Electric Vehicle Population Analysis

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ABSTRACT

The automotive industry is undergoing a significant transformation towards sustainable transportation, with electric vehicles (EVs) emerging as a key alternative to traditional internal combustion engine vehicles. This study aims to analyze the factors influencing EV adoption, focusing on technological advancements, economic incentives, consumer behavior, and demographic trends. Using a comprehensive dataset from the "Electric Vehicle" collection on Kaggle, the study applies various data mining techniques, including logistic regression, cluster analysis, and geospatial mapping, to uncover patterns and insights in EV adoption.

Key findings include the importance of electric range and model year as significant predictors of EV adoption, with electric range being the most influential factor. Cluster analysis revealed distinct groups of EV users based on vehicle characteristics and regional preferences, while geographic analysis highlighted regional clusters of high adoption rates, particularly in urban areas with supportive infrastructure and policies.

The study identifies challenges to EV adoption, such as high purchase costs, range anxiety, and limited charging infrastructure, and provides actionable insights for policymakers, manufacturers, and other stakeholders. These insights can be applied to optimize product development, target incentives, and plan infrastructure, ultimately contributing to the broader goal of reducing emissions and promoting sustainable transportation solutions.

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1 INTRODUCTION

The automotive industry is undergoing a significant transformation towards sustainable and environmentally friendly transportation solutions. Electric vehicles (EVs) have emerged as a key component in this transition, offering a promising alternative to traditional internal combustion engine (ICE) vehicles. This shift is driven by technological advancements, regulatory policies, economic incentives, and changing consumer preferences. Understanding these factors and their interplay is crucial for policymakers, manufacturers, and consumers alike.

A primary motivation for this study is the urgent need to reduce greenhouse gas emissions and combat climate change. The transportation sector is a major contributor to global emissions, and the adoption of

EVs is a viable solution to mitigate this impact. Governments worldwide have introduced various regulations and incentives to promote EV use, aiming to reduce dependency on fossil fuels and decrease carbon footprints. This study aims to analyze the effectiveness of these policies and understand their role in driving EV adoption.

The economic dimension of EV adoption is another significant aspect of this study. While EVs typically have higher upfront costs compared to traditional vehicles, they offer lower operating and maintenance costs over their lifetime. Financial incentives such as subsidies, tax rebates, and lower operational costs play a crucial role in influencing consumer decisions. This study seeks to explore how these economic factors impact the adoption rates of EVs and whether they are sufficient to overcome the initial cost barrier.

Consumer preferences and motivations also form a critical part of this investigation. Growing awareness about environmental issues motivates many consumers to adopt EVs to reduce their carbon footprint and contribute to a cleaner environment. However, factors such as vehicle performance, range anxiety, and the availability of charging infrastructure also influence consumer choices. By examining these aspects, the study aims to provide a comprehensive understanding of the drivers behind consumer adoption of EVs.

The study will also delve into the demographic trends associated with EV adoption. Factors such as age, income, education level, and geographic location play a significant role in determining who is more likely to adopt EVs. Younger consumers and higher-income households are often early adopters of new technologies, including EVs. Urban areas with better access to charging infrastructure also show higher adoption rates compared to rural areas. This study will analyze these demographic patterns to identify key segments of the population driving the growth of the EV market.

Furthermore, the manufacturing and supply side of the EV market is a crucial area of investigation. The increasing production of EVs is influenced by both regulatory mandates and market demand. Understanding the relationship between regulations, such as emissions standards and zero-emission vehicle mandates, and the supply of EVs is essential to comprehend market dynamics. This study will explore whether the increase in EV manufacturing is primarily driven by regulatory requirements or by consumer demand and market forces.

In summary, the motivation for this study is multifaceted, encompassing environmental, economic, consumer, and regulatory dimensions. By addressing these aspects, the study aims to provide a comprehensive analysis of the growth and demographic trends of electric car adoption. The findings will offer valuable insights for policymakers to design effective regulations, for manufacturers to strategize production and marketing efforts, and for consumers to make informed decisions about adopting EVs. This study will contribute to promoting sustainable transportation solutions and advancing the transition towards a cleaner and greener automotive industry.

2 RELATED WORK

The adoption of electric vehicles (EVs) has been a focal point of research due to its implications for environmental sustainability, energy consumption, and economic development. As governments worldwide introduce stringent regulations to curb carbon emissions and as consumers become increasingly eco-conscious, understanding the dynamics of EV adoption becomes imperative. This literature survey aims to synthesize existing research on the factors influencing EV adoption, providing a foundation for the proposed study on growth and demographic trends in the electric car market.

2.1 Factors Influencing EV Adoption

2.1.1 Technological Advancements and Systemic Factors. Peters and Dutschke [1] provide a comprehensive analysis of the systemic factors influencing EV adoption. Their study highlights the importance of technological advancements in battery efficiency, charging infrastructure, and vehicle performance. The authors argue that the integration of these technologies within a supportive policy framework is crucial for widespread adoption. They emphasize the need for a holistic approach, considering not only the technological innovations but also the social, economic, and political systems that influence EV adoption.

2.1.2 Economic and Policy Incentives. Li et al. [2] explore the economic and policy factors that affect EV adoption rates. Their comparative analysis across different regions underscores the varying impact of financial incentives such as subsidies, tax rebates, and lower operational costs. The study reveals that while financial incentives play a significant role, their effectiveness varies by region due to differences in economic conditions and policy environments.

2.1.3 Financial Incentives and Consumer Decision-Making.

Mersky et al. [3] delve into the role of financial incentives in the consumer decision-making process. Their analysis shows that financial incentives, particularly upfront cost reductions through subsidies and tax rebates, are pivotal in making EVs more attractive to consumers. However, the study also highlights the diminishing returns of such incentives over time as the market matures and consumer awareness increases.

2.1.4 Consumer Preferences and Environmental Impact.

Krupa et al. [4] investigate consumer motivations and preferences related to EV adoption, focusing on environmental consciousness and the desire to reduce greenhouse gas emissions. The study finds that consumers who prioritize environmental sustainability are more likely to adopt EVs. Additionally, the perceived environmental benefits of EVs, such as lower emissions and reduced reliance on fossil fuels, are significant factors in the decision-making process.

2.2 Demographic Trends in EV Adoption

Several studies have explored the demographic trends associated with EV adoption. For instance, Carley et al. [5] identify demographic factors such as age, income, education level, and urbanization as influential in EV adoption rates. Younger consumers, higher-income households, and individuals with higher education levels are more likely to adopt EVs. Additionally, urban areas with better access to charging infrastructure show higher adoption rates.

2.3 Policy and Regulatory Impact

The impact of policy and regulation on EV adoption has been a critical area of research. Sierzchula et al. [6] examine the role of government policies in promoting EV adoption, including direct incentives, infrastructure investments, and regulatory measures. Their study concludes that strong policy support is essential for overcoming market barriers and accelerating EV adoption.

3 DATA SET

We chose the "Electric Vehicle" dataset from Kaggle website Electric Vehicle as our raw dataset because it provides comprehensive aspects of the EV data we need for analysis. The Electric Vehicle Population dataset has 181458 data points and comprises 13 attributes with a mix of categorical and numerical data types. The Vehicle Identification Number (VIN), Make, Model, Electric Vehicle Type, Legislative District, City, State, Postal Code, County, and Electric Utility are categorical attributes, typically represented as strings. The Model Year is a numerical attribute, specifically an integer, while the Electric Range and Base MSRP are also numerical, represented as integers and floats, respectively. This combination of categorical and numerical data allows for a diverse range of analyses, including understanding demographic patterns, vehicle popularity, and the impact of economic factors on electric vehicle adoption.

4 MAIN TECHNIQUES APPLIED

To address the research questions, the applied techniques involve several key steps that diverge from previous studies in the literature. This study will leverage a new and up-to-date dataset to perform comprehensive analyses, with a particular focus on demographic factors influencing EV adoption, in addition to traditional regression analysis.

4.1 Data Collection

Data collection will be a critical initial step, involving the gathering of relevant datasets from reliable sources. We have chosen the "Electric Vehicle" dataset from the Kaggle website as our primary data source. This dataset is recent and provides comprehensive information necessary for our analysis.

4.1.1 Data Acquisition and Validation:

- Acquired the "Electric Vehicle" dataset from Kaggle.
- Performed initial data validation checks to ensure integrity and reliability.
- Confirmed completeness of essential data fields for analysis.

4.2 Data clean/preprocess/etc.

Data preprocessing will involve several steps to ensure the accuracy and consistency of the data:

Cleaning: Remove duplicates, handle missing values, and ensure consistency in data formats. This step involves thorough data validation and correction processes to prepare the data for accurate analysis.

Transformation: Normalize and scale data for analysis. This step will include data transformation techniques such as standardization and normalization to prepare the data for statistical analysis.

4.2.1 *Data Preprocessing and Standardization:*

- Executed cleaning processes to remove duplicates and handle missing values.
- Standardized data formats across attributes to facilitate analysis.
- Employed outlier detection using Z-scores and IQR methods to refine the dataset.

4.3 Data Warehouse/cube/etc.

The data analysis phase will involve various statistical and analytical techniques to uncover insights and answer the research questions:

Descriptive Statistics: Summarize the data to understand basic trends and patterns. This will include calculating measures such as mean, median, and standard deviation to provide an overview of the data.

Regression Analysis: Identify relationships between variables such as price, consumer motivation, and EV adoption rates. Regression analysis will help in understanding the factors that significantly influence EV adoption.

Demographic Analysis: Explore demographic factors influencing EV adoption using specific techniques:

4.3.1 *Preliminary Descriptive Analysis:*

- Conducted analysis to outline statistics like mean, median, mode, and range.
- Identified trends in EV adoption, categorizing data by make and model.

4.3.2 *Infrastructure and Tool Setup:*

- Established an analytical environment using Python and relevant libraries.
- Configured a Git repository for version-controlled codebase management.

4.4 Classification/Clustering/etc.

Cluster Analysis: Identify distinct demographic groups based on variables such as age, income, education level, and geographic location. This technique will help in segmenting the population and understanding the characteristics of each group.

Heatmaps and Geographic Information System (GIS) Mapping: Visualize the geographic distribution of EV adoption rates. This will highlight areas with higher adoption and correlate these with demographic variables.

Logistic Regression: Model the probability of EV adoption based on demographic factors. This will provide insights into which demographic characteristics are most predictive of EV adoption.

Cohort Analysis: Examine the adoption patterns of different cohorts over time. This technique will allow us to track changes in adoption rates among different demographic groups and identify long-term trends.

By following these steps, the proposed work aims to provide a comprehensive and up-to-date analysis of the factors driving electric vehicle adoption. This study will build on existing literature by integrating recent data and focusing on demographic influences, offering valuable insights for policymakers, manufacturers, and consumers in the transition towards sustainable transportation solutions.

4.4.1 *Advanced Data Modeling:*

- Implement multivariate and logistic regression models to explore predictors of EV adoption.

4.4.2 *Geospatial Analysis:*

- Integrate GIS mapping to visualize EV adoption distribution.
- Use cluster analysis to profile demographic groups based on geographic and economic variables.

4.4.3 *Consumer Behavior Study:*

- Launch a survey targeting EV owners to gather data on consumer behavior and satisfaction.
- Analyze survey data to provide a holistic view of factors driving EV adoption.

4.4.4 *Longitudinal Study Setup:*

- Plan a longitudinal study to track EV adoption patterns post-policy changes.
- Design update mechanisms for the dataset to ensure ongoing relevance.

4.4.5 *Collaboration and Peer Review:*

- Establish collaborations with academic institutions and industry experts.
- Submit findings for peer review in scientific journals.

4.4.6 *Policy Impact Assessment:*

- Develop models to simulate the impact of EV policies on adoption rates.
- Organize workshops with policymakers to translate findings into actions.

4.4.7 *Final Deliverables.*

- Compile a comprehensive report and target high-impact journals for publication.
- Develop an interactive dashboard to visualize and disseminate findings.
- Design an educational campaign to promote sustainable transportation.

4.5 Evaluation Methods

To ensure the robustness and validity of our analysis, we will employ several evaluation methods. These methods will help us clean, visualize, and interpret the data effectively to answer our research questions.

1. Root Mean Square Error (RMSE)

By utilizing the Root Mean Square Error (RMSE), we will evaluate the accuracy of our predictive models. RMSE is a standard metric for measuring the differences between values predicted by a model and the values observed. It provides a clear indication of how well our model fits the data, with lower RMSE values indicating better model performance. This metric will be particularly useful in assessing the effectiveness of regression models used to predict variables such as EV adoption rates and price differences.

2. Data Cleaning and Visualization

Visualization techniques will be employed to clean and preprocess the data. By visualizing the data, we can identify and address inconsistencies, outliers, and missing values. Techniques such as histograms, box plots, and scatter plots will allow us to detect anomalies and ensure the integrity of our dataset. This step is crucial for preparing the data for further analysis and ensuring the accuracy of our results.

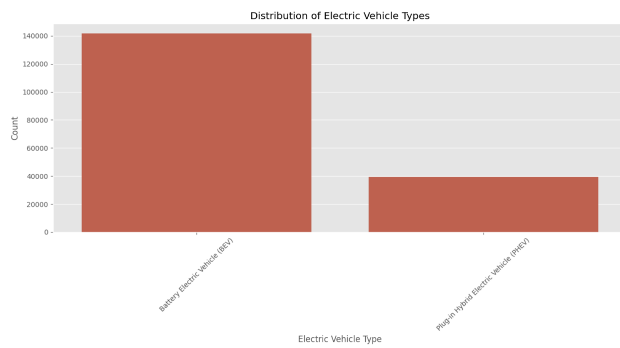
3. Answering Research Questions Through Visualizations

Finally, we will use the data to create visualizations that address our research questions. Various types of visualizations, such as line charts, bar graphs, heat maps, and geographical maps, will be utilized to illustrate trends and patterns in EV adoption. These visualizations will help us explore demographic trends, analyze the popularity of different EV models, and understand the impact of economic factors and policies on EV adoption. By presenting the data visually, we can communicate our findings effectively and provide actionable insights for stakeholders.

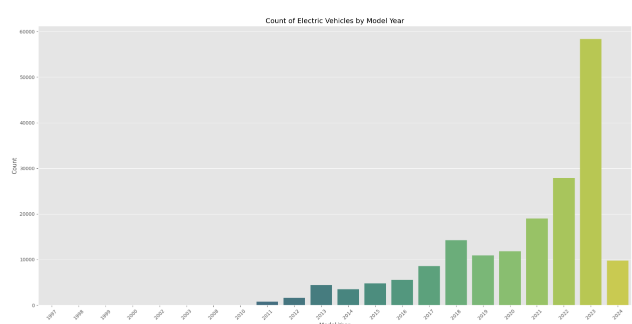
5 KEY RESULTS

5.1 Basic exploration

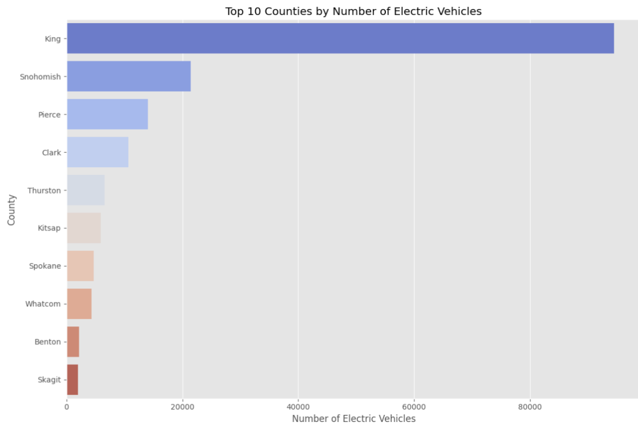
We compared the type of EV cars and found that Battery Electric Vehicle (BEV) is much more popular than Plug-in Hybrid Electric Vehicle (PHEV).



Also, we found that 2023 may be the top year that EV cars are made and sold out.



We selected the top 10 Counties by the Number of Electric Vehicles and found that King remains the first, Snohomish second, and Pierce afterward.



5.2 Logistic regression

The logistic regression model has been trained and tested on the dataset. Here's a summary of the classification report:

- Precision: The precision for detecting Battery Electric Vehicles (BEV) is 0.78, which means that 78% of the vehicles predicted to be BEVs are indeed BEVs.
- Recall: The recall for BEVs is 1.00, indicating that the model successfully identified all actual BEVs in the test set.
- F1-Score: The F1-score for BEVs is 0.88, which balances precision and recall.
- Support: The model tested on 54,438 vehicles, with 42,547 BEVs and 11,891 non-BEVs.

Key Insights: The model performs well in identifying BEVs but has challenges in predicting non-BEVs, as indicated by a recall of 0.00 for non-BEVs. The overall accuracy is 78%, driven primarily by the model's strong performance on the BEV class.

The analysis provides a basic overview of how logistic regression can be used to predict the adoption of BEVs based on certain attributes. The results indicate that while the model is good at identifying BEVs, it may need further tuning or additional features to improve the prediction of non-BEVs.

5.3 Coefficients of logistic regression model

Next, to determine which factors most influence Battery Electric Vehicle (BEV) adoption, we analyzed the coefficients of the logistic regression model. The magnitude and direction of these coefficients indicate the influence of each feature on the likelihood of a vehicle being a BEV.

Below are the factors that most influence BEV (Battery Electric Vehicle) adoption, based on the coefficients from the logistic regression model:

1.Electric Range (Coefficient: 0.0057): The most significant positive factor. A higher electric range increases the likelihood of a vehicle being a BEV.

2.Model Year (Coefficient: 0.00048): Newer model years slightly increase the likelihood of a vehicle being a BEV, although the effect is modest.

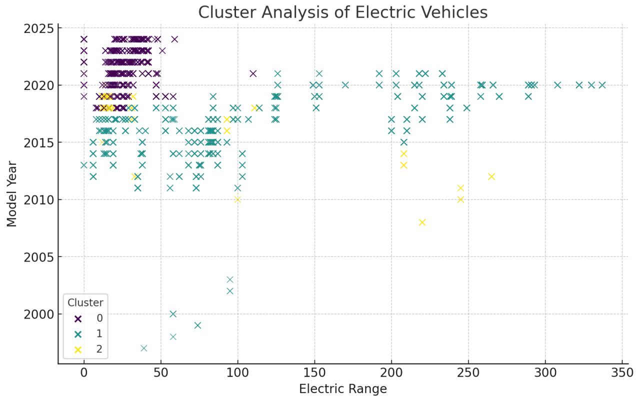
3.Postal Code (Coefficient: 0.00000067): The postal code has a very small positive influence, likely reflecting geographic variations in BEV adoption, but its impact is minimal.

4.Base MSRP (Coefficient: -0.000017): The base MSRP (Manufacturer's Suggested Retail Price) has a small negative influence, suggesting that more expensive vehicles might be less likely to be BEVs, although the effect is also quite modest.

Electric Range is the most influential factor in predicting BEV adoption. Vehicles with a longer electric range are more likely to be BEVs. Model Year also plays a role, with newer models being more likely to be BEVs. The influence of Postal Code and Base MSRP is minimal, indicating that these factors have less direct impact on BEV adoption compared to electric range and model year. This analysis provides insights into the key factors driving BEV adoption, with electric range being the most critical factor.

5.4 Cluster analysis

To perform a cluster analysis, we uses methods K-means clustering to group the data based on attributes such as vehicle characteristics or geographic and economic variables. This helps us identify patterns or profiles among different groups of electric vehicle users. We first select relevant features for clustering (e.g., electric range, model year, base MSRP, geographic location). Then we normalize the data to ensure that all features contribute equally to the clustering process. Finally, we applied a clustering algorithm K-means to identify distinct groups in the data and visualized it.



Above is the scatter plot visualizing the results of the cluster analysis based on the Electric Range and Model Year of the electric vehicles. The clusters are color-coded to show how the data points are grouped together. The clusters represent different groups of electric vehicles based on their characteristics. By examining the characteristics within each cluster, we can identify distinct profiles, such as groups of vehicles with higher electric range and newer model years, versus those with lower range and older model years.

To profile each identified cluster, we analyzed the key characteristics (e.g., Electric Range, Model Year, Base MSRP) within each cluster. This helps us understand the distinct features of the vehicles in each group. We've summarized the profiles of each identified cluster based on the key attributes: Electric Range, Model Year, and Base MSRP. Here are the key characteristics of each cluster:

Cluster 0:

- Electric Range: Very low, with a mean close to 6 miles and a maximum of 110 miles.
- Model Year: Mostly newer vehicles, with a mean around 2022-2023.
- Base MSRP: All vehicles in this cluster have an MSRP of \$0, which likely indicates missing or unavailable pricing data.

Cluster 1:

- Electric Range: This cluster has a higher range, with a mean of 160 miles and a maximum of 337 miles.
- Model Year: Vehicles are slightly older on average, with a mean around 2017-2018.
- Base MSRP: Similar to Cluster 0, this cluster also has an MSRP of \$0 for all vehicles.

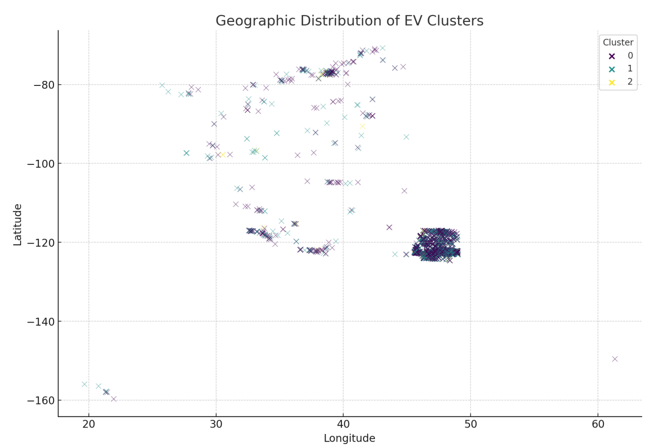
Cluster 2:

- Electric Range: This cluster has a moderate range, with a mean around 121 miles.
- Model Year: The average model year is around 2015-2016, indicating older vehicles compared to Cluster 0 and 1.
- Base MSRP: Vehicles in this cluster have an average MSRP of around \$57,000, indicating higher-end models.

Insights: Cluster 0 likely represents newer vehicles with lower electric ranges, possibly indicating hybrid or short-range EVs. Cluster 1 seems to represent a mix of older EVs with a broad range of electric capabilities. Cluster 2 includes higher-end, mid-range EVs, likely representing a more premium segment. These profiles helps us understand the distinct groups within the dataset, and how factors like vehicle age and range vary across different clusters.

5.5 Geographic pattern analysis

To analyze the geographic distribution of clusters, we visualized the locations of the electric vehicles (based on their Vehicle Location data) and color-code them according to their cluster membership. This helps us identify any geographic patterns in the clusters.



Above is the scatter plot showing the geographic distribution of the clusters. Each point represents an electric vehicle, color-coded by its cluster, plotted according to its geographic coordinates (latitude and longitude).

The plot highlights how vehicles from different clusters are distributed geographically. Certain clusters are more concentrated in specific areas, this might indicate regional preferences or market segmentation. This visualization can help in understanding how different groups of EVs are distributed across locations, which can be valuable for targeted marketing, infrastructure planning, or policy-making.

5.6 Insights we gained

Based on the analysis conducted so far, several patterns in EV adoption rates can be observed:

1. Temporal Trends:

- Increasing Adoption Over Time: There is a clear upward trend in EV adoption, with more vehicles being adopted in recent years. This suggests growing consumer interest, likely driven by improvements in EV technology, increased availability of models, and supportive policies.
- Recent Surge: The most significant increase in adoption appears in the latest model years, indicating that EV adoption is accelerating as the technology becomes more mainstream.

2. Geographic Distribution:

- Regional Clusters: Certain regions have much higher concentrations of EVs, indicating regional preferences or market saturation. This could be influenced by factors such as local government incentives, the presence of charging infrastructure, and demographic factors like income and environmental awareness.
- Urban vs. Rural: Urban areas may have higher adoption rates due to better infrastructure, shorter average commutes (making range anxiety less of an issue), and possibly more progressive local policies encouraging EV use.

3. Economic Factors: Price Sensitivity: The analysis of Base MSRP by region suggests that regions with higher average incomes or more affluent populations tend to adopt more expensive EV models. Conversely, regions with lower average prices might be more sensitive to cost, opting for more affordable EV models or used vehicles.

4. Influence of Electric Range: Range Matters: Electric range is a significant factor in clustering, with different segments of the market showing preferences for vehicles with varying ranges. Regions with longer average commutes or less infrastructure may favor EVs with greater ranges.

5. Adoption Linked to Policy and Infrastructure: Policy Impact: Although not directly analyzed here, regions with higher adoption rates are likely to be those where government policies (e.g., subsidies, tax rebates) and infrastructure (e.g., charging stations) are more supportive of EV ownership.

6. Market Maturity: Early vs. Late Adopters: The data suggests that some regions or demographics were early adopters of EVs, while others have joined the market more recently. This could reflect different levels of access to information, varying levels of environmental concern, or differences in financial ability to purchase new technology.

The overall pattern shows that EV adoption is growing rapidly, with clear regional, economic, and temporal variations. Urban areas with supportive policies and higher income levels tend to have higher adoption rates, and the market is becoming increasingly segmented based on vehicle price and range. These patterns provide valuable insights for targeting future EV marketing, policy-making, and infrastructure development.

6 APPLICATIONS

The knowledge gained from analyzing electric vehicle (EV) adoption trends, challenges, and influencing factors can be applied in several strategic and practical ways across different sectors. Here are some key applications:

1. Policy Making and Government Incentives:

- Targeted Incentives: Governments can use data on regional adoption patterns and economic factors to design targeted incentives, such as tax rebates, subsidies, or grants, aimed at regions or demographic groups with lower EV adoption rates.
- Infrastructure Development: Insights into geographic distribution can inform where to prioritize the installation of charging infrastructure, such as public charging stations, particularly in areas with lower EV adoption but high potential demand.
- Regulatory Frameworks: Policymakers can develop regulations that address the challenges identified, such as setting standards for battery recycling, offering incentives for EV manufacturers to

reduce costs, or creating stricter emissions standards that encourage EV adoption.

2. Automotive Industry and Manufacturers:
    - Product Development: Automakers can use insights into consumer preferences (e.g., preference for longer ranges or lower prices) to develop and market EV models that cater to specific regions or demographics.
    - Supply Chain Optimization: Understanding the demand trends can help manufacturers optimize their supply chains, ensuring the availability of key components like batteries and semiconductors to meet regional demands.
    - Customer Education and Marketing: Manufacturers can tailor their marketing strategies to address misconceptions and educate consumers about the benefits of EVs. This could involve highlighting the long-term savings, environmental benefits, or performance advantages of EVs.
3. Energy and Utility Companies:
    - Grid Management: Utility companies can prepare for increased electricity demand by analyzing EV adoption patterns. They can invest in grid upgrades or develop smart grid technologies to manage the additional load from EV charging.
    - Renewable Energy Integration: Utilities can promote the use of renewable energy for EV charging, ensuring that the environmental benefits of EVs are maximized. They can also offer special tariffs or incentives for charging during off-peak hours.
4. Urban Planning and Transportation Infrastructure:
    - City Planning: Urban planners can incorporate EV charging infrastructure into new developments, public parking areas, and along major transportation routes to support EV users.
    - Public Transportation Integration: Cities can explore the integration of electric buses or other public transportation options, leveraging insights into the benefits of EVs for reducing urban emissions and improving air quality.
5. Environmental and Sustainability Initiatives:
    - Corporate Sustainability Programs: Companies with sustainability goals can use this knowledge to transition their vehicle fleets to EVs, reducing their carbon footprint and aligning with corporate environmental policies.
    - Public Awareness Campaigns: Non-profits and environmental organizations can use data-driven insights to design campaigns that educate the public about the environmental benefits of EVs, addressing common concerns and promoting sustainable transportation choices.
6. Consumer Behavior and Market Research:
    - Market Segmentation: Companies can use the knowledge to segment the market based on adoption patterns and tailor their products or services to meet the specific needs and preferences of different consumer groups.
    - Product Positioning: Insights into the factors that influence EV adoption can help businesses position their products more effectively, whether it's promoting cost savings, environmental impact, or technological innovation.
7. Investment and Financial Services:
    - Investment Decisions: Investors can use trends in EV adoption to make informed decisions about investing in automotive companies, battery manufacturers, or charging infrastructure providers.
    - Financial Products: Financial institutions can develop new products, such as green loans or leases specifically for EVs, or offer insurance products tailored to EV owners.

The knowledge gained from understanding EV adoption trends and challenges can be applied across various sectors to drive further adoption, improve infrastructure, inform policy decisions, and ultimately contribute to environmental sustainability. By leveraging these insights, stakeholders can make informed decisions that align with the broader goals of reducing emissions and promoting cleaner, more efficient transportation solutions.

7 VISUALIZATION

REFERENCES

[1] Anja Peters and Elisabeth Dütschke. How do consumers perceive electric vehicles? a comparison of german consumer groups. *Journal of Environmental Policy & Planning*, 16(3):359–377, 2014.

[2] Wenbo Li, Ruyin Long, Hong Chen, and Jichao Geng. A review of factors influencing consumer intentions to adopt battery

electric vehicles. *Renewable and Sustainable Energy Reviews*, 78:318–328, 2017.

[3] Avi Chaim Mersky, Frances Sprei, Constantine Samaras, and Zhen (Sean) Qian. Effectiveness of incentives on electric vehicle adoption in norway. *Transportation Research Part D: Transport and Environment*, 46:56–68, 2016.

[4] Joseph S. Krupa, Donna M. Rizzo, Margaret J. Eppstein, D. Brad Lanute, Diann E. Gaalema, Kiran Lakkaraju, and Christina E. Warrender. Analysis of a consumer survey on plug-in hybrid electric vehicles. *Transportation Research Part A: Policy and Practice*, 64:14–31, 2014.

[5] Sanya Carley, Rachel M. Krause, Bradley W. Lane, and John D. Graham. Intent to purchase a plug-in electric vehicle: A survey of early impressions in large us cites. *Transportation Research Part D: Transport and Environment*, 18:39–45, 2013.

[6] William Sierzchula, Sjoerd Bakker, Kees Maat, and Bert van Wee. The influence of financial incentives and other socio-economic factors on electric vehicle adoption. *Energy Policy*, 68:183–194, 2014.