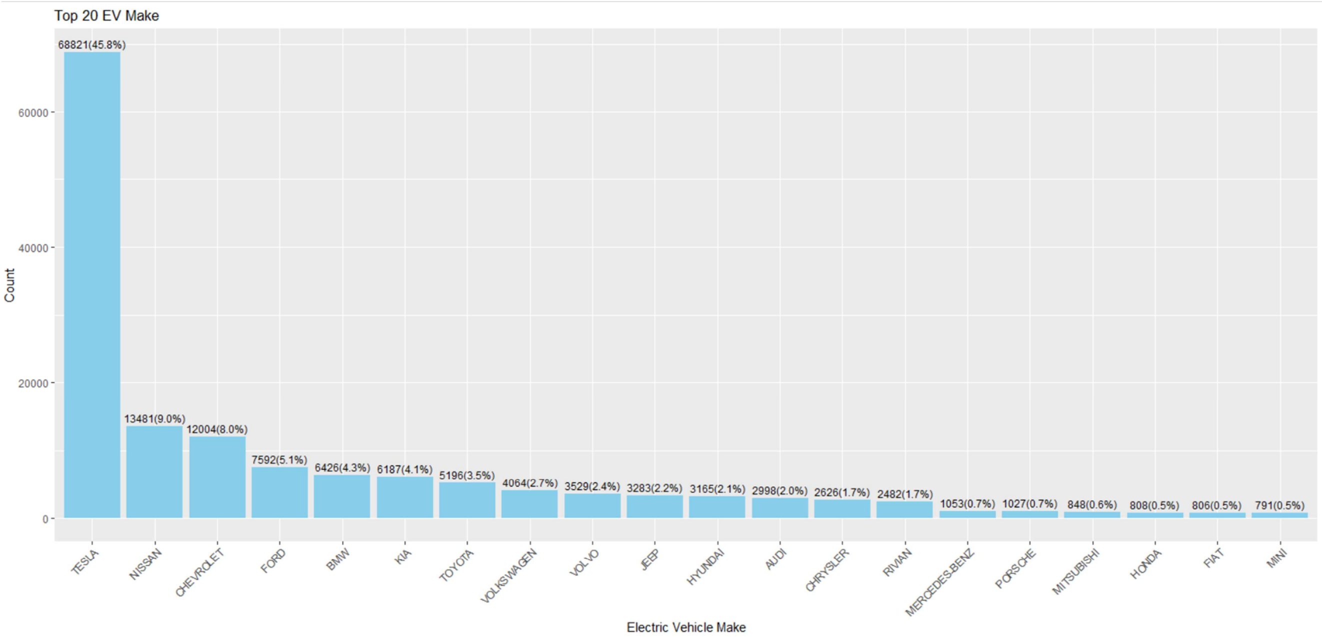


Figure 7. *Top 20 EV manufacturers.*

The result of the barplot show that Tesla is the top producer of electric vehicle with 45.8%, followed by Nissan with 9.0%, closely followed by Chevrolet with 8.0%. In descending order, other manufacturers include Ford, BMW, KIA, Toyota, Volkswagen, Volvo, Jeep, Hyundai, Audi, Chrysler, Rivian, Mercedes Benz, Porsche, Mitsubishi, Honda, Fiat, and Mini. This comprehensive list offers insights into the prominent players in the electric vehicle market, reflecting the varied choices available to consumers and the competitive landscape within the automobile industry.

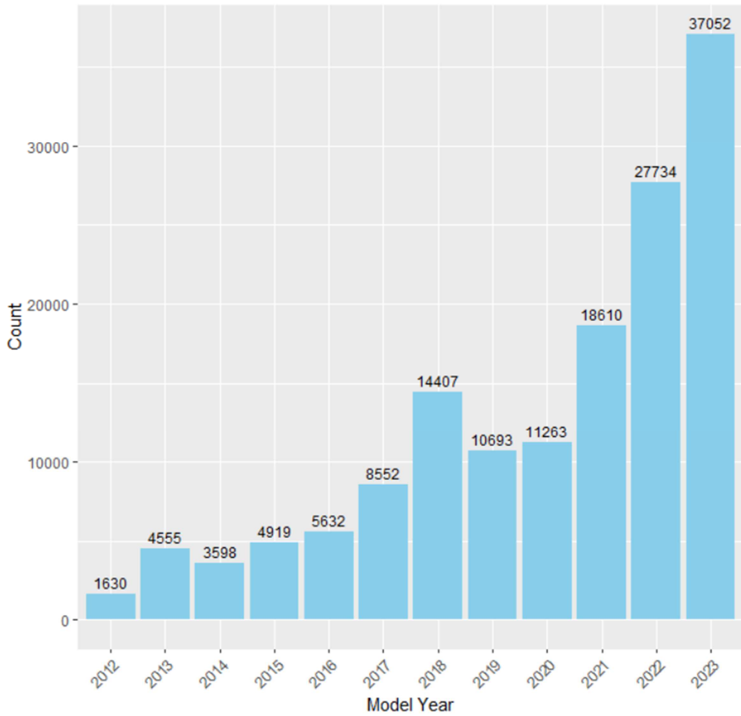


Figure 8. *Chart showing evolution of EV from 2012 to 2023.*

From the barplot shown in figure 8, it shows that there has been an upward trend in the electric vehicle industry. This could be as a result of technological innovations and campaigns for switching from convention source of automobiles to electric vehicles. In the years 2019 and 2020, this growth stagnated a bit before shooting up in the preceding years, this is as a result of the global pandemic COVID-19, where there was total lockdown across the world. Lots of manufacturing and other business were affected.

2.2.6. Box Plots for Pairs of Categorical and Numeric Variables

The boxplot was used to display the distribution of categorical variables, namely electric vehicle type and clean fuel eligibility, with respect to model year. The boxplot serves as a summary, aiding in the identification of the presence of outliers in the dataset.

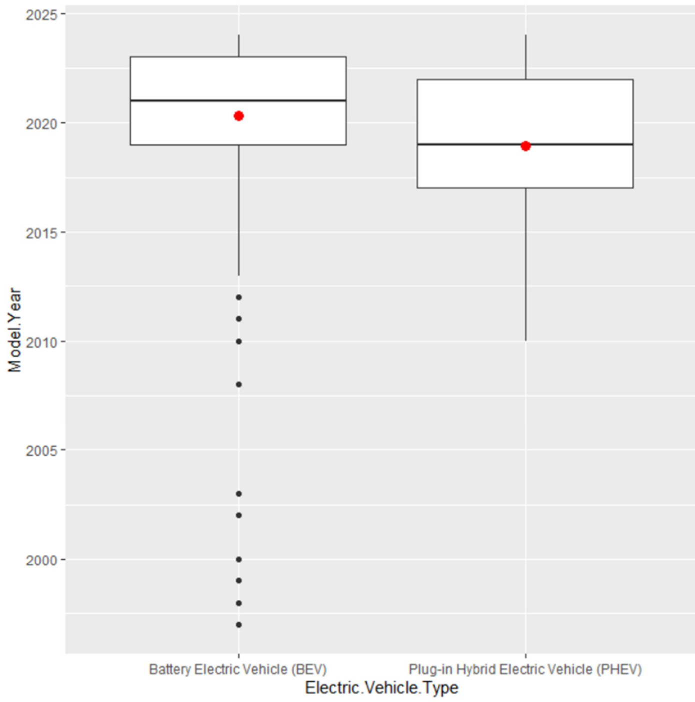


Figure 9. *Box plots for electric vehicle type vs model year.*

For Electric Vehicle Type vs Model Year, the box plot illustrates that 50% of the model years for Battery Electric Vehicles (BEV) fall within the range of 2018 to 2023, whereas for Plug-in Hybrid Electric Vehicles (PHEV), the range is from 2017 to 2022. The median for BEV is positioned halfway across the box, suggesting a concentration of data in the middle, while for PHEV, it is skewed towards lower values. Additionally, the plot indicates that BEV has more outliers compared to PHEV. This discrepancy can be attributed to the longer production history of battery electric vehicles and the relatively lower production numbers during that period.

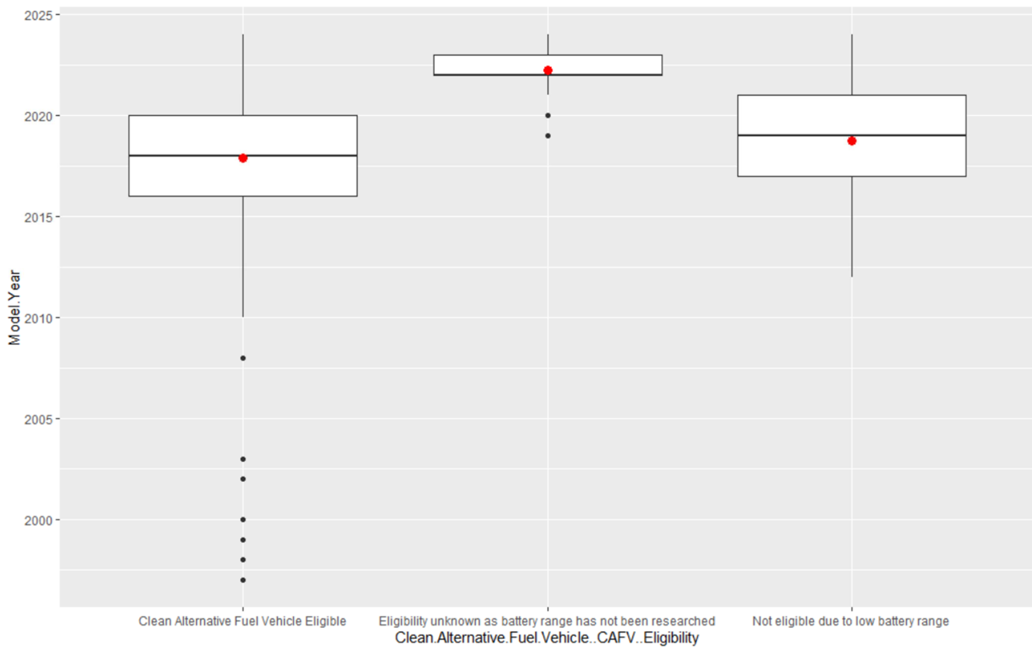


Figure 10. *Box plots for clean alternative fuel vehicle eligibility vs model year.*

The result for the box plot for Clean Fuel Eligibility show that more data were recorded for vehicles with clean fuel eligibility, while vehicles with the most recent year of production and are still under research, hence their eligibility for clean alternative fuel is unknown.

2.2.7. K-means Clustering

K-means clustering was used as an unsupervised machine learning algorithm to partition the dataset into clusters. It classified observations into k groups, based on their similarity. Each group is represented by the mean value of points in the group, known as the cluster centroid. To calculate the number of clusters needed, the elbow method was employed, using with sum squares (wss). From the result of the graph shown in figure 11, we have 3 clusters using the subjective cluster elbow method (i.e points 2, 3, and 4).

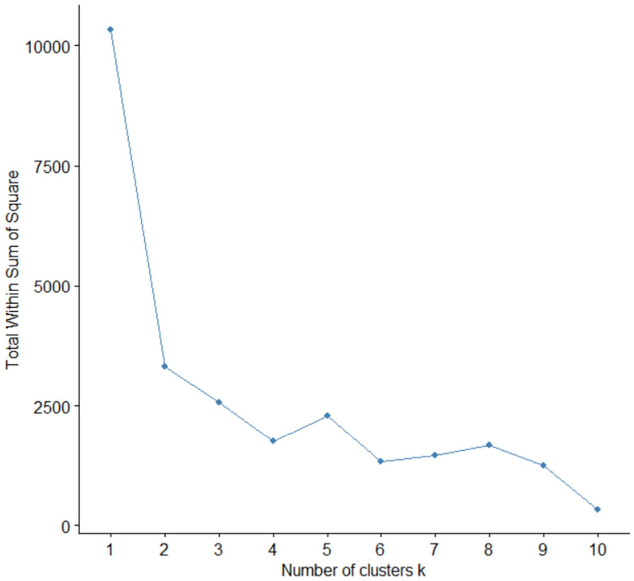


Figure 11. *Using elbow method to show optimal number of clusters.*

The cluster plot shown in Figure 12 provides a sum of square and total sum of squares of 79.1%. A 79% classification of an observation within a group is considered acceptable.

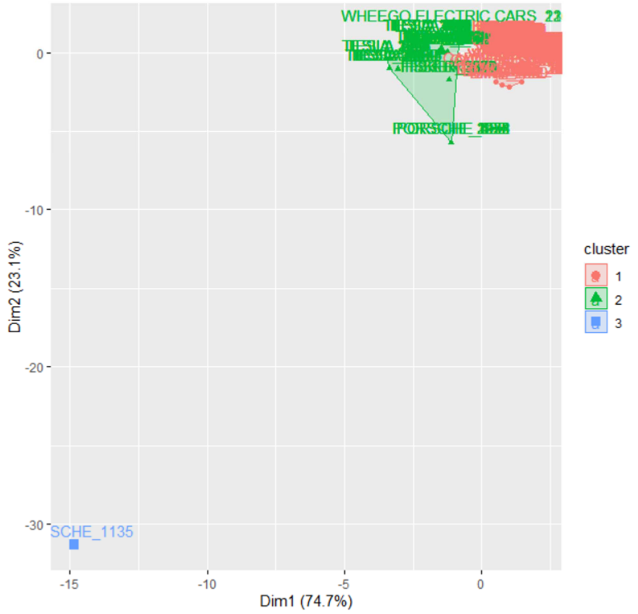


Figure 12. *Cluster plot showing EV electric range and base retail prices.*

The clustering algorithm successfully identified meaningful groups in the data (i.e. model year of vehicles, electric range and retail price). A 79.1% of variance explained indicates that the clusters capture a substantial portion of the overall variability, suggesting that the grouping is meaningful and relevant. The algorithm shows similar data points together while it kept a different group separate. The observation Porsche_1135 is seen as an outlier.

The outlier is a 2015 Porsche 918 Spyder, a luxury brand of automobile. It is understandable that the retail price for Porsche is considerably higher compared to other brands of electric vehicles.

Table 2. *Cross-tabulating clustering result.*

km.evclusters	ALFA ROMEO	AUDI	AZURE DYNAMICS	BENTLEY	BMW	CADILLAC	CHEVROLET	CHRYSLER
1	0	0	0	0	504	15	0	116
2	0	0	0	0	0	0	0	0
3	0	0	0	0	0	0	0	0

km.evclusters	FIAT	FISKER	FORD	GENESIS	HONDA	HYUNDAI	JAGUAR	JEEP
1	0	0	0	0	0	0	0	0
2	0	16	0	0	0	0	0	0
3	0	0	0	0	0	0	0	0

km.evclusters	KIA	LAND ROVER	LEXUS	LINCOLN	LUCID	MAZDA	MERCEDES-BENZ	MINI
1	624	0	0	0	0	0	0	154
2	0	0	0	0	0	0	0	0
3	0	0	0	0	0	0	0	0

km.evclusters	MITSUBISHI	NISSAN	POLESTAR	PORSCHE	RIVIAN	SMART	SUBARU	TESLA
1	0	0	0	19	0	0	63	0

km.evclusters	MITSUBISHI	NISSAN	POLESTAR	PORSCHE	RIVIAN	SMART	SUBARU	TESLA
2	0	0	0	11	0	0	0	1618
3	0	0	0	1	0	0	0	0

km.evclusters	TH!NK	TOYOTA	VOLKSWAGEN	VOLVO	WHEEGO ELECTRIC CARS
1	0	0	0	301	0
2	0	0	0	0	3
3	0	0	0	0	0

Table 2 displays a contingency table, cross-tabulating the clustering results.

In Cluster 1, there are 504 BMWs, 15 Cadillacs, 116 Chryslers, 624 KIAs, 154 Minis, 19 Porsche, 63 Subarus, and 301 Volvos.

In Cluster 2, there are 16 Fiskers, 11 Porsches, 1618 Teslas, and 3 Wheego Electric Cars.

In Cluster 3, there is 1 Porsche.

This table provides a breakdown of the distribution of electric vehicle makes across different clusters offering insights into how the k-means algorithm has grouped the vehicles based on their electric range and base retail prices.

h. Factor Analysis

Factor Analysis as a supervised learning was used to determine if the factors are correlated with each other.

Table 3. *Factor analysis using principal axis: Standardized loadings (pattern matrix) based upon correlation matrix.*

	PA1	PA2	h2	u2	com
Model.Year	-0.78	-0.61	0.98	0.022	1.9
Electric.Range	0.86	0.43	0.92	0.076	1.5
Base.MSRP	0.25	0.45	0.26	0.738	1.6
SS loadings	1.40	0.77			
Proportion Var	0.47	0.26			
Cumulative Var	0.47	0.72			
Proportion Explained	0.65	0.35			
Cumulative Proportion	0.65	1.00			

Table 4. *Factor analysis using maximum likelihood: Standardized loadings (pattern matrix) based upon correlation matrix.*

	ML1	ML2	h2	u2	com
Model.Year	-0.66	-0.74	0.98	0.016	2.0
Electric.Range	0.86	0.49	0.98	0.016	1.6
Base.MSRP	0.23	0.43	0.24	0.764	1.5
SS loadings	1.22	0.98			
Proportion Var	0.41	0.33			
Cumulative Var	0.41	0.73			
Proportion Explained	0.56	0.44			
Cumulative Proportion	0.56	1.00			

The cumulative variance output for the principal axis method is 0.72 as shown in Table 3, while for the maximum likelihood (ML) method, it is 0.73 as shown in Table 4. Because the cumulative variance for maximum likelihood is slightly higher than for the principal axis, the ML method was adopted. The results show that ML1 is positively related to Electric Range and negatively related to Model Year. This factor loading corresponds to the quality and technology of the battery used in the production of electric vehicles concerning the year of production. ML2 is related to electric range and base retail price and negatively related to Model Year. This loading also indicates that the quality of the battery corresponds to the electric range of the electric vehicle and, ultimately, the retail price of these electric vehicles concerning Model Year. The h2 value of 0.98 shows that a significant portion of the variance is being explained both positively and negatively by the two given factors, ML1 and ML2. Meanwhile, u2 indicates the amount of variance not explained by the factor loading. Principal Component Analysis (PCA) was further carried out because the factor loading did not correspond clearly to the expected relationships.

2.2.8. Principal Component Analysis (PCA)

PCA was used to explore patterns in the dataset without specific emphasis on the underlying factors while retaining as much variance. The results obtained in the factor analysis did not clearly show any variables is influenced by an underlying factor. Hence the need for PCA. The PCA gives us the variables and the principal component values, and standard deviations.

Larger standard deviations (Comp.1 = 1.49) suggest that the corresponding principal components explain more variability in the data. This implies that the model year captures a significant amount of variability in the original data compared to the other variables.

Table 5. *Principal Component Analysis for numeric variables.*

	Comp.1	Comp.2	Comp.3
Standard deviation	1.4972927	0.8321101	0.2563347
Proportion of Variance	0.7472951	0.2308024	0.0219025
Cumulative Proportion	0.7472951	0.9780975	1.0000000

Table 5 shows Comp. 1 (model year) explains approximately 74.7% of the variance, Comp. 2 (electric range) explains about 23.1%, and Comp. 3 (Base retail price) explains about 2.2%. This provides insights into the relative importance of each component in explaining the overall variability in the dataset. Comp. 1 is the most important component, explaining a substantial portion (74.7%) of the total variance. Comp. 2 also contributes significantly, explaining an additional 23.1% of the variance. While Comp. 3, having a smaller contribution individually, completes the cumulative variance to 100%.

Table 6. *Eigen vectors and Eigen values for each loadings.*

Eigen Vectors (pc.ev$loadings) Loadings:	Comp.1	Comp.2	Comp.3
Model.Year	0.639	0.273	0.720
Electric.Range	-0.626	-0.359	0.692
Base.MSRP	-0.447	0.893	
SS loadings	1.000	1.000	1.000
Proportion Var	0.333	0.333	0.333
Cumulative Var	0.333	0.667	1.000

Eigen Vectors (pc.ev$loadings) Loadings:	Comp.1	Comp.2	Comp.3
Eigen Values (pc.ev$sdev*pc.ev$sdev)	2.2418853	0.6924072	0.0657075

Table 6 shows Comp.1 has the largest eigenvalue (2.2418853) which is greater than 1, suggests that it explains the most variance in the dataset. Positive contributions from Model.Year and negative contributions from Electric.Range and Base.MSRP suggest a combination of features related to the year of the model, electric range, and retail price. Comp.2 has a smaller eigenvalue (0.6924072) which is less than 1, indicating a lesser amount of variance explained compared to Comp.1. Positive contributions from Model.Year and Base.MSRP and negative contributions from Electric.Range suggest a different combination of features. Comp.3 has the smallest eigenvalue (0.0657075) which is also less than 1, suggesting that it explains the least amount of variance among the three components. Positive contributions from Model.Year, Electric.Range, and possibly Base.MSRP suggest another distinct combination of features.

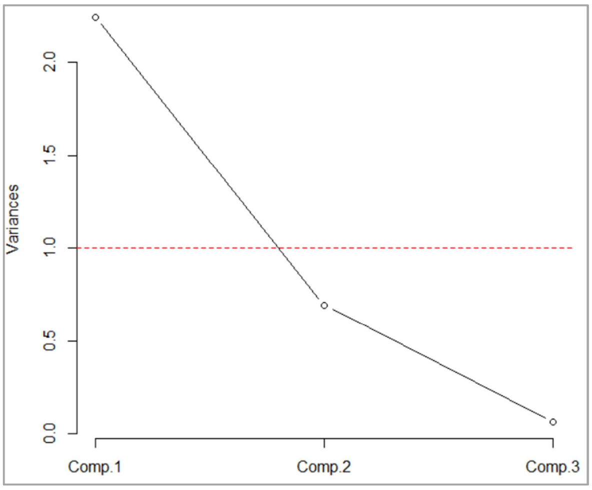


Figure 13. *Screeplot showing Principal Components vs Variances.*

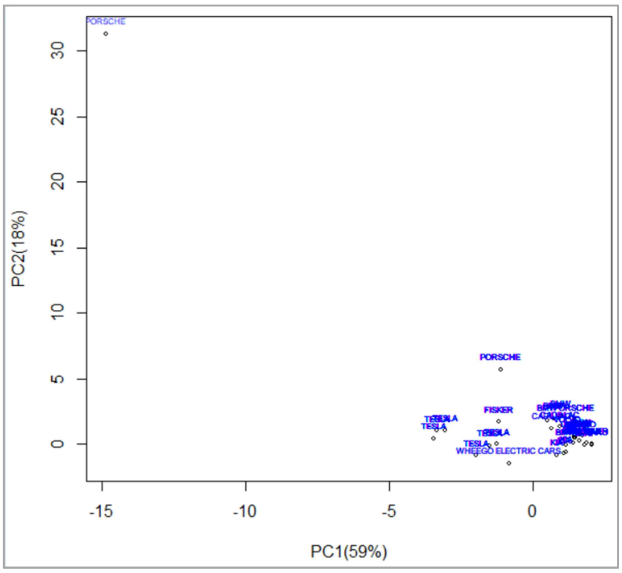


Figure 14. *Scatter plot of Principal Components.*

Figure 14 shows the scatter plot of principal components. The plot obtained is similar to the k-means cluster. The observation "Porsche" is identified as an outlier concerning Model Year, Electric Range, and Retail Price. The outlier is a luxury brand of automobiles. It is understandable that the retail price for Porsche is considerably higher compared to other brands of electric vehicles. Other electric vehicle manufacturers like Tesla and Kia produce electric vehicles with lower retail prices and higher electric ranges compared to Porsche.

3. Conclusion

This study reflects the dynamic landscape in electric vehicle production, with improvements in electric range and a diverse pricing structure across different models, as year of production increases. Anomalies in the data were present, such as a median and mean of 0 for Base.MSRP, which required data cleaning and investigation. The wide range of Base. MSRP values indicates the existence of EVs with diverse pricing strategies, catering to various market segments. K-means clustering algorithm categorized observations into k groups based on their similarities. The clustering algorithm effectively identified meaningful patterns within the data, particularly in relation to the model year of vehicles, electric range, and retail price. With a variance explained of 79.1%, it is evident that the formed clusters capture a substantial portion of the dataset. The algorithm successfully grouped similar data points together while maintaining separation between different groups. Notably, the observation "Porsche_1135" emerged as an outlier, likely due to its status as a luxury and high-priced brand of automobile. This outlier status aligns with expectations, given the distinct characteristics associated with luxury vehicles in terms of both cost and exclusivity. Future research should be conducted using datasets with more observations covering the period from 2020 to 2024, focusing on the prices of electric vehicles and their electric ranges because these considerations are essential for a comprehensive understanding of the electric vehicle market.

ORCID

0000-0002-9744-5895 (Afeez Jimoh)
0009-0000-0603-0807 (Sulaiman Afolabi)
0009-0009-8021-0895 (Teslim Jimoh)

Conflicts of Interest

The authors declare no conflicts of interest.

References

[1] Hug H and Rojas JA (2008) Feedstock pretreatment strategies for producing ethanol from wood, bark, and forest residues. BioResources 3(1): 270–294.

[2] Louisiana Climate Action Plan, 2022, Climate Initiatives Task Force gov.louisiana.gov/page/climate-initiatives-task-force.

[3] Jimoh AO, Namadi MM, Ado K and Muktar B (2016) Proximate and Ultimate Analysis of Eichornia natans (Water Hyacinth), Pistia stratiotes (Water Lettuce) and Nymphaea lotus (Water Lily) in the Production of Biofuel. Adv. Appl. Sci. Res. 7(4): 243-249.

[4] Cheng HG, Srinivasan S, Nielsen CP (2019) Does neighborhood form influence low-carbon transportation in China? Transport Res Transport Environ. 67: 406-420.

[5] Xinyu C, Liu Y, Wang Q, Jiajun L, Wen J, Chen X, Kang C, Cheng S, McElroy MB (2021), Pathway toward carbon-neutral electrical systems in China by mid-century with negative CO_2 abatement costs informed by high-resolution modelling. Joule, 5(10): 2715-2741.

[6] Lin H, Liu Y, Sun Q, Xiong R, Li H, Wennersten R (2018) The impact of electric vehicle penetration and charging patterns on the management of energy hub–A multi-agent system simulation. Appl Energy, 230: 189-206.

[7] Li X, Wang Z, Zhang L, Sun F, Cui D, Hecht C, Figgener J, Sauer DU (2023) Electric vehicle behavior modeling and applications in vehicle-grid integration: an overview. Energy, 268: 126647.

[8] Chan CC (2002), The state of the art of electric and hybrid vehicles. Proc. IEEE, 90(2): pp. 247-275.

[9] Du J and Ouyang D (2017), Progress of Chinese electric vehicles industrialization in 2015: a review Appl. Energy, 188: pp. 529-546.

[10] Majumder P (2021) Data analysis and price prediction of electric vehicles. https://www.analyticsvidhya.com/blog/2021/09/data-analysis-andprice-prediction-of-electric-vehicles/.

[11] Sierzchula W and Nemet G (2015) Using patents and prototypes for preliminary evaluation of technology-forcing policies: lessons from California's Zero Emission Vehicle regulations. Technol. Forecast. Soc. Change, 100: pp. 213-224.

[12] Wen W, Yang S, Zhou P, Gao SZ (2021) Impacts of COVID-19 on the Electric Vehicle Industry: Evidence from China. Renewable and Sustainable Energy Reviews, p. 111024.

[13] Lin H, Bian C, Wang Y, Li H, Sun Q, Wallin F (2022), Optimal planning of intra-city public charging stations. Energy, 238: 121948.

[14] Yang Z, Ziyue J, Xinyu C, Peng L, Tianduo P, Zhan S. (2023), Toward environmental sustainability: data-driven analysis of energy use patterns and load profiles for urban electric vehicle fleets. Energy: 285, 129465.

[15] Data Catalog, “Electric Vehicle Population Data” Available from https://catalog.data.gov/dataset/electric-vehicle-population-data. [Accessed 4 January 2024].

[16] Versus, “Porsche 918 Spyder (2015) vs Tesla Roadster” Available from https://versus.com/en/porsche-918-spyder-2015-vs-tesla-roadster. [Accessed 4 January 2024].

[17] Jimoh AO, Ijege KO, Babagana M, Amusan VO (2017) Investigation of Eichornia Natans, Pistia Stratiotes and Nymphaea Lotus in Relation to Their Calorific Values and Elemental Composition for Efficient Biofuel Utilization. International Journal of Environmental Chemistry. 2(5): 69-72.