# Policy-Driven Market Transformation: Predictive and Diagnostic Analysis of Electric Vehicle Uptake, Pricing, and Infrastructure Needs in the UK Toward 2035

Name : Anwesha Dhar

Institution : University Of Exeter

Module : Business project(BEMM466_A_3_202425)

Instructor/Mentor : Fanlin Meng

(MSc. Business Analytics Batch 2024-25)

## Author Note

There was no specific grant awarded for this study by public, private, or nonprofit funding organizations.The data dictionary, code, and dataset utilized in this work are accessible on GitHub and Onedrive. Every resource has documentation to promote reproducibility and transparency.

My name is Anwesha Dhar, and I studied computer application for my bachelor's degree at The Heritage Academy and my master's degree at The Heritage Institute of Technology in Kolkata,West Bengal, India. In the past, I held a dual position with Shyam Sundar Jewellers in

Kolkata, which involved coordinating marketing and retail sales. My current academic endeavors at the University of Exeter involve pursuing an MSc in Business Analytics.

This study has been carried out on its own initiative as an aspect of coursework in the module Business Project((BEMM466_A_3_202425). I, Anwesha Dhar, would like to express my gratitude to the faculty of the University of Exeter, my module convenor Stuart So, my mentor Fanlin Meng, my pastoral mentor Sophie Corner for immense support, and the university study skills support team for their invaluable help on the subject during the project. There are no disclosed conflicts of interest.

Contact information: Anwesha Dhar

University Of Exeter

ad1119@exeter.ac.uk

**Table of contents**

## Executive Summary

### Context

The global automobile business is changing in a way never seen before. The 2015 Paris Agreement and a series of national and regional climate pledges have sparked a shift in the commitment of governments, corporations, and consumers toward decarbonization and sustainability. Regulations intended to gradually phase out the sale of gasoline and diesel vehicles in favor of zero-emission alternatives are among the most important policy tools.In the United Kingdom, for example, legislation mandates that all new automobiles be emission-free by 2035, with the interim goal of having 70% of new vans and 80% of new cars be emission-free by 2030. Following suit, Canada has declared a goal to stop selling new internal combustion engine (ICE) vehicles by 2040, while France, Germany, and Sweden have set a plan to do the same for light-duty vehicles by 2035.

The automotive industry, including manufacturers, infrastructure providers, legislators, and end users, will be significantly impacted by these pledges in the near future. A paradigm shift in supply chains, market dynamics, research and development agendas, and investment strategies has been brought about by them.Developments in battery electric and hybrid powertrains are quickly replacing conventional fossil-fuel car technology. There is still much uncertainty surrounding consumer behavior, producer adaptation, regulatory compliance, and infrastructure implementation, thus the pace, scope, and trajectory of this change are still the focus of heated discussion and ongoing research.

## Research Problems

In spite of the abundance of forecasts and policy plans, there is still a crucial evidence gap at the nexus of infrastructure preparation, market reaction, and public policy. In particular, efficient capacity planning requires an awareness of how net-zero requirements and legislative milestones affect the relationship between car sales, pricing, manufacturing capacity, and the installation of charging infrastructure.The capacity to model and predict these relationships becomes not only important but also necessary for sustaining competitiveness and achieving societal objectives when past trends of automobile demand wane and infrastructure needs increase.

Thus, the main research question is how much diagnostic analytics, which are aimed at identifying correlations and cause-and-effect links, when paired with predictive analytics, can help guide evidence-based, strategic planning for the automotive ecosystem of the future. There are subproblems within this general query:

1.Changes in the car market as countries like the UK, European countries like France, Germany and Sweden and Canada meet their net-zero climate goals by switching to zero- emission vehicles like EV cars and vans.

2.Public acceptance towards the transition shift to zero emission vehicles

3.What if the government bans ICE vehicles?

4. How far is the UK ahead of the above mentioned countries in EV market and sales?

## The purpose and goals of the research

In order to analyze and anticipate the primary dynamics of the automotive sector, this dissertation will use advanced diagnostic and predictive analytics. It will concentrate on the dual challenges of the UK's transition away from fossil fuels and the adoption of electric vehicles, as well as comparative foreign contexts.

These are the particular goals:

- Firstly,to examine the effects of present and upcoming legislative requirements on EV and ICE vehicle sales, pricing, and consumer adoption.
- Secondly,to measure the causal link between the growth of charging infrastructure and the adoption of EVs.
- Thirdly,to create and put into practice reliable predictive models (such as ARIMA, perato analysis, and time-series forecasting) for up to 2035 and 2040 regarding future production capacity, sales, prices, and the need for charging infrastructure.
- Lastly,comparing the UK's capacity planning and policy-driven market transitions to those in France, Germany, Sweden, and Canada in order to identify key areas for intervention and best practices.

## Rationale and Importance

This study is critically needed and at the ideal moment. As the automobile industry develops, it is essential to include thorough data analytics into strategic planning and policy. With the help of this dissertation's diagnostic and predictive toolkit, stakeholders can:

1. Identify the production and infrastructure constraints and prepare for the future adjustments.

2. Provide estimates that are based on the empirical study rather than the speculation to help the manufacturers, legislators, infrastructure developers, and investors make informed buying decisions.
3. By comparing the achievements and difficulties of the UK manufacturer to those of its international peers, information sharing and cross-border policy learning are encouraged.

The research project's emphasis on equity and ethical issues makes it noteworthy as well. Risks associated with disparities in access to charging infrastructure, data privacy issues, rural/urban differences, and possible unforeseen repercussions of swift policy changes arise when electrification picks up speed. In order to ensure a just and inclusive transition to low-carbon mobility, it is imperative that all of these variables be addressed.

## Scope and delimitation

This dissertation focuses on the passenger eco-friendly cars market in the UK and the world sales on EV including France, sweden, Germany and Canada, taking into account both the comparative goal and the national policy context. It uses academic literature, government statistics, and industry data from 2015 forward to bolster its empirical analyses.The focus of the project is not completely about providing technical evaluations of battery chemistries, grid integration, or carmaker R&D processes, but rather about estimating and forecasting the commercial and infrastructure implications of net-zero policies.

The research project is constrained by the availability of data, regional differences (some results could be obscured by national averages), and the unpredictable nature of disruptive market shocks like supply chain problems, global pandemics, or geopolitical upheavals. Adoption elasticities and technological learning rates are two examples of model assumptions that may generate bias; these limitations will be openly stated.

## Methodology Overview

Statistical models will be used to find and statistically validate cause-effect links. Time-series techniques Time series decomposition(seasonal_decompose),Stationarity testing(Dickey-fuller test),Autocorrelation analysis(plot_acf,plot_pacf),ARIMA, scenario modeling, and capacity gap analysis are examples of predictive analytics that will offer forward-looking insights into the infrastructure requirements and market evolution. Through comparative case analysis, key models will be modified for every national situation, exposing the advantages and disadvantages of each strategy.

### The dissertation's outline

The format of this dissertation is as follows :

Chapter 1: Introduction

Chapter 2: Literature Review

Chapter 3: Methodology

Chapter 4: Data collection and preparation

Chapter 5: Analysis and findings

Chapter 6: Discussion

Chapter 7: Reference

Chapter 9: Appendix

## Conclusion

In sum, this dissertation responds to a critical knowledge gap at the heart of the automotive sector’s most urgent transition: the shift towards zero-emission vehicles and sustainable infrastructure in an era of ambitious climate policies.Through a multidisciplinary approach that fuses diagnostic and predictive analytics, it aspires to equip decision-makers with the evidence they need to navigate complexity and uncertainty in pursuit of a net-zero future.

**Dissertation - Introduction**

What is Paris agreement?"At the 21st COP in Paris, France, in 2015, a landmark, legally-binding agreement was made. It requires the UNFCCC Parties to limit "the increase in the global average temperature to well below 2°C above pre-industrial levels". However, the agreement also states that every effort should be made to keep the increase below 1.5°C. Only then can the worst effects of climate change be avoided." - ( Published by Elspeth Rider, April 25, 2025)

An essential part of the Paris Agreement, each nation's official climate action plan is represented by its Nationally Determined Contributions (NDCs). Every five years, these plans—which describe how countries will cut greenhouse gas emissions and adapt to climate change—must be updated to reflect growing ambition.For example, the United Kingdom's most recent NDC, which was unveiled at COP29 in November 2024, pledges to cut all greenhouse gas emissions by at least 81% by 2035 as compared to 1990 levels, except shipping and international aviation. This goal reaffirms the UK's position as a global climate leader and is consistent with its larger plan to reach net-zero emissions by 2050.In addition to being an instrument to guide policy, NDCs are also used as standards for monitoring advancement, leading sustainability analytics across industries, and influencing investment choices.

Transportation is one industry where NDCs are already having an impact on investment and innovation, especially with the move to electric vehicles.A key policy mechanism in the UK's all-encompassing Net Zero Strategy, the Zero Emission Vehicle (ZEV) mandate is also a crucial part of the country's Nationally Determined Contributions (NDC) under the Paris Agreement. This progressive legislative framework, which goes into effect in 2024, requires automakers to gradually raise the percentage of zero-emission vehicles in their portfolios. Eventually, it will be necessary for all new car sales to consist solely of zero-emission vehicles within ten years.

In an effort to cut greenhouse gas emissions, governments throughout the world have set ambitious goals for the switch from internal combustion engine vehicles (ICEVs) to electric cars (EVs).Businesses from all industries must strategically shift toward the adoption of electric fleets as a result of this regulatory shift, which calls for a fundamental overhaul of the commercial vehicle market.

Although businesses face immediate financial difficulties as a result of this shift, the financial load is anticipated to lessen as a result of a combination of specific government incentives for the purchase of electric vehicles and expected market-driven cost reductions brought about by a wider variety of models and larger manufacturing operations. The requirement provides prolonged timetables for Heavy Goods Vehicle (HGV) operators due to present supply and technological restrictions in the zero emission HGV market, acknowledging sectoral disparities in transition feasibility.But the growing number of zero-emission cars will put more strain on the infrastructure that charges them, which might lead to operational snags for business fleets. The government has put in place supportive frameworks to help with these issues, such as the Workplace Charging Scheme and the Electric Vehicle Infrastructure Grant for employees and fleets, which are intended to make the necessary infrastructure development easier. In order to successfully navigate the uncertainties that come with this regulatory transition, industry analysts stress the vital role of proactive strategic planning. They also stress the necessity for firms to stay informed about changing government assistance mechanisms as policy efforts continue to change.A thorough analysis of cause-and-effect relationships, correlation patterns, and predictive forecasting is necessary to inform strategic capacity planning and investment decisions in both vehicle production and the deployment of charging infrastructure. This is made possible by the intricate interactions between regulatory requirements, market dynamics, and infrastructure development.

**Literature Review**

Despite recent improvements in the automobile sector, new technologies, legislative reforms, and production improvements have come more slowly across comparable platforms and by comparable companies. With the rapid advancement of electric vehicles, not only for passenger cars but for the entire transportation sector, this appears to be about to change.Many revolutionary changes are taking place simultaneously. In addition to being technological, as electric vehicles gradually supplant internal combustion engines, these changes also have an effect on ownership patterns, as completely autonomous vehicles become more feasible and automobile ownership becomes less of an ideal.

These shifts will lead to a number of problems, such as consumer preference, lightweighting, and safety concerns, even if electric vehicles appear to have many advantages, not the least of which is the environment.

In addition to posing problems for established manufacturers, the growing popularity of electric vehicles is opening up opportunities for new businesses to enter the industry. For example, Although Tesla is the EV industry's poster child, it's by no means the only dominant force. In the electric vehicle sector, a number of businesses have established significant positions; some even compete with Tesla in terms of innovation, scale, or pricing. BYD in China is one of the biggest manufacturers of EVs worldwide,strong in fleet and passenger EVs. Volkswagen in Germany has its ID series (ID.3, ID.4, ID.7) which is being expanded rapidly and is well-represented in Europe. BMW in Germany offers a quality range of electric vehicles models like i4,iX and i5 with luxury appeal. Porsche in Germany, the Taycan is a high-performance electric vehicle that rivals the Model S from Tesla. Renault in France has low-cost EVs such as the Scenic E-Tech and Zoe which are thriving in metropolitan markets.

Due to these shifts in the automotive industry, new components and materials are needed for all aspects of vehicle manufacturing, not simply batteries for the upcoming generation of cars.There are scale-related concerns as well. For instance, the UK now produces about 2 million engines annually, but 20 billion welds would be needed only to connect the battery cells.

The electric vehicle (EV) market is expanding rapidly. Its value was approximately $384 billion in 2022 and might reach $8.8 trillion by 2030. By 2050, it might reach $56.7 trillion if this trend keeps up. By 2040, it is anticipated that 60% of automobiles worldwide will be electric, up from just 2% in 2020.

Europe has long been a leader in the production of conventional gasoline and diesel automobiles, but it is lagging behind in the development of electric vehicles (EVs). In terms of EV innovation, the United States and China are ahead of the curve since they started earlier. Europe is now China's largest market for electric vehicles; in 2022, 28% of all EVs sold in the EU were imported from China, and 40% of China's EV exports are sent to Europe. Europe has imported four times as many automobiles from China as it has sent to China during the past five years. China currently sells significantly more automobiles to Europe than Europe sells to China, indicating a reversal of the trade balance.

The majority of electric vehicles (EVs) that are shipped from China to Europe are really produced by American corporations with plants in China. Chinese businesses are simultaneously attempting to increase their EV sales in Europe. This puts double strain on the European auto industry, which may lead to major supply chain issues.The car industry is very important to Europe—it made up **7**% of the EU's economy and supported over 13.8 million jobs in 2022. So, any threat to this sector could hurt Europe's economic growth, job market, and overall stability, and needs to be taken seriously.

**Post-pandamic effect**

Prior to the epidemic, it was predicted that 80 million cars would be sold internationally. This was the first year where automobile sales surpassed pre-pandemic levels, even though 2023 sales are still well below that target. In 2023, the automotive industry saw a number of difficulties, such as North American strikes, layoffs, and supply shortages. Nevertheless, in 2024, the North American market, along with Eastern Europe and Asia, grew at one of the fastest rates due to the year-over-year growth in auto sales in these regions.China's economy lost steam in 2022 after years of double-digit expansion, and it has been recovering slowly until 2023. With almost 25.8 million cars sold in 2023, China topped the global auto market in terms of sales. In April 2022, however, China's monthly car sales fell precipitously, in part because of shortages, concerns about an impending recession, and the COVID-19 epidemic. By June of that year, China's monthly sales had gotten closer to 2021 figures.

Even though the aforementioned report did not contain any specific datasets, a scenario analysis was conducted on the data points that were discovered using Statista. Figure 1 (under Analysis and findings) illustrates the COVID-19 pandemic-related market shock and significant comeback, forecasting a strong recovery.The study also delves into the Statista market data article's insight that gasoline-powered vehicles continue to hold the largest share, which indicates consumer preference. It also shows how this distribution pattern has a significant impact on automakers' supply chain strategies, production planning, and R&D investments, as the 29.47%

electric car share in Figure 2 is likely a tipping point that will accelerate further EV adoption through network effects, economies of scale, and ongoing technological advancements.

**Access to EV vehicle charging is a hurdle in the UK market**

In Statista Market Insight, an article published by Mathilde Carlier on Nov 19,2024, mentions that access to charging infrastructure is one of the primary obstacles that the UK must overcome in order to meet its fleet electrification goals. The public charging network is expected to reach 300,000 charging stations by 2030, according to government projections from 2022. ChargeUK, the trade association for charge point operators, has committed to investing over 6 billion GBP in charging infrastructure before that date. And in comparison to on-street charges, which are found in residential areas, there were around 29% more destination chargers as of July 2024. This lack of charging access is not one of the top three consumer concerns, despite the differences in charging locations.

The following study in the dissertation ( Analysis and findings) demonstrates the conclusions drawn from the graph in figure 5 & figure 6 produced using data from Statista Market Insight itself: UK electric vehicle charging infrastructure has a big impact on consumer and market competition.

.

## Methodology :

1. **Data collection and preparation**

The statistics used in this study came from the extensive "Global EV Outlook 2025" report published by the International Energy Agency (IEA). This source was chosen for its authoritative and current analysis of the world's electric car markets, which serves as a solid basis for strong business analytics. Time-series data pertaining to worldwide sales of electric vehicles, the main variable for analysis, made up the raw dataset. To fix missing values and guarantee data integrity, a methodical cleaning procedure was used in the first stage of data preparation. The isnull().sum() function in Python was used to identify the missing data points after a careful analysis of the dataset. There was no explicit code for cleaning or dealing with missing data (NaN values) in the Python programming used to work on the dataset that presented nationwide Ev sales. Except for differencing for stationarity tests (e.g., df['EV Sales (World)'].diff().dropna()), which merely eliminates NaNs produced by the differencing procedure, there are no calls to functions like dropna(), fillna(), or any imputation methods applied directly to your DataFrames.

The dataset used in the study and research was gathered from a number of reliable Statista sources, such as "Global car sales 2019–2024," "UK: on-street EV charging points by leading network," "UK: leading EV charging point networks," "Electric vehicles: charging points Germany 2025," "Europe: number of electric vehicle charging points," and "Electric vehicles in the United Kingdom – Statistics & Facts." Regarding the infrastructure and market trends for electric vehicles (EVs) in Europe and the UK, these sources offered organized, region-specific insight. These can be further downloaded in pdf,xls,png,ppt.After being gathered, the data was combined into a single format and loaded into Python for preliminary processing. Standardizing column names, switching data types, addressing missing values using imputation and removal techniques, and guaranteeing consistency across categorical and temporal variables were all part of the cleaning process.After performing exploratory data analysis to find distribution patterns, anomalies, and outliers, normalization and feature engineering were carried out to improve model readiness. In line with moral principles and industry best practices for business analytics, this meticulous data preparation guaranteed analytical reproducibility and integrity.

2. **Visualization**

Pandas, NumPy, Seaborn, Matplotlib, and Statsmodels are Python modules that were used to facilitate exploratory data research and effectively convey insights. In order to read Excel files, handle missing values, and convert tabular data into formats suitable for analysis, Pandas was widely employed for data manipulation.Array transformations and statistical computations were among the numerical operations that NumPy offered, especially during feature engineering and normalization. Together, Seaborn and Matplotlib were utilized for visualization; Seaborn was used for visually appealing plots such as line plots and boxplots, while Matplotlib was used to customize the layout, labels, and axes. These visualizations made it easier to evaluate the evolution of regional infrastructure, analyze trends in EV adoption, and identify anomalies in the distribution of sales and charging stations.Further insights into distribution patterns and temporal dependencies were provided by the autocorrelation and Empirical Cumulative Distribution Function (ECDF) plots that were produced using Statsmodels. When combined, these libraries made it possible to create a reliable, open, and repeatable analytical process that adhered to industry standards for business analytics.

| | Year | EV Sales (World) |
|---|---|---|
| 0 | 2010 | 7000 |
| 1 | 2011 | 40000 |
| 2 | 2012 | 58000 |
| 3 | 2013 | 110000 |
| 4 | 2014 | 200000 |
| 5 | 2015 | 330000 |
| 6 | 2016 | 470000 |
| 7 | 2017 | 760000 |
| 8 | 2018 | 1400000 |
| 9 | 2019 | 1500000 |
| 10 | 2020 | 2000000 |
| 11 | 2021 | 4700000 |
| 12 | 2022 | 7300000 |
| 13 | 2023 | 9500000 |
| 14 | 2024 | 11000000 |

For an example, in this above image ,it simply allows one to visually inspect the data that was loaded from excel file of Global EV Outlook 2025.

3. **<u>Statistical models used</u>**

- Time series decomposition(seasonal_decompose): A basic analytical method in econometrics and statistics, time series decomposition—also referred to as seasonal decomposition—involves dissecting a time series into its component parts in order to better comprehend the underlying patterns and structure of the data.The trend component, which captures the long-term directional movement or growth pattern in the data, the seasonal component, which represents regular, predictable fluctuations that occur at fixed intervals (such as monthly, quarterly, or annual cycles), the cyclical component, which accounts for longer-term fluctuations that do not have a fixed period and are frequently related to business cycles or economic conditions, and the irregular or random component, also known as the error or noise component, which takes into account all the remaining variation that cannot be attributed to trend, seasonal, or cyclical patterns, are the four distinct components of a time series.Depending on whether the seasonal fluctuations stay constant or alter proportionately with the series level, the decomposition can be carried out using either an additive model, in which the components are added together ($Y(t) = T(t) + S(t) + C(t) + I(t)$), or a multiplicative model, in which the components are multiplied ($Y(t) = T(t) \times S(t) \times C(t) \times I(t)$).

The main goals of time series decomposition are numerous and are essential for applications in forecasting and descriptive analysis. By separating and measuring the contribution of each component to the total variance, decomposition first gives researchers and analysts important information about the underlying structure of the data and helps them identify the factors that influence the patterns they see in their time series.When it comes to determining whether an apparent increase or drop in the series is a true trend or just seasonal variation, this knowledge is especially crucial for spotting seasonal patterns that could otherwise mask underlying trends. Second, decomposition is a potent preprocessing step for forecasting because it enables analysts to model each component independently using methods that are most appropriate for their characteristics. For example, trend analysis can be applied to the trend component, seasonal indices to the seasonal component, and stochastic models to the irregular component. These methods can then be combined to produce predictions that are more accurate.Third, the method makes it easier to spot anomalies that might need extra care or research by looking at the irregular component of the data after eliminating the seasonal effects and predictable trend. This makes it easier to identify structural breaks, outliers, or odd patterns in the data. Furthermore, by assisting in the differentiation between short-term fluctuations that may not necessitate intervention and long-term trends that may indicate the need for strategic responses, decomposition facilitates policy analysis and decision-making. It also makes it possible to assess the efficacy of interventions by analyzing changes in the trend component after taking seasonal and cyclical variations into account.

Methodologically speaking, decomposition aids in the selection and validation of models in econometric analysis by giving researchers a better grasp of the data generation process. This aids in the selection of suitable modeling techniques and the evaluation of whether the models accurately represent the different components of variation in the series.

- Stationarity testing(Dickey-fuller test):The Augmented Dickey-Fuller (ADF) test, in particular, is a critical diagnostic technique in time series econometrics that determines whether a given time series has statistical characteristics that don't change over time. Instead of depending on the precise time at which the observations were made, a stationary time series has a constant mean, constant variance, and covariance that are solely influenced by the lag between observations.In order to avoid spurious regression results, invalid hypothesis tests, and unreliable forecasting models, most traditional econometric techniques and statistical inference procedures rely on the assumption that the underlying data generating process is stationary. This makes the concept of stationarity essential.

David Dickey and Wayne Fuller created the Dickey-Fuller test in 1979 to check for the existence of a unit root in autoregressive time series models. A unit root is a sign of non-stationarity. The alternative hypothesis of the ADF test contends that the time series is stationary or trend-stationary, while the null hypothesis asserts that the series has a unit root and is hence non-stationary instead.To perform the test, a regression equation of the following form is estimated: $\Delta yt = \alpha + \beta t + \gamma yt\text{-}1 + \delta 1 \Delta yt\text{-}1 + \delta 2 \Delta yt\text{-}2 + \ldots + \delta p \Delta yt\text{-}p + \varepsilon t$. The test statistic is the t-statistic for the coefficient $\gamma$, and $\Delta$ stands for the first difference operator. The null hypothesis of a unit root is rejected, revealing stationarity, if $\gamma$ is significantly different from zero (usually when the test statistic is more negative than the critical value).

The augmented form of the test is more robust than the straightforward Dickey-Fuller test because it includes lagged difference terms to account for any serial correlation in the error terms. Information criteria like the Bayesian Information Criterion (BIC) or the Akaike Information Criterion (AIC) can be used to choose the right lag length, which is an important decision. For series that fluctuate around zero, the ADF test can be conducted without a constant or trend; for series that fluctuate around a non-zero mean, it can be conducted with a constant only; and for trending but trend-stationary series, it can be conducted with both a constant and deterministic time trend.

In both practical applications and empirical research, stationarity testing fulfills a number of vital functions. It first assists researchers in identifying the best modeling strategy for their time series data because different analytical methods are needed for stationary and non-stationary series. Before using traditional econometric techniques on non-stationary series, it is frequently necessary to differentiate or transform them. Secondly, to prevent misleading regression issues, where two or more non-stationary variables could seem to be highly correlated even though there isn't a real economic relationship between them, stationarity testing is crucial. Third, cointegration analysis, in which researchers look at long-term equilibrium relationships between non-stationary variables that may move together over time despite being individually non-stationary, is informed by the findings of stationarity tests.

- Autocorrelation analysis(plot_acf,plot_pacf):In time series analysis, autocorrelation analysis is a basic statistical method that looks at the linear relationship between a time series and its own delayed values. This method offers important information about the patterns and temporal dependencies in sequential data. To determine how strongly current values are related to historical values at particular intervals, the autocorrelation function (ACF), which is implemented using tools such as plot_acf, evaluates the correlation between observations at various time lags.The correlation coefficient between the original series and the series that has been shifted by that many time periods is displayed for each lag in the ACF plot. The values range from -1 to 1, where values near 1 indicate a strong positive correlation, values near -1 indicate a strong negative correlation, and values around 0 indicate little to no linear relationship. By measuring the correlation between observations separated by k time periods and adjusting for the influence of all intervening observations, the partial autocorrelation function (PACF), which can be accessed through plot_pacf, expands on this analysis and successfully isolates the direct relationship between time points without the confounding effects of intermediate values.

  When it comes to time series modeling and forecasting, these analytical tools fulfill several vital functions. Because regular patterns of high correlations at particular intervals suggest seasonal components, and persistent positive autocorrelations at many lags frequently indicate trending behavior, the ACF plot aids in identifying the presence of trends, seasonality, and cyclical patterns within data.The PACF plot is a useful tool for choosing models for ARIMA (AutoRegressive Integrated Moving Average) processes because it displays a sharp cutoff after the real autoregressive order, which is especially useful for figuring out the proper order of autoregressive (AR) models. These functions work together to help researchers and analysts understand the memory structure of their data, choose the best parameters for different time series models, discover the degree of differencing required to achieve stationarity, and establish the proper lag lengths for predictive models.

In real-world applications, autocorrelation analysis aids quality control engineers in seeing systematic patterns in manufacturing processes, helps financial analysts estimate market volatility, and aids economists in understanding business cycles. Autocorrelation is an essential tool for anyone working with temporally ordered observations, and its importance goes beyond simple pattern recognition. It serves as the theoretical basis for many sophisticated time series techniques, such as spectral analysis, state-space modeling, and various machine learning approaches to sequential data.

- ARIMA : A popular statistical method for time series analysis and forecasting, the AutoRegressive Integrated Moving Average (ARIMA) model integrates three essential elements to capture various facets of temporal data trends. When examining sequential data, where observations show consistent patterns and are correlated across time, ARIMA models are especially useful for making predictions.

4. **<u>Tools for dissertation</u>**

In order to effectively support the research goals, the methodology of this dissertation incorporates a thoughtful and complementary selection of digital tools: GitHub and OneDrive for project storage and sharing, Microsoft Excel for data storage, Python programming within Visual Studio Code (VS Code) for analysis, and Google Docs for document preparation. An emphasis on cooperation, data integrity, analytical rigor, transparency, and reproducibility is evident in the thoughtful selection and integration of these technologies.

- Google docs : Document preparation - The selection of Google Docs as the main instrument for writing the dissertation was driven by a number of scholarly and practical factors. Beyond the benefits of typical desktop programs, Google Docs is a cloud-based word processor that is particularly useful for contemporary collaborative, iterative, and data-driven research projects.

  In order to enable focused composition while yet offering the "big picture" overview required for logical flow and thematic coherence, the workflow consisted of developing a master Google Doc document that was divided into chapters and sections that were updated on a regular basis. In order to facilitate asynchronous review and iterative improvements, collaborative writing with supervisors was implemented through shared links with regulated editing permissions. As a result of this strategy, Google Docs became an essential component of the dissertation process, improving writing quality, workflow efficiency, and transparency.
- Python programming language in VS code : Analytical modelling - Python, an academic and industry standard tool for quantitative analysis, coding, and data science, was used at the heart of the present research's analytical modeling. It was implemented using the

Visual Studio Code (VS Code) integrated development environment. This combination was chosen due to its adaptability, extensibility, and extensive ecosystem that supports machine learning, advanced statistics, and reproducible research processes.

Python has been utilized for these important analytical missions:

1. Python programming processed the cleaned data using the pandas and numpy libraries, providing summary statistics and correlation matrices to show cause-and-effect linkages. In order to support the narrative for both diagnostic and inferential results, Matplotlib and Seaborn were used for high-impact visualization, which is essential for spotting certain trends.
2. Python's robust ecosystem, which includes the scikit-learn toolbox and statsmodels, made it possible to perform regression analyses, scenario simulations, and time-series forecasting models. The main objectives of the dissertation, which included predicting future demand for EVs and ICEs, estimating price trends, and detecting infrastructural gaps year over year, were quantitatively supported by these methodologies. Open access to code and the reproducibility of Python scripts made it possible for other researchers to independently evaluate or expand any models, which is a best practice in modern data science and academic integrity.

The integration of VS Code with Git version control protected the codebase from unintentional overwrites and offered a clear development history, both of which were particularly helpful when reacting to supervisor comments regarding code selections or the interpretation of results. Code that was clearer, more dependable, and thoroughly documented was made possible by Visual Studio Code's debugging and environment management tools.Python was chosen because it is open-source, has a vibrant community, and aligns with employability skills that are valued in both academia and the automotive industry, as opposed to other options like R, MATLAB, or proprietary platforms like SPSS. Because Python is compatible with both Google Docs and Excel through export plugins and APIs, workflow management and end-to-end process integration are made possible.

- Microsoft Excel : Dataset Storage - The primary datasets used in this dissertation were all stored in Microsoft Excel, which served as the sole platform for this purpose. Excel was chosen as the primary means of organizing, archiving, and managing unprocessed quantitative data before it was subjected to any kind of analysis because of its accessibility, dependability, and broad popularity in academia and business. All datasets, including annual car sales worldwide-2010-2024 with a forecast for 2025-2026, passenger car sales by fuel/drive type in the UK in 2024, leading EV charging point networks in the UK as of 2024, forecast electric vehicle revenue by vehicle type 2016-2029, on-street EV charging points by leading network as of January 2024, support for gasoline and diesel cars phase-out in the UK 2024 by type, were meticulously entered, labeled, and sorted within separate Excel sheets. As a result, data integrity and workflow efficiency were supported since all original data, regardless of source, were aggregated in a logical and easily navigable electronic format.
- Github : Project management and cooperative Storage - The written dissertation report, executive summary, study proposal, code files, data dictionaries, and datasets were all stored and version-controlled on GitHub, which was chosen as the primary platform to guarantee reliable, open, and well-organized management of all dissertation assets. In both academic and commercial research, GitHub is widely acknowledged for its capacity

to support teamwork, prevent data loss, and preserve accurate version histories. By beginning with a specific repository, all significant papers and analytical tools were kept in a well-organized directory system, which separated the written content away from the raw and processed datasets, the data dictionary, and the computational scripts and analysis files. In addition to making it simple to find your way and get the information, this promoted best practices for repeatability and transparency in research.

During the course of the research, the platform's integrated Git version control system made it possible to effectively track each change, commit, and update made to the project files. With pull requests and commit histories, supervisors' comments and recommendations may be put into practice and recorded, guaranteeing a transparent audit trail for any significant modifications. The ability for authorized users (such peers or advisers) to safely and remotely access the most recent versions of all project components, regardless of their physical location, also significantly improved sharing and cooperation.Pre-publication documents or sensitive datasets were kept safe until the right time to reveal them thanks to GitHub's public and private repository options.

- Onedrive : Sharing link - In order to share research files and data with peers, supervisors, and collaborators, OneDrive was utilized extensively in this dissertation project as a safe and effective platform. The platform's powerful sharing features and user-friendly design made it much easier to distribute critical or huge data while upholding stringent access limits. Specific sharing links were made in OneDrive to facilitate file sharing, eliminating the need to transmit large attachments or deal with version incompatibilities that are sometimes found in conventional email workflows. This allows recipients to view only the intended documents.

Links were given special rights through OneDrive's sharing settings, indicating whether or not recipients could view, comment on, or edit files. This degree of fine-grained control made guaranteed that private information and drafts of work were shielded from unwanted alteration or dissemination. Secure sharing also included limited editing capabilities where teamwork necessitated input or modifications from peers or supervisors, or "view-only" access to prevent downloads or editing. Furthermore, password restrictions and expiration dates could be added to shared links, providing further security for sensitive research data.

Real-time collaboration and simultaneous editing by several users were made possible by OneDrive's smooth interface with Microsoft Office products, which allowed collaborative document work to be done immediately within the browser or local applications. This decreased redundancies and significantly improved communication efficiency without sacrificing data security. Furthermore, because to OneDrive's automatic device syncing, shared files or datasets were instantly visible to all receivers, guaranteeing that everyone was using the most recent version and enabling clear traceability of modifications.

Overall, OneDrive's sharing link features demonstrated best practices for managing research data in a safe, scalable, and user-friendly manner. This allowed for seamless cooperation throughout the dissertation lifetime and complied with institutional data governance standards.

**Rationale for Choosing Tools and Integrating Workflow**

The selected set of tools was purposefully created to meet the many requirements of this dissertation, which is analytically sophisticated and heavily data-driven. Each instrument was chosen based on its special advantages, serving various but related functions throughout the study lifecycle:

1. Google Docs provided robust support for academic formatting and version control, ensuring effective, accessible, and collaborative document authoring and editing.
2. In order to maximize accessibility and data provenance without prematurely exposing it to danger via analytical errors, Microsoft Excel always maintained primary data in a simple, standardized format.
3. Python in Visual Studio Code offered a robust platform that addressed all aspects of quantitative analytics, from advanced modeling to data cleansing, with a focus on transparency and reproducibility.
4. OneDrive and GitHub improved code and document lifecycle management by sharing version control, collaboration, storage, and safe distribution.

This combination provided strong control, dependability, and adaptability, allowing for the thorough and open analysis of intricate automotive industry dynamics in the context of shifting environmental regulations. The research workflow reduced errors, duplication, and data fragmentation with unambiguous handoffs across tools, resulting in a high-caliber dissertation that complied with contemporary data-focused research objectives and best academic practices.

## Analysis and findings

### Outcome 1:

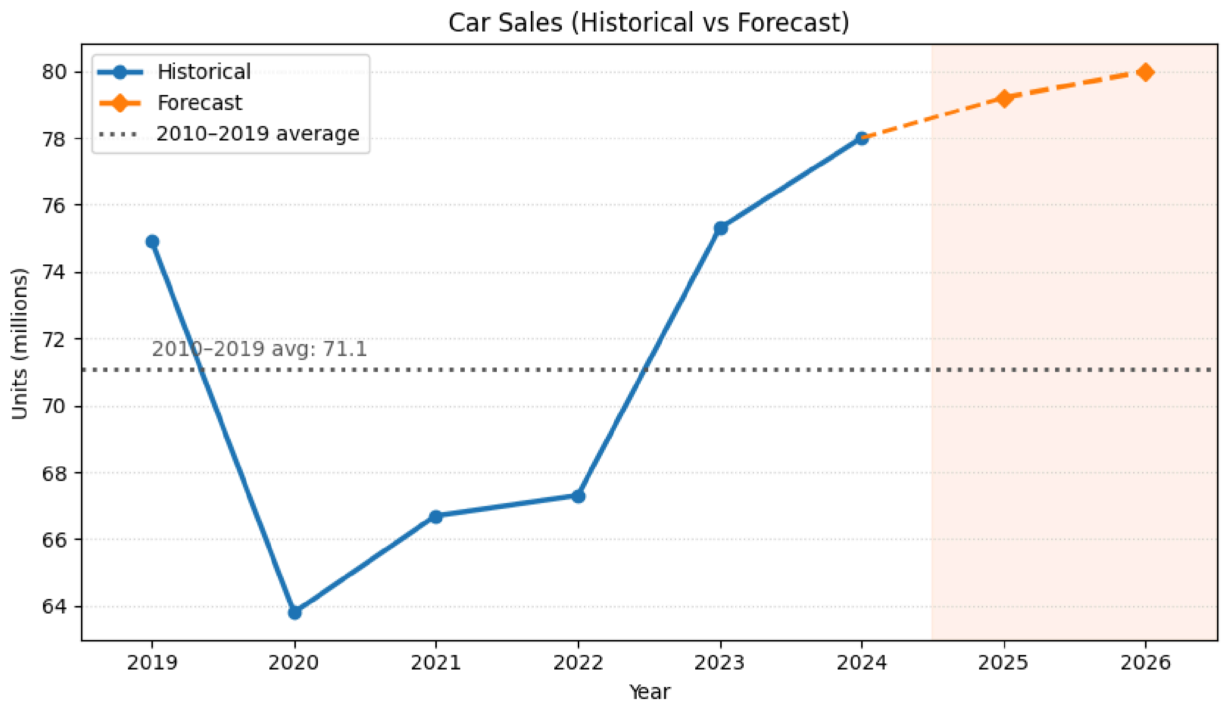



Figure 1. Number of cars sold worldwide from 2010 to 2024,with a 2025-2026 forecast(in millions units)

In Figure 1, a line graph comparing actual and projected car sales in units (millions) from 2019 to 2026 is displayed. According to the historical sales data, which is represented by a solid line and blue markers, there was a notable decline in sales between 2019 and 2020, with the market shock associated with the COVID-19 pandemic probably contributing to the low of 64 million units.Following this low point, the sales pattern turns around, increasing gradually starting in 2021 and reclaiming ground lost to reach about 78 million units in 2024. With sales expected to reach over 80 million units in 2025 and 2026, the orange dashed line, which represents the forecast, indicates hope for additional market expansion.The average from 2010 to 2019 is shown as a horizontal dotted line at 71.1 million units, which acts as a standard for comparison. Remarkably, current sales and projections are higher than this long-term average, suggesting a significant comeback and better performance in the next years compared to the last ten. The projected period is indicated by the shaded area, which visually separates it from the past data. In general, the graph indicates notable fluctuations in the early 2020s, which were succeeded by a robust rebound and consistent expansion, highlighting anticipations of a robust automobile market trajectory through 2026.

**Outcome 2:**

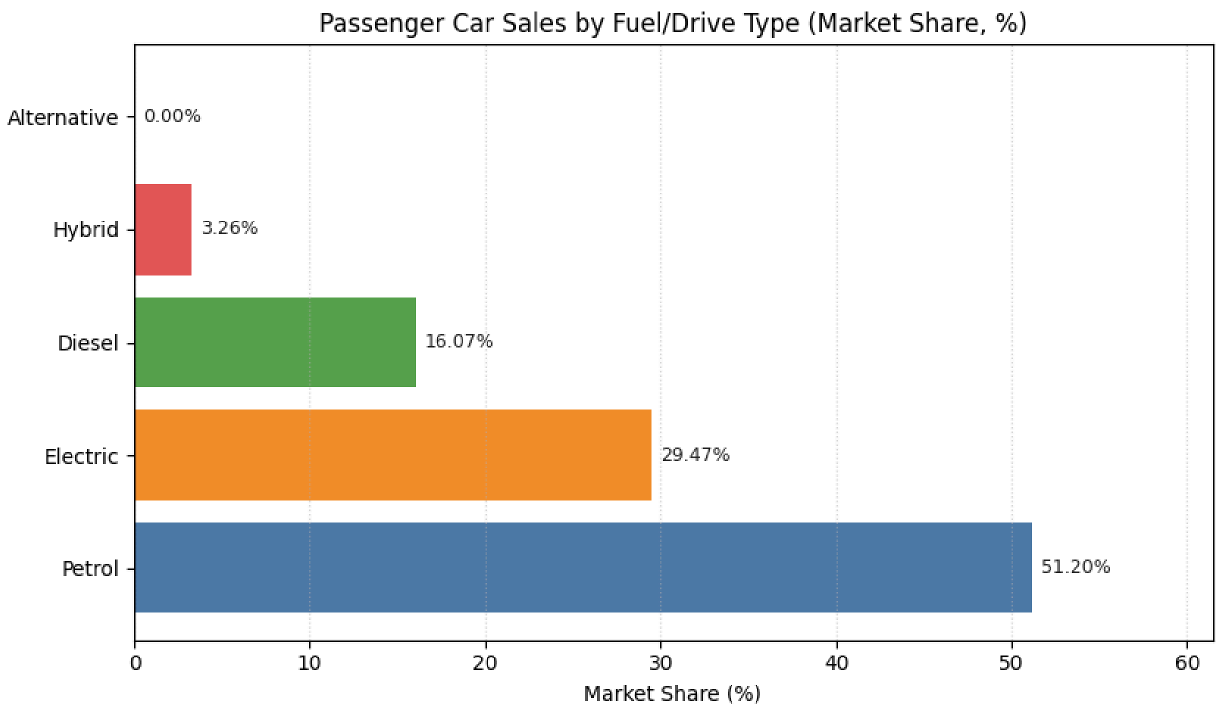



Figure 2. Passenger car sales by fuel/drive type in the UK in 2024 (in percent)

Several important conclusions that clearly depict the contemporary automobile scene and its transitional dynamics may be drawn from Figure 2.The data shows that gasoline-powered vehicles still hold a dominant market share of 51.20%, or slightly more than half of all passenger car sales. This suggests that most consumers still prefer conventional internal combustion engine vehicles even as the trend toward electrification gains traction.The most remarkable discovery, however, is the substantial 29.47% market share that electric vehicles have taken, making them the second-largest segment and exhibiting remarkable penetration that indicates the EV revolution is not just beginning but has already established a significant market presence. This rate of adoption of electric vehicles, which is close to 30%, signifies a radical change in consumer preferences and is probably the result of a combination of government incentives, better charging infrastructure, an increase in the number of models available, and consumers' increased environmental conscience.The market for diesel, which accounts for 16.07% of the market, seems to be continuing to fall from its peak. This is probably because of emissions laws, environmental concerns, and the diesel emissions scandals that have afflicted the automotive industry recently.Only 3.26% of cars are hybrids, indicating that buyers may be choosing totally electric alternatives over this transitional technology. This could be because of the intricacy of hybrid systems, the short range of electric-only vehicles, or cost factors that make pure EVs more alluring.The fact that there are zero percent alternative fuel vehicles shows that hydrogen fuel cell and other alternative propulsion technologies are still mostly in the experimental stage or are only used in specialized applications, and have not yet reached commercial viability or consumer acceptance.The information taken together points to a market that is undergoing fast change, with the classic gasoline-electric duopoly taking hold, diesel declining secularly, and hybrid technologies finding it difficult to maintain consumer interest.The production planning, supply chain strategies, and R&D investments of automakers are all significantly impacted by this distribution pattern because the 29.47% electric share is probably a tipping point that will hasten further EV adoption through network effects, economies of scale, and ongoing technological advancements.Additionally, the results show that any market forecasting models or policy interventions must take into consideration this already sizable EV base because estimates based on the premise of a modest EV presence would greatly underestimate the rate and scope of the ongoing transformation.

**Outcome 3 :**

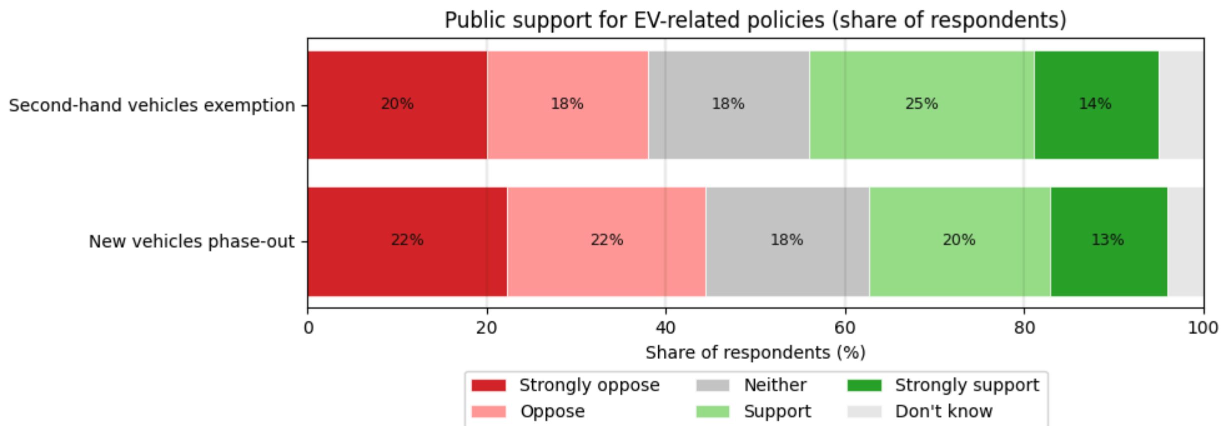



Figure 3. Support for gasoline and diesel cars phase-out in the UK 2024, by type

A number of significant findings about the distribution of public opinion in Figure 3 can be drawn from the poll data on support for EV-related measures. Public opinion is noticeably divided on the two proposals under consideration, with about equal shares of strong opposition and favor. In contrast to the new vehicles phase-out policy, which has 22% strong objection and 13% strong support, the second-hand vehicle exemption policy has 20% strong opposition and 14% strong support. Both schemes encounter comparable levels of opposition when combining opposing categories (38% for the second-hand exemption and 44% for the phase-out of new vehicles), however the phase-out of new vehicles faces somewhat more opposition overall. Support ratings for the two measures are similar; 39% of people support the second-hand exemption overall, while 33% support the phase-out of new cars.Several complex trends in public opinion are revealed by further investigation. For both of these policy, strong opposition routinely outnumbers strong support by 6–9 percentage points, suggesting that opposition is more intense than support.A sizable bloc is represented by moderate opposition ("Oppose"), especially for the phase-out of new automobiles (22%), indicating that policy concerns go beyond only fierce ideological opponents to encompass more reasonable doubters. Neutral replies (18% for both programs) are consistent, suggesting that there is a stable portion of the population that is truly unsure rather than uncertainty related to a particular policy.Additionally, both policies fall short of 50% acceptance and fail to garner majority support, underscoring the difficult political environment for EV policy implementation. The slight variations among policies raise the possibility that public opinion is influenced more by broad sentiments regarding government involvement in auto markets than by particular policy tools, suggesting that it may be difficult for legislators to form broad coalitions in support of EV transition programs.

**Outcome 4:**

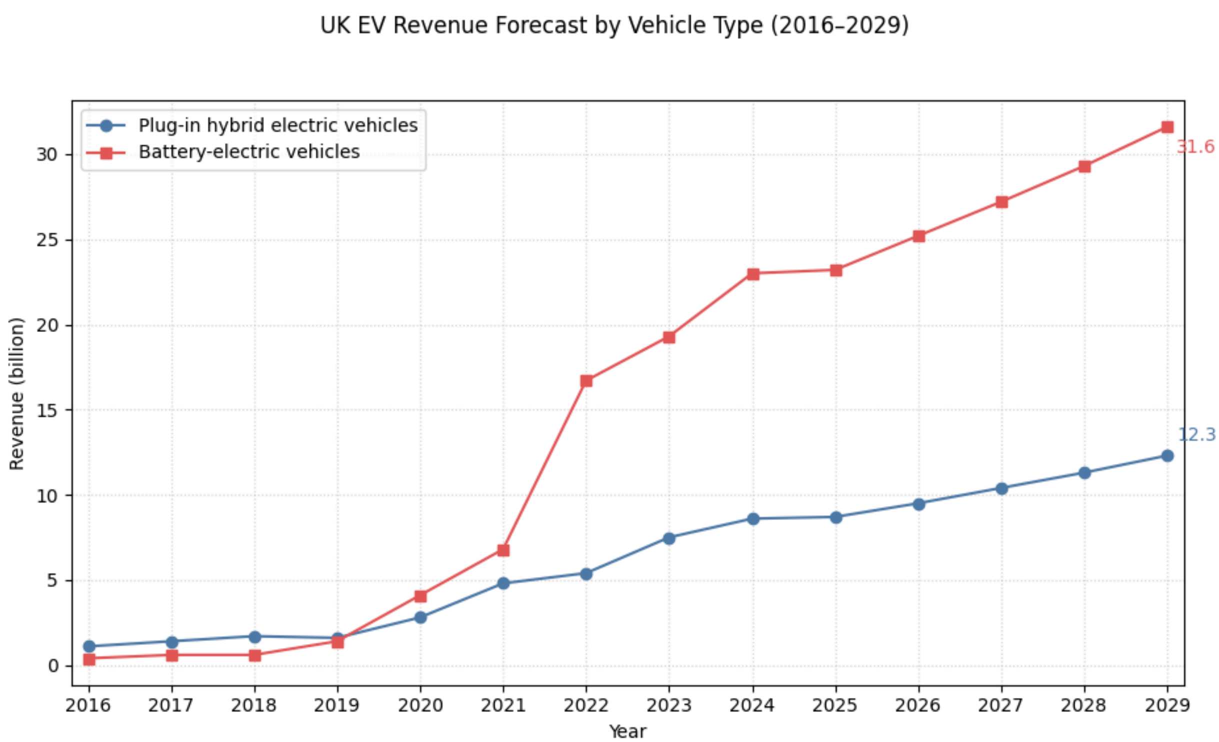



Figure 4.Projected electric vehicle revenue in the United Kingdom between 2016 and 2029, by vehicle type (in billion Great British Pounds)

The UK EV sales prediction data from 2016–2029 in Figure 4 shows a number of noteworthy trends and patterns that demonstrate the market's remarkable development.According to the analysis, battery-electric vehicles (BEVs) have an exponential development trajectory. Their start-up revenue was only around £0.5 billion in 2016, but by 2029, it is expected to reach £31.6 billion, a startling 6,220% increase over the predicted period.On the other hand, plug-in hybrid electric vehicles (PHEVs) exhibit continuous but modest linear growth, increasing by 1,140% from £1 billion in 2016 to £12.4 billion in 2029. A significant turning point is reached in 2020–2021, when BEV revenue starts to rapidly increase, overtaking PHEV revenue and establishing unmistakable market domination.Further analysis reveals a number of complex market dynamics and forecasting consequences. The 2019–2021 convergence era is a technological and market turning point, with BEV and PHEV revenues roughly similar (ranging from £1–4 billion), indicating that this was a crucial time for customers and manufacturers to make decisions.Between 2021 and 2023, BEV sales nearly tripled from £7 billion to £19 billion, demonstrating the technology's rapid development and market adoption. This is the period of greatest growth acceleration for BEVs.The growth curves indicate distinct S-curve adoption patterns. PHEVs seem to be approaching a plateau phase with decreasing growth rates in subsequent years (2025–2029), whilst BEVs continue to exhibit strong growth momentum over the course of the projected period.In addition to showing market preference, the revenue difference continues to grow beyond 2021, reaching £19.2 billion by 2029, which may indicate that hybrid technology is no longer a viable long-term solution. According to the compound annual growth rate (CAGR) analysis, BEVs are achieving about 41% CAGR, while PHEVs are only achieving 21%. This indicates that the market dynamics are accelerating and that full electrification infrastructure should be given more priority in policy and investment than transitional hybrid solutions.

## Outcome 5:

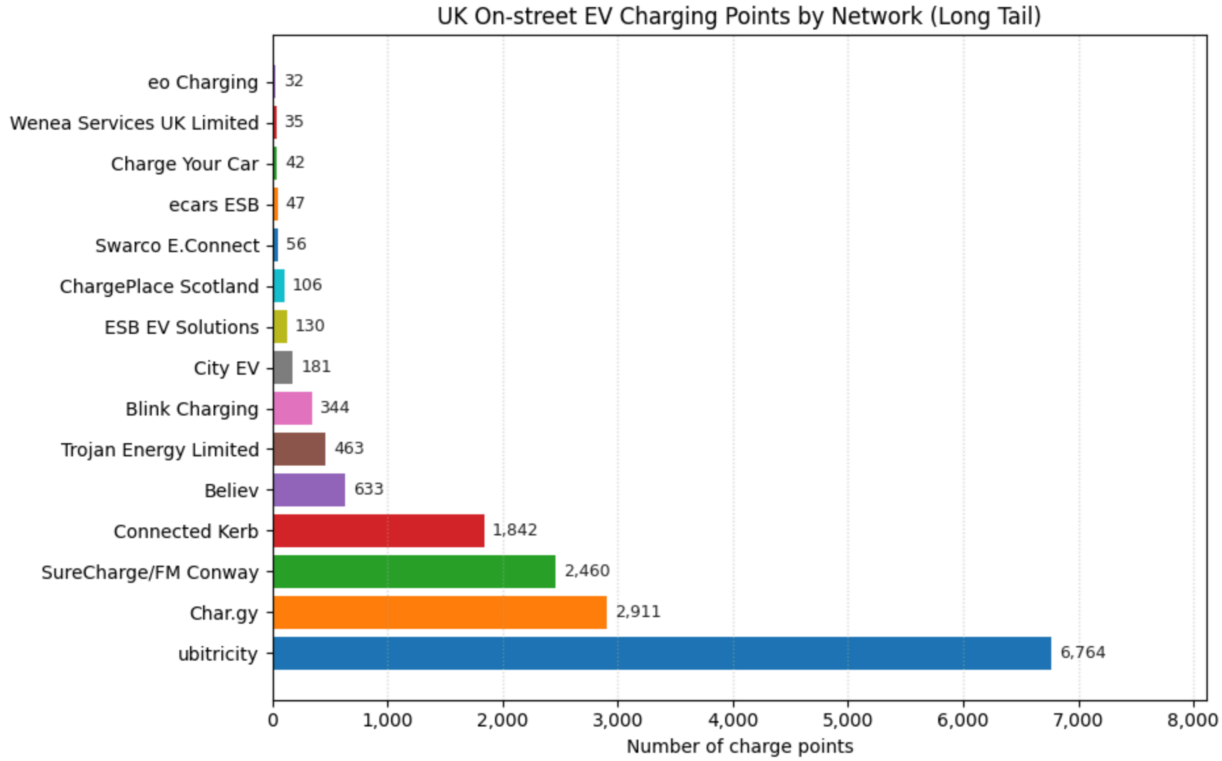



Figure 5.UK: on-street EV charging points by leading network as of January 2024

The infrastructure for charging electric vehicles in the UK is extremely concentrated and controlled by a few powerful companies, as this figure 5 illustrates. This has important ramifications for customer choice and market competition.Ubitricity has the most charging stations (6,764 total, or around 35% of the visible infrastructure), followed by SureCharge/FM Conway (2,460) and Char.gy (2,911). The distribution of the data shows a typical "long tail" pattern, with the top three networks controlling over 60% of the market and the remaining 11 networks operating less than 2,000 charging stations apiece, with some smaller operators running less than 100 stations each.Since larger networks probably have more resources to construct infrastructure in desirable regions, they may underserve less commercially appealing areas. This concentration raises concerns about regional coverage equality and highlights possible obstacles to entry for new market actors. In order to cater to the large percentage of the population without private driveways, the UK has strategically focused on residential street-side charging, as evidenced by the dominance of ubitricity (renowned for lamppost charging solutions).Policymakers and industry stakeholders should take note of this distribution, which emphasizes the need to strike a balance between market efficiency, guaranteeing geographic coverage, and avoiding monopolistic practices that could hinder innovation or result in unfair pricing structures as EV adoption picks up speed.

**Outcome 6:**

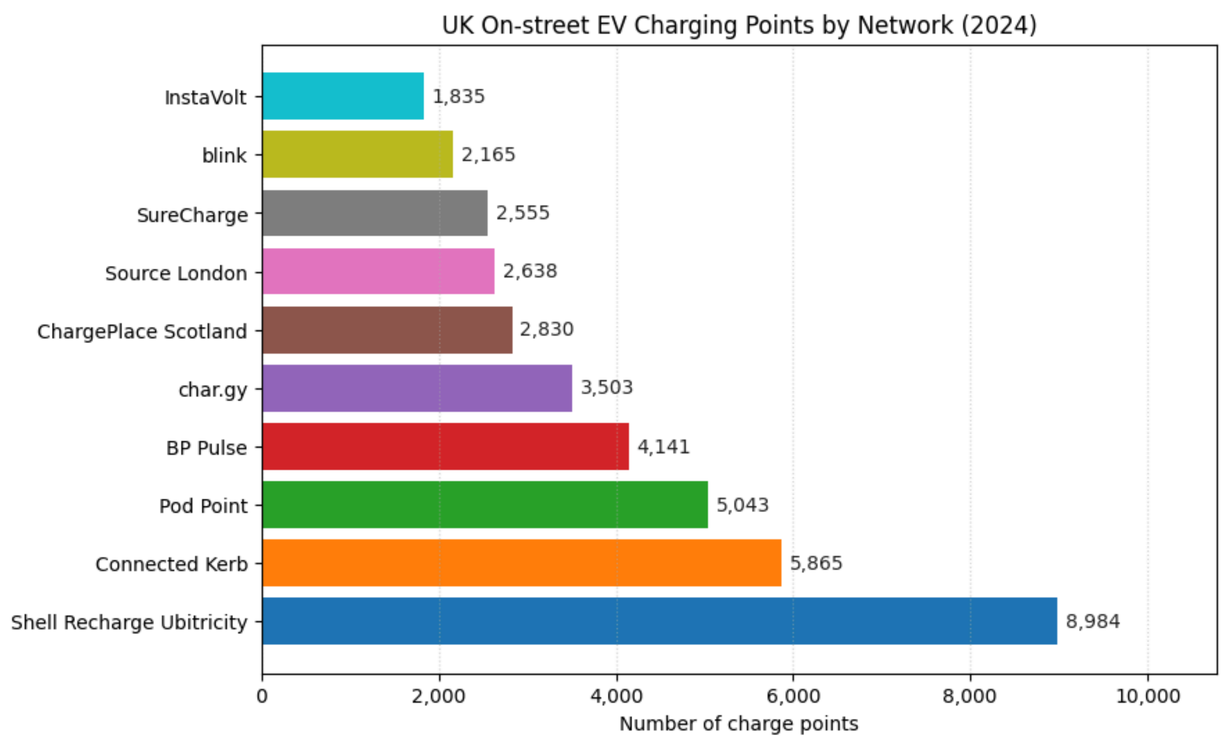
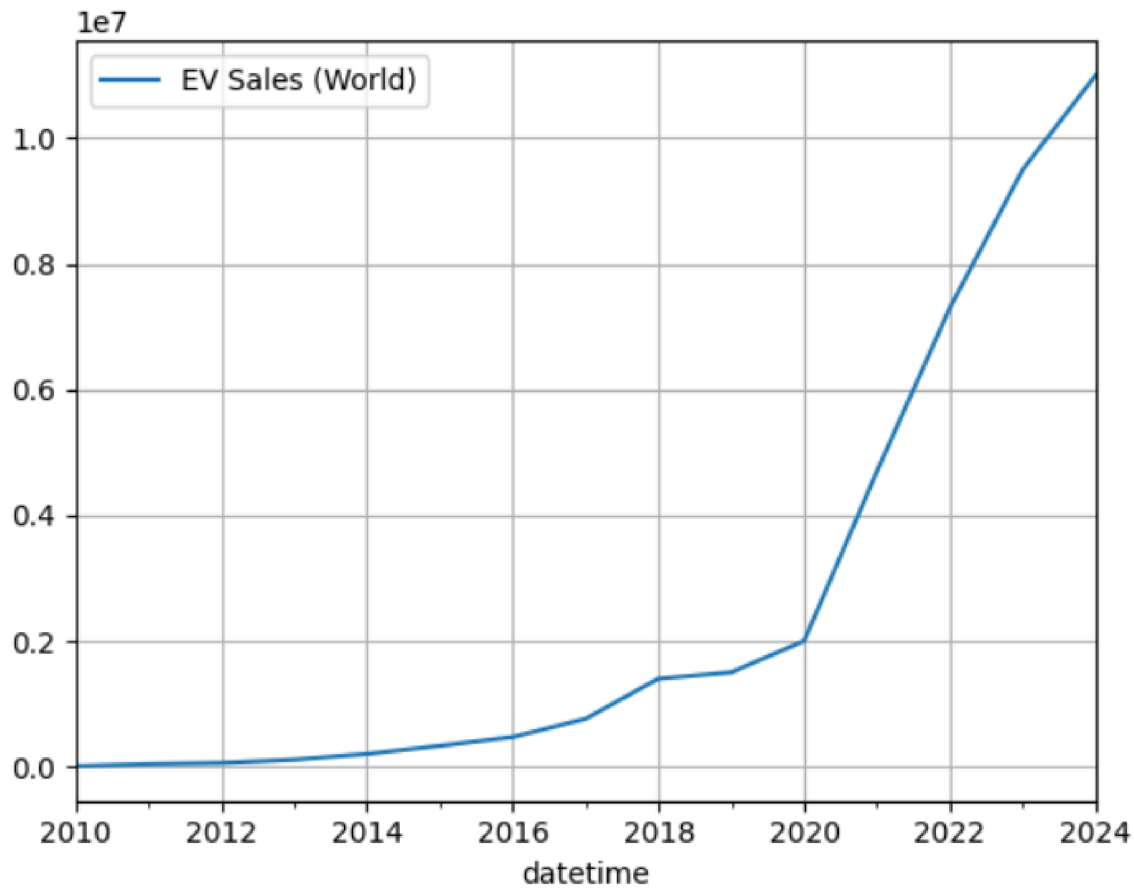
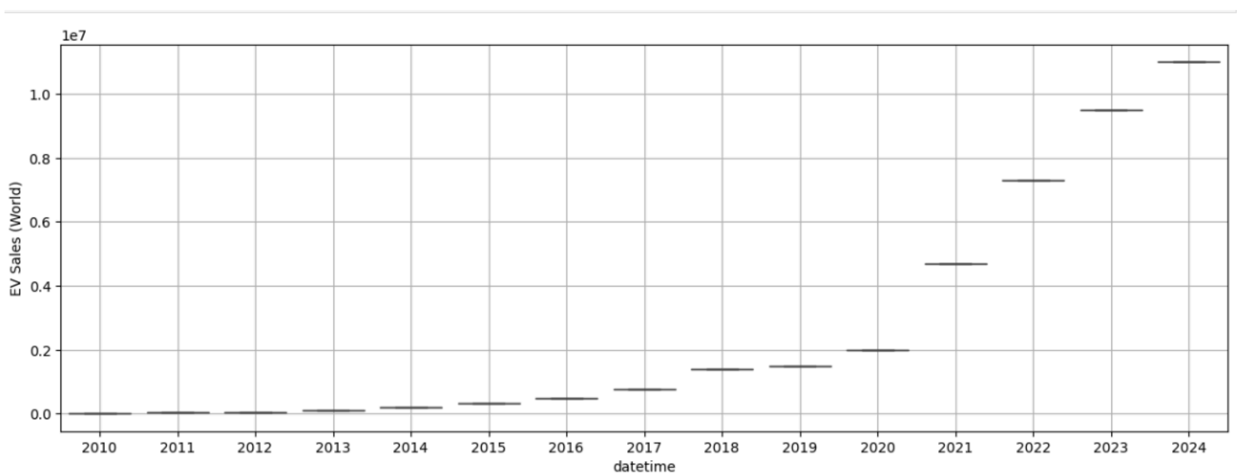



Figure 6.Leading electric vehicle charging point networks in the United Kingdom as of December 2024

A drastically changed EV charging scenario in the UK is revealed by this December 2024 data in figure 6, which supports a number of forecasts regarding market consolidation and business strategic positioning.Most importantly, Shell's purchase of Ubitricity and subsequent rebranding of the company to "Shell Recharge Ubitricity" (8,984 points) shows how big energy companies are utilizing their current retail networks and financial resources to join the EV infrastructure market with intensity. Shell Recharge is the market leader, followed by a competitive middle tier of four to six big companies (Connected Kerb through BP Pulse, with a range of 3,500 to 5,865 points), and a fragmented lower tier of smaller operators. The market is clearly stratified into three categories.This structure implies that the market has progressed from the early stages of entrepreneurship to a more developed, capital-intensive sector where well-funded infrastructure experts and well-established energy businesses are gaining market share. This trend of traditional fuel retailers switching to electric infrastructure is further supported by the rise of BP Pulse (4,141 points) as another significant energy company player.While the tenacity of smaller regional players suggests niche markets and specialized solutions still have viability in this changing ecosystem, the relatively even distribution among the top five players (ranging from 3,503 to 8,984 points) indicates healthy competition at the top tier, which should benefit consumers through competitive pricing and service quality.

**Outcome 7: All the figures below will show the sales for the Worldwide EV sales and sales of EV in UK, France, Sweden, Germany and Canada,thus, displaying a comparative analysis among all.**



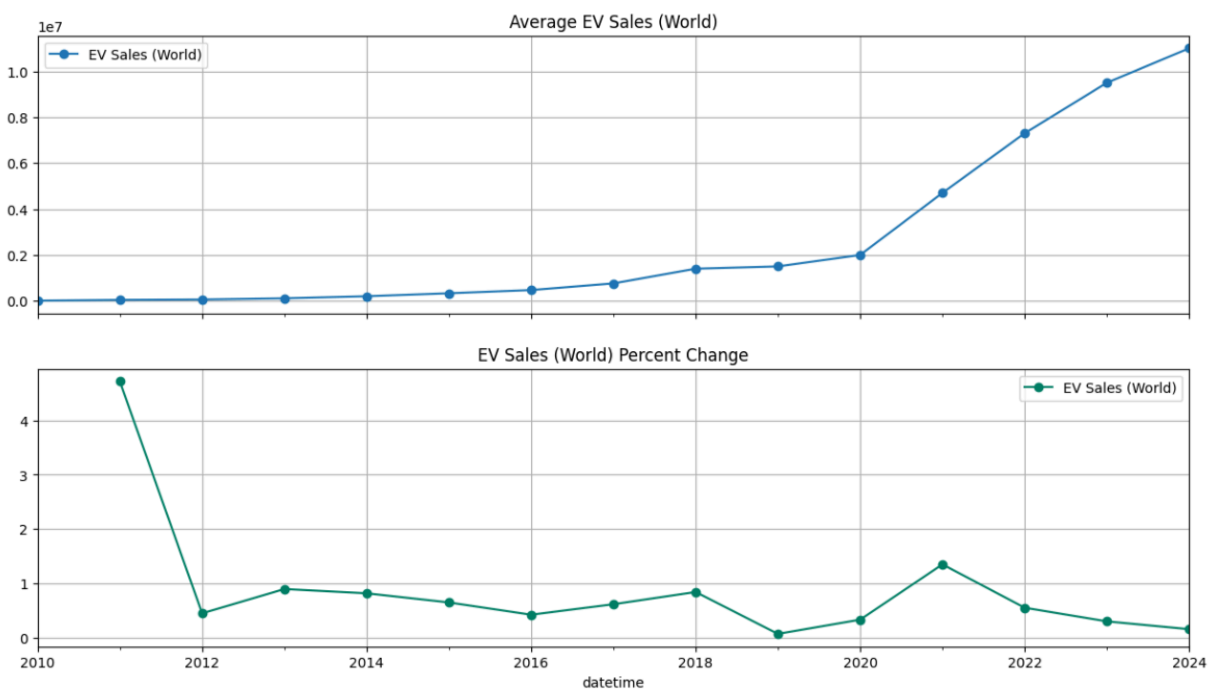



| | EV Sales (World) |
|---|---|
| count | 1.500000e+01 |
| mean | 2.625000e+06 |
| std | 3.707571e+06 |
| min | 7.000000e+03 |
| 25% | 1.550000e+05 |
| 50% | 7.600000e+05 |
| 75% | 3.350000e+06 |
| max | 1.100000e+07 |

These three pictures above allow an analyst to look at the global electric vehicle (EV) sales data from 2010 to 2024. This study also yields a number of other important conclusions that show how drastically the automotive business has changed.The first chart shows an exponential growth trajectory that adheres to the traditional S-curve adoption pattern. From 2010 to 2019, EV sales remained relatively flat at less than 2 million units annually, but in 2020, there was a turning point that set off an explosive growth trajectory that reached about 11 million units by 2024. With a compound annual growth rate of more than 50% in the years after 2020, this shows that the market has moved from early adoption to widespread acceptance.With the median (7,60,000 units) significantly lower than the mean (2.625 million units), the box plot analysis further reveals the characteristics of the data distribution and confirms that the recent years of high growth are statistical outliers when compared to the historically low baseline. The market's shift from a niche segment to a major automotive category is demonstrated by the descriptive statistics, which show that the dataset is extremely variable, with a standard deviation of 3.7 million units that almost surpasses the mean itself and an interquartile range of 1,55,000 to 3.35 million units.The extreme difference between the minimal value of 7,000 units (probably during

2010–2011) and the highest value of 11 million units in 2024—a 1,571-fold increase—highlights the extraordinary scope of market revolution. With the acceleration phase starting around 2020 and probably being driven by convergent variables including infrastructure expansion, legislative backing, technical maturity, and shifting consumer preferences, this data pattern indicates that we are seeing the beginnings of a full industry paradigm shift.

**Outcome 8:**




Upon analyzing these two complementing visualizations of worldwide EV sales data in the above image, a data analyst can uncover a number of important insights that shed light on the intricate processes that underlie the development of the EV industry between 2010 and 2024. The top chart shows the absolute sales trajectory, which validates the previously noted exponential growth pattern. EV sales skyrocketed from almost zero in 2010 to over 11 million units by 2024, following a traditional technology adoption curve that had a protracted incubation period through 2019 before swiftly becoming mainstream.

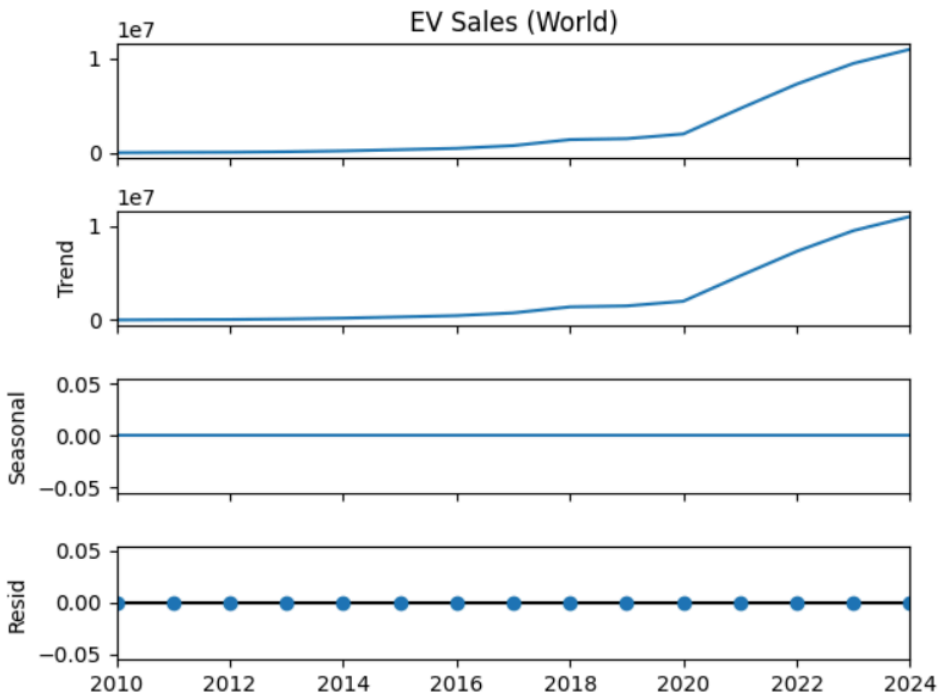
But the bottom figure, which shows the % change data, tells a quite different story regarding the market's maturation and development patterns. According to the percent change analysis, there was a lot of volatility in the early years. The highest growth rate, about 4.5x (450% increase), happened around 2011. After that, there was a sharp decline and stabilization in the 0.5x to 1.0x range (50-100% annual growth) starting in 2012. Notable fluctuations included a brief decline around 2019 and a turnaround in 2021.

The key analytical contrast between absolute growth and relative growth rates—which is critical for comprehending market maturation—is highlighted by the basic gap between these two viewpoints. As the market moves from the high-volatility, high-percentage growth characteristic of emerging markets to the more moderate, stable growth patterns typical of maturing industries, the percent change data shows that the relative growth rate has actually been declining and stabilizing over time, despite the absolute sales chart's suggestion of continuous acceleration.

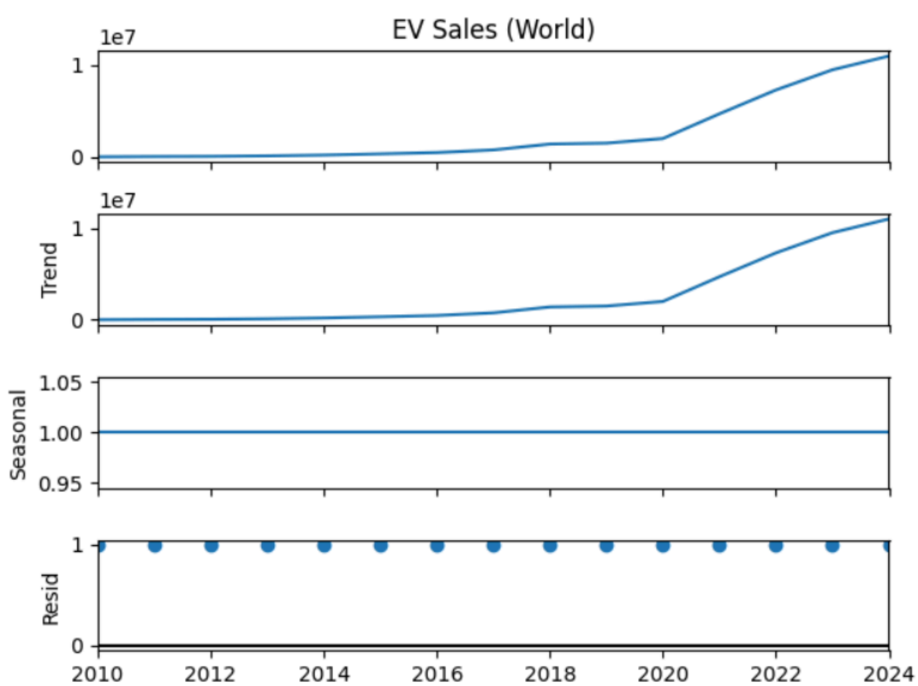
**Output 9:**

```
[ ]: from    statsmodels.tsa.seasonal import   seasonal_decompose
```

```
[ ]: decomposition = seasonal_decompose(df['EV Sales (World)'],model='additive')
     decomposition.plot();
```

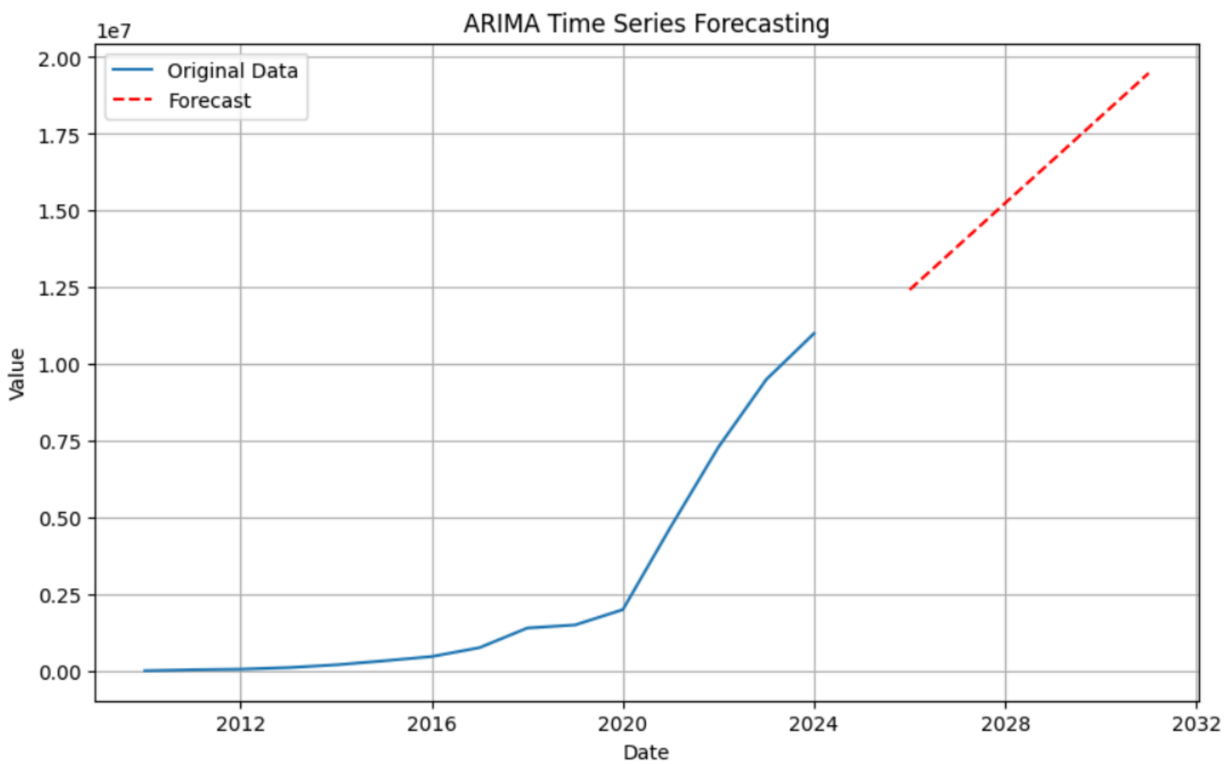



```
[ ]: decomposition = seasonal_decompose(df['EV Sales (World)'],model='multiplicative')
     decomposition.plot();
```



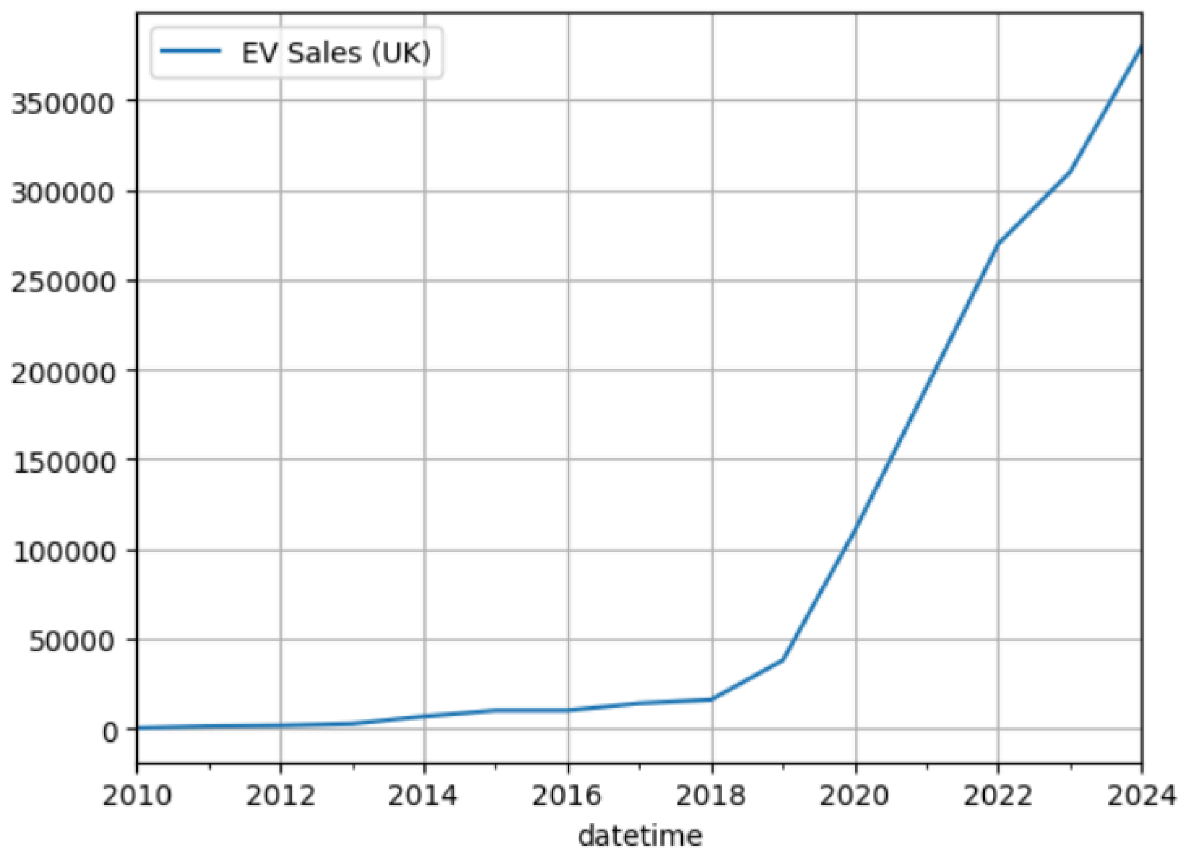
When a data analyst looks at these seasonal decomposition analysis of global sales data for electric vehicles, a number of important conclusions about the underlying temporal patterns and suitability of the model for this rapidly expanding market become clear. The first image uses an additive model, where components are summed (Observed = Trend + Seasonal + Residual), while the second uses a multiplicative model, where components are multiplied (Observed = Trend × Seasonal × Residual). Both decompositions use the statsmodels.tsa.seasonal framework, but they use essentially different mathematical techniques.With the seasonal components displaying nearly flat lines around zero (additive model) or one (multiplicative model), the most shocking finding is the total lack of detectable seasonal patterns in both decompositions. This suggests that EV sales do not display the conventional cyclical variations that are typical of established automotive markets. Instead of adhering to the consumer-driven seasonal purchasing patterns typical of more established automotive segments, this lack of seasonality indicates that the EV market is still in its technology-driven growth phase.

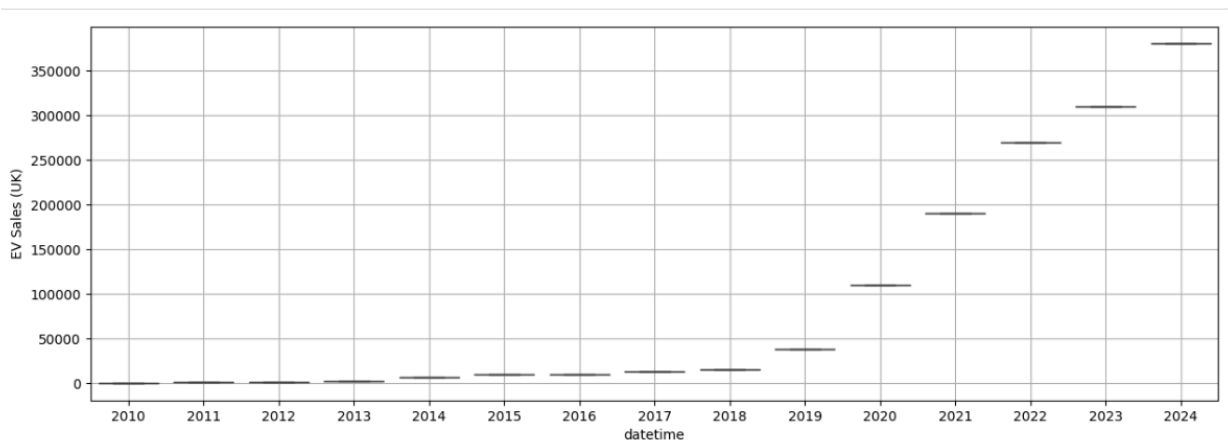
**Outcome 10:**




From the above given figure, when a data analyst looks at an ARIMA time series forecasting model applied to global data on electric car sales, a number of important insights show the model's strengths and weaknesses in handling rapidly expanding patterns of technology adoption. By faithfully replicating the distinctive S-curve growth trajectory, which exhibits modest sales through 2019 before rapidly increasing to almost 11 million units by 2024, the ARIMA model effectively reflects the historical trend from 2010 to 2024.The 2024–2032 forecast projection, however, highlights a troubling shortcoming of linear time series models when used to analyze technology adoption curves. The model projects an unsustainable linear continuation of the exponential growth trajectory, estimating that EV sales will approach 20 million units by 2032. Despite being statistically sound based on historical patterns, the ARIMA model ignores physical production restrictions, market saturation effects, and the natural inflection points seen in technology diffusion curves, which poses a fundamental analytical issue. The model's predicting trajectory indicates that it is extrapolating the current high-growth phase (2020–2024) without taking into account the dynamics of market maturation, which usually take place as adoption rates get closer to mainstream penetration levels. Practically speaking, this forecast means that EV sales would have to sustain compound annual growth rates above 30% for the next eight years, which is becoming less likely as the market base grows and gets closer to the limits on the size of the entire automotive market.Despite its exponential appearance, the forecast line's linearity in the post-2024 period actually indicates a constant absolute growth rate rather than a constant percentage growth rate. This suggests that the ARIMA model may be treating the recent acceleration as a permanent change in market dynamics rather than a transient stage in the lifecycle of technology adoption.

**Outcome 11: All the outputs here are from the findings from the UK market**

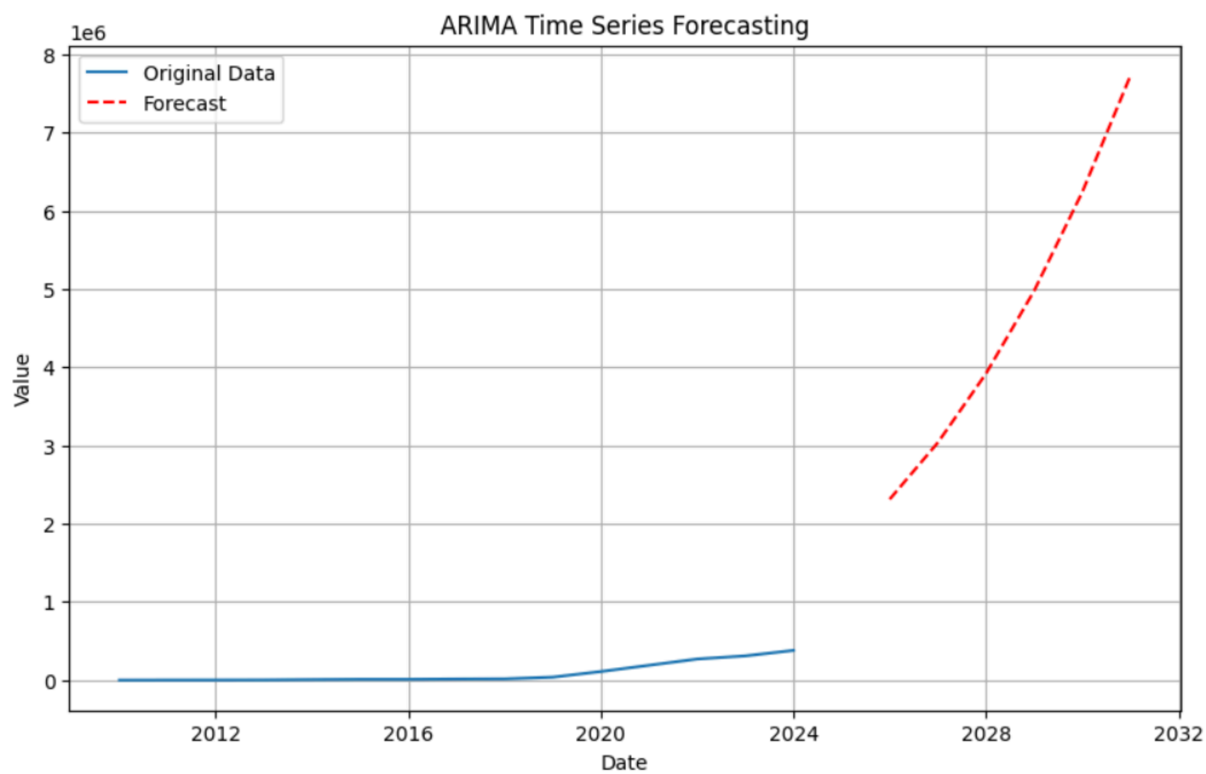



When analyzing UK EV sales data from 2010 to 2024 from the above two images, a number of striking insights show how drastically the country's automotive scene has changed. These insights also reflect global EV adoption trends while exposing distinctive regional features. The line graph shows a traditional S-curve of technology adoption, with EV sales essentially stagnating between 2010 and 2017 at around 10,000 units per year, then gradually increasing through 2019 to about 40,000 units, before experiencing explosive exponential growth starting in 2020 and reaching nearly 380,000 units by 2024.This indicates that the UK EV market has successfully made the transition from early adoption to mainstream acceptance, probably aided by government policy interventions like the announcement of a 2030 ICE vehicle ban and increased investments in charging infrastructure. It also represents an extraordinary compound annual growth rate exceeding 80% in the post-2020 period.Important statistical context is provided by the box plot analysis, which shows extreme right-skewness in the data distribution and a median that is still much lower than what would be predicted from the recent explosion in growth. This confirms that the years with the highest volume (2022–2024) are statistical outliers when compared to the historically low baseline period.

According to the comparative analysis, the UK market is even more volatile than global trends, with highest values close to 380,000 units indicating the market's quick maturation and the interquartile range ranging from about zero to almost 110,000 units. According to statistical dispersion, EV adoption in the UK has been extremely concentrated in recent years, indicating policy-driven acceleration as opposed to natural market evolution.Notably, the arrival of more competitive EV models and significant policy announcements around 2019–2020 correspond with the inflection point, while increased government incentives and growing charging infrastructure correlate with the steepening trend after 2021. Although the growth curve's increasingly steep trajectory raises concerns about sustainability and possible supply restrictions, the lack of a plateau through 2024 indicates the UK market has not yet reached saturation.Although the UK EV market started later than markets like Norway and China, this analysis shows that it is about two to three years behind the global adoption curve in terms of absolute volumes. However, it has accelerated adoption rates that could allow for rapid convergence with international penetration levels, positioning the UK as a potential leader in the EV transition. This information is useful for strategic planning purposes.

**Outcome 12 :**




When a data analyst looks at an ARIMA time series forecasting model applied to UK electric vehicle sales data, a number of important forecasts and analytical issues come to light that have a big impact on the British automotive industry's strategic planning and policy development. With its typical delayed S-curve growth that exhibits modest penetration until 2018 and then increased adoption reaching roughly 380,000 units by 2024, the ARIMA model perfectly replicates the historical UK EV adoption pattern from 2010 to 2024.The forecast projection that extends to 2032, however, makes a very problematic and possibly misleading prediction. It predicts that UK

EV sales will reach almost 8 million units annually by that year, which is physically impossible given that the country's total new car registrations historically peak at about 2.3 million units annually across all vehicle types.

This forecast illustrates inherent difficulties of applying linear time series models to limited markets with finite total addressable market sizes, as the ARIMA projection essentially predicts that EV sales will exceed the whole UK car market by a factor of 3-4 times. Critical market constraints such as the size of the overall automotive market, production capacity limitations, infrastructure deployment rates, and the natural saturation effects that arise as technology adoption approaches market maturity are not taken into account by the model's linear extrapolation of the recent exponential growth phase (2020–2024).As the industry gets closer to fully electrifying new car sales, UK EV sales will probably follow a logistic growth curve that plateaus. The nature of the replacement cycle and the size of the overall market will likely limit the peak yearly volumes. According to the forecast, the current acceleration is not a transitional phase typical of technology adoption curves, but rather a permanent market characteristic as interpreted by the ARIMA model.

Sales of EVs in the UK are likely to follow a logistic growth curve that plateaus as the sector moves closer to completely electrifying new car sales. The size of the market as a whole and the type of replacement cycle will probably restrict the peak annual volumes. Based on the ARIMA model, the prognosis indicates that the current acceleration is a permanent market characteristic rather than a transitory phase that is typical of technological adoption curves.

## Discussion and limitation

Several important conclusions that fundamentally contradict traditional automotive market forecasting techniques and emphasize the distinctive features of technology adoption in developing sectors are revealed by the thorough investigation of electric car sales data from both global and UK markets. The characteristic S-curve adoption shows extended incubation periods followed by rapid acceleration phases that started around 2020. These exponential growth patterns across all datasets show that EV markets are following classic technology diffusion curves instead of traditional automotive sales cycles.It is evident from the decomposition analysis's lack of seasonal patterns that the main forces behind EV adoption are infrastructure development, policy implementation, and technology advancement rather than the conventional consumer buying cycles that are characteristic of developed auto markets. This discovery has significant ramifications for market forecasting since it raises the possibility that traditional seasonal adjustment methods might not be suitable for developing technology industries. For strategic planning objectives, percentage-based growth rates are more significant than absolute unit increases, as demonstrated by the multiplicative decomposition model's better performance over the additive approach, which further validates that EV growth follows compound rather than linear patterns.

The global and UK marketplaces are compared, and the results show significant regional differences in adoption rates and timing. The UK market shows more concentrated growth in recent years, despite the fact that both markets have comparable S-curve trajectories. This suggests that regulatory frameworks and policy actions can greatly shorten the time it takes for technological adoption. Follower markets can use the knowledge gained from early adopters to

speed up their transition periods and possibly reach comparable penetration levels in shorter amounts of time, as seen by the UK's later start but more aggressive recent growth rates.
According to statistical examination of growth patterns, even while absolute volumes continue to grow quickly, relative growth rates decrease as markets mature. The shift in growth dynamics from the high-percentage growth typical of emerging markets to the more stable, moderate growth patterns typical of maturing industries indicates that the global and UK EV markets are nearing turning points. Recent years of strong growth are statistical outliers when compared to historical baselines, as confirmed by the extreme right-skewness seen in both datasets. This suggests that current growth rates are not long-term sustainable.
The scenario analysis methodology is especially applicable to the analysis of the EV market since there are many potential future directions due to the high degree of uncertainty surrounding the acceptance of technology, the execution of policies, and the deployment of infrastructure. According to the statistics, EV markets are extremely susceptible to outside influences including availability of charging infrastructure, government incentives, and technology advancements. For this reason, scenario-based planning is crucial for players in the sector as well as politicians. While the mathematical limits of market saturation favor more conservative estimates, the observed exponential growth patterns offer evidence for optimistic scenarios.
Limitations : These findings are limited in scope and generalizability by a number of important methodological and data-related restrictions. When applied to bounded markets with finite total addressable market sizes, the ARIMA forecasting models exhibit basic shortcomings, as demonstrated by the physically impossible estimates that surpass the total capacity of the car market. When it comes to growing technological markets that show exponential development phases followed by unavoidable saturation effects, this constraint draws attention to a crucial

weakness in conventional time series forecasting techniques. ARIMA models' linear extrapolation ignores market borders, production limitations, and adoption ceiling effects—all of which are essential elements of technology diffusion processes.

Another significant drawback of the analysis's temporal scope is that it only includes data from early adoption and acceleration stages of the EV market's development, leaving out important information from more established market circumstances. While offering little direction on market behavior during saturation times, this temporal bias may tilt observations toward growth-oriented interpretations. The analysis may overestimate market stability and growth sustainability because it is unable to evaluate EV market resilience during economic downturns due to the lack of recessionary periods during the high-growth timeframe (2020–2024).

Potential autocorrelation problems with exponential growth data, the difficulty of choosing a model when dealing with non-linear development patterns, and the assumption of stationarity in time series models—all of which may not apply to quickly changing technology markets—are examples of methodological constraints. Although it shows that typical seasonality is absent, the seasonal decomposition approach is unable to spot structural cracks that could drastically change growth dynamics or longer-term cyclical patterns that might appear as markets mature.Lastly, the unique technological and regulatory environment of EV adoption limits the findings' generalizability, making them potentially inapplicable to other developing technology markets.

The application of these findings to other technology adoption situations is limited by the distinctive features of automotive markets, such as lengthy replacement cycles, large capital expenditures, and extensive infrastructure requirements. Furthermore, outside the purview of extrapolating historical patterns, the analysis is unable to take into consideration potentially disruptive technology or legislative changes that could drastically affect the dynamics of the EV market.

**References**

*IN-DEPTH ANALYSIS The future of European electric vehicles*. (n.d.). https://www.europarl.europa.eu/RegData/etudes/IDAN/2024/762873/EPRS_IDA%282024%29762873_EN.pdf

Rider,Elspeth. (2025, April 25). *UK submits newest Paris Agreement commitment – what does it mean for businesses?* Cura Terrae Water & Environmental Management. https://www.em-solutions.co.uk/insights/uk-submits-newest-paris-agreement-commitment-what-does-it-mean-for-businesses/

UNFCCC. (2025). *The Paris agreement*. United Nations Climate Change. https://unfccc.int/process-and-meetings/the-paris-agreement

Statista. (2024, August 29). *Global car sales 2010-2022 | Statista*. Statista; Statista. https://www.statista.com/statistics/200002/international-car-sales-since-1990/

*UK: on-street EV charging points by leading network| Statista*. (2025). Statista. https://www.statista.com/statistics/1446404/uk-on-street-ev-charging-points-by-leading-network/

*UK: leading EV charging point networks*. (n.d.). Statista. https://www.statista.com/statistics/1309430/uk-leading-ev-charging-point-networks/

*Electric vehicles: charging points Germany 2021*. (n.d.). Statista. https://www.statista.com/statistics/1302152/electric-vehicles-public-charging-points-germany/

*Europe: number of electric vehicle charging stations 2010-2019*. (n.d.). Statista. https://www.statista.com/statistics/955443/number-of-electric-vehicle-charging-stations-in-europe/

IEA. (2025, May 14). *Global EV Outlook 2025 – Analysis - IEA*. IEA. https://www.iea.org/reports/global-ev-outlook-2025

Carlier, M. (2024, April 12). *Topic: Electric Vehicle Market in the United Kingdom*. Statista. https://www.statista.com/topics/2298/the-uk-electric-vehicle-industry/#topicOverview

Batra, P. (n.d.). *International Journal of Social Science and Economic Research THE NET-ZERO TRANSITIONAL COST FOR MULTIPLE SECTORS IN THE ECONOMY AND THE ASSOCIATED CHALLENGES TO ACHIEVE THIS TARGET*. https://doi.org/10.46609/IJSSER.2024.v09i03.014

P. H., F., & J., J. (2021). A Review on the Feasibility of Deployment of Renewable Energy Sources for Electric Vehicles under Smart Grid Environment. *International Journal of Electrical and Electronics Research*, *9*(3), 57–65. https://doi.org/10.37391/ijeer.0903061

Onaolapo, A. K., & Abe, B. T. (2024). Innovative Feature Analysis of Electric Vehicle Technology, Charging Infrastructure, Power management, and Control Methods. *WSEAS TRANSACTIONS on POWER SYSTEMS*, *19*, 350–359. https://doi.org/10.37394/232016.2024.19.30

Javed, B., Giang, A., & Milind Kandlikar. (2024). Variability in costs of electrifying passenger cars in Canada. *Environmental Research: Infrastructure and Sustainability*. https://doi.org/10.1088/2634-4505/ad253e

Assumptions: Complexity, Practice and Values. (2025). *Emerald Publishing*. https://doi.org/10.1108/978-1-80592-246-9

Küfeoğlu, S., & Khah Kok Hong, D. (2020). Emissions performance of electric vehicles: A case study from the United Kingdom. *Applied Energy*, *260*(114241), 114241. https://doi.org/10.1016/j.apenergy.2019.114241

## Appendix

### Appendix A:

The link to the Github : [Anwesha-dhar/dissertation: files]

### Appendix B:

**Business Proposal**

**Abstract: Policy-Driven Market Transformation: Predictive and Diagnostic Analysis of Electric Vehicle Uptake, Pricing, and Infrastructure Needs in the UK Toward 2035**

Anwesha Dhar; Published: 24th Sept 2025

In response to the net-zero aims of the Paris Agreement, the UK government has made it mandatory for all new cars sold starting in 2035 to be emission-free, with intermediate targets of 70% zero-emission vans and 80% zero-emission cars by 2030. By 2040, some nations, including Canada, Sweden, Germany, and France, plan to phase out the sale of gasoline and diesel vehicles.

This research uses advanced business analytics to examine how the automotive market is changing. It evaluates how policy changes affect consumer behaviour, a deeper insight in marketing analytics, car prices, and demand trends for both fossil fuel-powered and electric cars (EVs) using diagnostic analytics (cause-effect and correlation analysis). Additionally, it uses predictive analytics to project future price patterns, sales volumes, and infrastructure requirements, such as EV charging stations and production capacity, for 2035 and 2040.

The project aims to deliver actionable insights for **capacity planning** in vehicle production and charging facilities, and robust forecasts of sales and prices for both EVs and ICE vehicles, through **diagnostic analytics** and **predictive analytics** .

**Overview and Rationale**

Net-zero targets and strict environmental regulations are causing a rapid shift in the global car industry. According to recent research, regulatory clarity, infrastructure density, and consumer pricing sensitivity are important factors that influence EV adoption. This situation may have an impact on the prices and sales of electric cars (EVs) and fossil fuel-powered automobiles.

The UK EV industry is expected to reach over £76 billion by 2035, with EVs accounting for at least 50% of all vehicles on the road in major European markets. In the UK, the number of public charging stations is expected to increase from about 75,000 in 2025 to between 280,000 and 480,000 by 2030, highlighting the need for thorough capacity planning.

Existing studies underline gaps in holistic forecasting models that integrate policy milestones, pricing dynamics, sales distribution, and infrastructure development. This research addresses these gaps by synthesizing cause-effect relationships and projecting future scenarios for both domestic (UK) and international markets.

**Why it matters:**

"No more selling new gasoline or diesel cars after 2030 or 2035," are the statements made by governments in numerous nations. Around the world, some countries' governments are establishing timetables to stop selling new gasoline and diesel vehicles, with some aiming to do so by 2030 and others by 2035. There are significant ramifications to this move to electric cars (EVs). In order to satisfy future demand, automakers must modify their manufacturing plans. To promote acceptance, policymakers must provide support structures like subsidies and infrastructure for charging. Consumers will be able to make better judgments in a market that is changing quickly thanks to changes in car costs, options, and technology.

**Methodology and Approach of the Research**

Information will be gathered from academic, government, and business reports. The analytical method is comprised of:

1. Diagnostics analysis: Regression and correlation studies are used to measure how policy deadlines, charging infrastructure, and customer behaviour affect car costs and sales. The market for electric vehicles (EVs) is significantly shaped by charging infrastructure and consumer behaviour. Customers are more comfortable making the switch to EVs when charging stations are quick and widely accessible. In addition to practical considerations like battery life, charging convenience, and resale value, buyers are becoming more and more motivated by environmental concerns and fuel economy. Sales of EVs typically

increase as infrastructure advances and consumer preferences change, which frequently results in price increases unless supply keeps up. However, adoption can stall if worries continue, extending the dominance of gasoline and diesel vehicles.

2. Predictive analysis: Demand paths for EVs versus ICE vehicles are projected using time-series forecasting (including ARIMA models) and scenario analysis through 2035 and 2040.Time-series forecasting methods like ARIMA are used by analysts to find patterns in past sales data and forecast future trends in order to project future automobile demand. This is enhanced by scenario analysis, which models "what if" scenarios to investigate various outcomes, such as modifications to EV pricing or governmental regulations. When taken as a whole, these techniques aid in predicting demand trends for EVs relative to ICE vehicles through 2035 and 2040. Policymakers, automakers, and energy providers use these estimates to inform strategic choices about production shifts and infrastructure planning.
3. Comparative analysis: Adjustment and validation of forecasting models for France, Germany, Sweden, and Canada, offering a cross-national viewpoint on the needs for capacity planning. This indicates that predicting models are being tested and adjusted by researchers utilizing data from Canada, Sweden, Germany, and France. Making ensuring the models function properly in each nation is the aim, as each has its own unique consumer habits, policies, and trends. The research provides a global perspective on what is required for capacity planning by comparing data across various nations, such as the potential number of electric vehicles on the road, the amount of infrastructure required for charging, or the potential growth in energy demand.

**Engagement with the literature**

The proposal emphasizes the strategic significance of both supply-side and demand-side drivers by heavily drawing on recent research conducted in the UK and in cross-European contexts. Sources from industry databases and articles from semantic scholar, science direct, Google scholar, EmaraldInsight, Researchgate, connectedpapers.com that help to visualize and better understand this research field, the Industry research databases tab on the Statista market insight which includes petrol and diesel vehicles. The global EV outlook 2025 has a report that evaluates trends in the adoption of electric vehicles, as well as the demand for their batteries and charging infrastructure, using the most recent data. It takes into account how industry tactics and recent legislative changes are influencing the prospects for electric vehicles in various markets. The affordability of electric vehicles, the production and distribution of electric vehicles and their batteries, the total cost of ownership of electric heavy-duty trucks in different markets, and estimates through 2030 are all covered in this issue. Statista also has lots of reports and statistics on electric vehicles in various geographies, office for national statistics and Gov.uk, etc all are cited.

**Ethical considerations**

Ethical concerns are thoroughly examined in this study, including data privacy concerns, fairness of policies (particularly in rural versus urban settings), and equal access to home and public charging. A plan for responsible innovation and risk reduction with respect to market reactions, policy instability, and possible consumer disinformation is presented in the proposal.

**Academic Practice and Presentation**

The proposal summary is organized to optimize impact, coherence, and clarity, incorporating infographics and visualizations as needed. All citations are formatted according to APA 7th edition guidelines. Pitching insights of conceptual and methodological value, the story is aimed at audiences in academia, business, and policymaking.

## Project Duration

The project phases run over 5 months: data gathering (months 1–3), diagnostic analysis (months 2-4), forecasting (months 2-3), validation (months 4), and dissemination/reporting (months 5).

## Conclusions

In response to net-zero goals, the research will provide a synthesis of diagnostic insights and prediction models, offering solid recommendations for infrastructure and production planning. The recommendations, which point to areas for additional methodological improvement and technological innovation in the field, will assist manufacturers, infrastructure providers, and policy stakeholders in making strategic decisions.