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Abstract

This dissertation develops a predictive framework to evaluate the performance of BYD dealerships across Europe, focusing on key metrics like sales volume, customer satisfaction (measured by Net Promoter Score, NPS), and operational efficiency. Utilizing five machine learning models—Gradient Boosting Machines (GBM), Random Forest, Linear Regression, Support Vector Machines (SVM), and AutoRegressive Integrated Moving Average (ARIMA)—the study examines how internal factors such as the number of salespeople, number of outlets, and service completion time, along with external localisation factors like regional economic conditions, regulatory environments, and demographic characteristics, influence dealership performance. By integrating synthetic data where real-world data are unavailable, the study enhances the predictive capabilities of the models. Additionally, the research employs Data Envelopment Analysis (DEA) to evaluate dealership efficiency and identify critical performance drivers. Emphasizing the importance of regional differences and external factors, the dissertation provides insights into optimizing dealership operations. Despite its contributions, the study acknowledges limitations, particularly regarding the use of synthetic data and its geographical focus on Europe. Future research could extend the analysis to other regions and include a broader set of variables for a more comprehensive understanding of dealership performance. Ultimately, this dissertation offers valuable insights for both the academic community and BYD's strategic efforts to improve its operations in the competitive European electric vehicle market.

Chapter 1: Introduction

The global automotive industry is at a pivotal point, driven by technological advancements, shifting consumer preferences, and stringent environmental regulations. In 2021, electric vehicle (EV) sales surged to over 6.6 million, representing nearly 9% of the global car market (International Energy Agency, 2022). Europe plays a crucial role in this growth, with a 65% year-on-year increase in EV sales in 2020, spurred by government incentives and rising environmental awareness (European Automobile Manufacturers Association, 2021). BYD (Build Your Dreams), a leading Chinese EV manufacturer, is expanding rapidly in Europe, but as competition intensifies, optimising dealership performance is essential for sustaining growth and establishing a strong market presence.

Dealership performance significantly influences a company's market success, directly impacting sales, customer satisfaction, and brand loyalty (Homburg et al., 2011). Research indicates that factors such as staff efficiency, service quality, and local market conditions play a critical role in dealership performance (Kumar and Shah, 2004). Additionally, localisation factors, including regional economic growth and regulatory environments, profoundly affect business operations, particularly in the automotive sector, where regulations vary widely (Porter, 2003; Jacobides et al., 2006). However, the specific drivers of EV dealership performance, especially in Europe's diverse market, remain underexplored. This research aims to fill this gap by analysing BYD's dealership network across Europe, considering the complexities of economic, regulatory, and cultural conditions.

Guided by the research question "*What are the key factors influencing the performance of BYD dealerships in Europe, and how can predictive models and DEA optimise sales volume, customer satisfaction, and operational efficiency?",* this dissertation sets out the following objectives:

1. Assess BYD dealership efficiency using Data Envelopment Analysis (DEA).
2. Develop predictive models to forecast performance metrics, including Monthly Sales Volume per Dealer, Net Promoter Score (NPS), and DEA Efficiency.
3. Identify key internal and external factors impacting dealership performance.
4. Provide strategic recommendations to optimise operations and improve customer satisfaction.

This research adopts a multi-method approach, integrating quantitative analysis with predictive modelling to assess the impact of internal dealership factors (e.g., staffing levels, service completion time) and external localisation factors (e.g., population density, economic growth) on performance. To address potential data limitations, the study also incorporates synthetic data, enhancing prediction accuracy, particularly for variables with sparse data.

The dissertation is structured into five chapters. Chapter 2 reviews existing literature on dealership performance and localisation factors. Chapter 3 details the research design, data sources, and analytical methods, including the use of machine learning models and synthetic data. Chapter 4 presents the findings, highlighting the models' predictive accuracy and the influence of various factors on performance. Chapter 5 summarises key findings, discusses limitations, and suggests future research directions.

This research is significant for its practical application to BYD’s strategic decision-making in Europe, offering a data-driven framework to optimise dealership operations. It also contributes to academic literature on dealership performance, particularly in the EV market and within the context of localisation factors. As the automotive industry evolves, understanding dealership dynamics remains crucial for maintaining a competitive edge in diverse markets like Europe.

In addressing BYD's dealership network in Europe, this study provides a robust framework for evaluating and optimising performance, offering insights that are expected to inform BYD’s strategies and contribute to the broader understanding of dealership performance in the expanding EV market.

Chapter 2: Literature Review

2.1. Introduction to Dealership Performance and Localisation

The increasing complexity of the global automotive industry has prompted a growing body of research focused on optimizing dealership performance and adapting to localisation challenges. Dealership performance optimization, encompassing improvements in sales volume, customer satisfaction, and operational efficiency, has been widely explored in the literature as a critical factor for maintaining competitiveness (Hansen and Mowen, 2005; Kumar et al., 2018). However, as companies expand into diverse markets, the importance of localisation—adapting business strategies to fit the cultural, economic, and regulatory environments of specific regions—has gained substantial scholarly attention (Ghemawat, 2007; Rugman and Verbeke, 2007).

Recent studies have highlighted the intersection of these two areas, suggesting that the integration of performance optimization and localisation strategies can significantly enhance the effectiveness of dealership networks (Palmer et al., 2018; Sirmon et al., 2011). Despite this, gaps remain in understanding how these strategies can be effectively implemented across varied regional contexts, particularly in markets as complex as the UK and Europe. This literature review aims to synthesize current research on these topics, with a particular focus on the application of predictive analytics and Data Envelopment Analysis (DEA) in enhancing dealership performance and localisation efforts. By examining existing studies, this review will identify key findings, gaps, and opportunities for further research, providing a foundation for the strategic recommendations that will follow in later chapters of this dissertation.

2.2. Theoretical Foundations of Predictive Modelling, DEA, and Localisation

Predictive modelling, Data Envelopment Analysis (DEA), and localisation theories are foundational methodologies for analysing and optimizing dealership performance. Predictive modelling encompasses a wide array of statistical techniques and machine learning algorithms designed to analyse historical and real-time data, allowing businesses to forecast future trends. According to Bertsimas, Kallus, and Weinstein (2016), the evolution of predictive analytics has been largely driven by advancements in computational power and data availability, enabling more accurate and robust predictions. Early models like regression analysis and time series forecasting laid the groundwork for modern approaches, which now include neural networks and ensemble methods (Makridakis, Wheelwright, and Hyndman, 1998; Goodfellow, Bengio, and Courville, 2016). These newer models are particularly valuable in industries with complex data environments, such as the automotive sector, where predicting sales trends, customer behaviours, and operational challenges is key to strategic success.

Data Envelopment Analysis (DEA), as introduced by Charnes, Cooper, and Rhodes (1978), is a non-parametric technique that evaluates the efficiency of decision-making units (DMUs) by comparing multiple inputs and outputs. This method has been widely applied across various industries, including the automotive sector, to assess the relative efficiency of dealerships, manufacturing plants, and service centres (Cook and Seiford, 2009). DEA provides a framework for benchmarking performance, identifying best practices, and guiding strategic improvements by highlighting inefficiencies. Studies by Lovell and Pastor (1999) and Zhu (2014) have further expanded on the methodology's applicability, showing how DEA can inform resource allocation decisions and enhance operational efficiency in competitive markets.

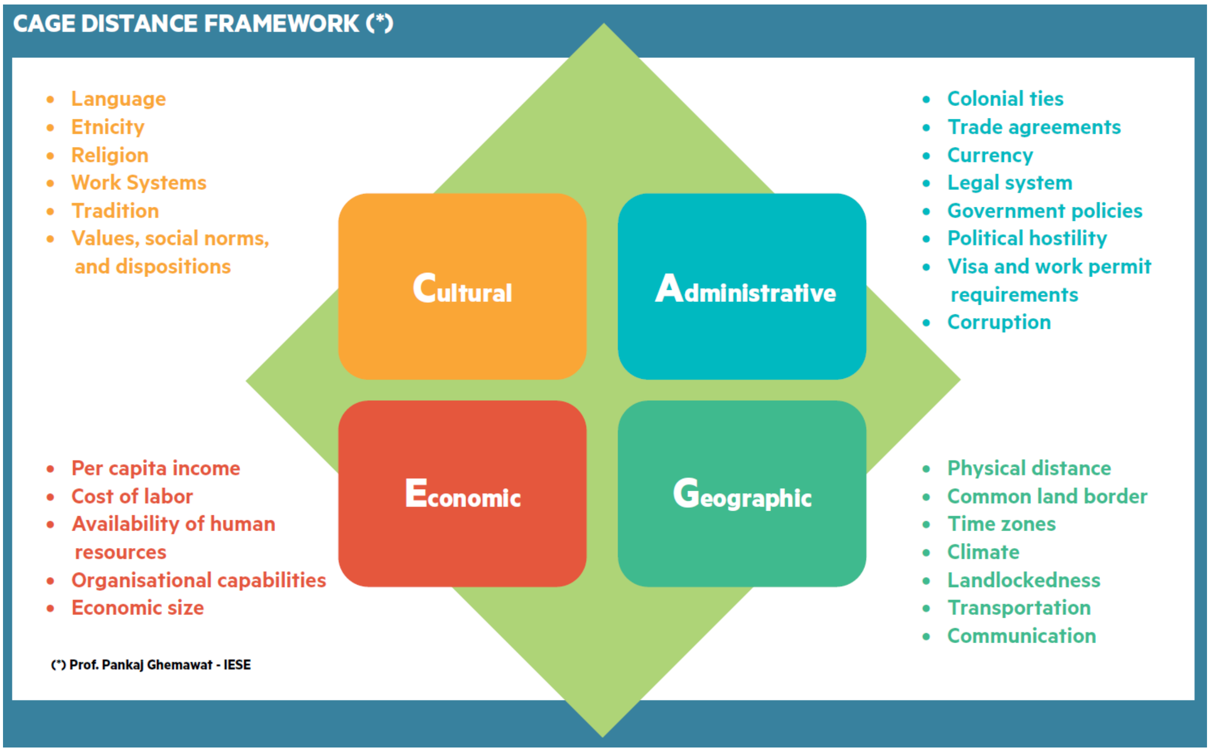

Figure 1. CAGE Framework (Saville et al., 2021, p. [20])

Localisation theories are equally critical for understanding how regional differences impact dealership performance. Ghemawat's (2007) CAGE framework is widely cited for its utility in analysing the cultural, administrative, geographic, and economic distances between markets, providing insights into how companies can tailor their strategies to fit local conditions (Rugman and Verbeke, 2007). Additionally, Hofstede's (1980) cultural dimensions theory underscores the importance of understanding cultural variations in consumer behaviour, which can significantly influence dealership operations and customer relations in diverse markets. These theoretical perspectives collectively inform the strategies that businesses, particularly those operating across multiple regions, can employ to optimize their operations while effectively responding to localized challenges.

2.3. Applications of Predictive Analytics in the Automotive Industry

The automotive industry faces numerous challenges, including fluctuating consumer demand, varying regional economic conditions, and rising operational costs (KPMG, 2023; Arkestro, 2023). These complexities necessitate the use of advanced analytical tools to make informed decisions about sales forecasting, customer satisfaction, and operational efficiency (Rožanec et al., 2021). Dealerships, in particular, must navigate these evolving market dynamics to maintain competitiveness. Addressing these challenges requires the application of predictive analytics, which offers various models tailored to different aspects of dealership operations (Arkestro, 2023).

Time series forecasting, for instance, can help dealerships anticipate future sales volumes. ARIMA (AutoRegressive Integrated Moving Average) models are widely used for this purpose due to their effectiveness in handling temporal dependencies. However, as dealerships encounter more intricate market conditions, ARIMA models may require supplementation with more sophisticated techniques that can account for non-linear relationships and external factors (Hyndman and Athanasopoulos, 2018).

When examining relationships between variables, Linear Regression is often the first choice due to its simplicity and interpretability. It is commonly used to predict outcomes such as sales volume based on inputs like advertising expenditure. Nevertheless, its reliance on linear assumptions can limit its effectiveness in more complex scenarios (Bartlett et al., 2019). In such cases, models like Support Vector Machines (SVM) offer a viable alternative, particularly when dealing with high-dimensional data and non-linear relationships, such as those encountered in customer behaviour analysis (Valkenborg et al., 2023).

Customer satisfaction is another critical area where predictive analytics can provide valuable insights. Sentiment analysis techniques, for example, can be used to analyse customer feedback and reviews. While Linear Regression models can identify factors influencing customer satisfaction, SVM can classify feedback into categories—positive, negative, or neutral—offering a more nuanced understanding of customer sentiment (Liu, 2012; Anderson et al., 2017).

Operational efficiency is another domain where dealerships face significant challenges. They must optimise service times, manage inventory effectively, and handle fluctuating customer traffic. In this context, ensemble methods like Random Forest and Gradient Boosting Machines (GBM) are powerful tools. These models can analyse large datasets with complex interactions, helping dealerships identify inefficiencies and make data-driven improvements to enhance overall efficiency (Breiman, 2001; Friedman, 2001).

In the context of BYD's dealership network in the UK and Europe, these predictive models present multiple pathways for improving key performance indicators such as sales volume and customer satisfaction. By integrating these models with Data Envelopment Analysis (DEA), BYD can assess dealership efficiency, pinpoint areas for improvement, and tailor strategies to specific challenges. The choice of model should be guided by the particular issues faced by each dealership, with careful consideration of the trade-offs between model complexity, interpretability, and accuracy (Ratner et al., 2023; Shaposhnikov et al., 2023; Li et al., 2020).

2.4. The Role of DEA in Dealership Efficiency Evaluation

Evaluating the efficiency of automotive dealerships presents significant challenges, especially in diverse and competitive markets like Europe. Dealerships vary in size, resource allocation, and market conditions, making it difficult to compare performance and determine which operations are truly efficient (Deshmukh et al., 2023). Traditional evaluation methods may fall short in capturing the multi-dimensional aspects of dealership performance, such as sales volume, customer satisfaction, and service efficiency (Ciborra and Schneider, 2023). Identifying inefficiencies, particularly in areas like resource utilization and output generation, is crucial for optimizing operations (Vargas et al., 2020). Dealerships often face the challenge of benchmarking their performance against industry best practices to understand how they can improve and stay competitive.

Data Envelopment Analysis (DEA) offers a solution to these challenges by providing a more comprehensive approach to evaluating dealership efficiency. DEA compares multiple inputs and outputs to construct an efficiency frontier, highlighting which dealerships are utilizing their resources most effectively (Charnes, Cooper, and Rhodes, 1978). Those on the efficiency frontier are deemed efficient, while others have opportunities for improvement. In addition to measuring efficiency, DEA facilitates operational benchmarking by identifying practices that lead to superior outcomes. This is particularly valuable for companies like BYD operating across various European regions, where economic conditions and consumer behaviours differ. By applying DEA, BYD can tailor its strategies to local contexts, ensuring each dealership operates at its full potential (Cook and Seiford, 2009).

2.5. Integration of Predictive Modelling and DEA for Strategic Decision-Making

Automotive dealerships face a range of challenges when it comes to strategic decision-making, particularly in balancing operational efficiency with future performance forecasting. The fluctuating nature of market conditions, coupled with regional economic disparities and evolving consumer behaviours, makes it difficult for dealerships to optimise resource allocation effectively (Shulze et al., 2015). While traditional methods provide a foundation for evaluating performance, they often lack the ability to capture the dynamic interactions between various factors that influence dealership success (Higueras-Castillo et al., 2020). This limitation can lead to decisions that do not fully consider the broader complexities of dealership operations, potentially hindering competitiveness and growth (Marković et al., 2015).

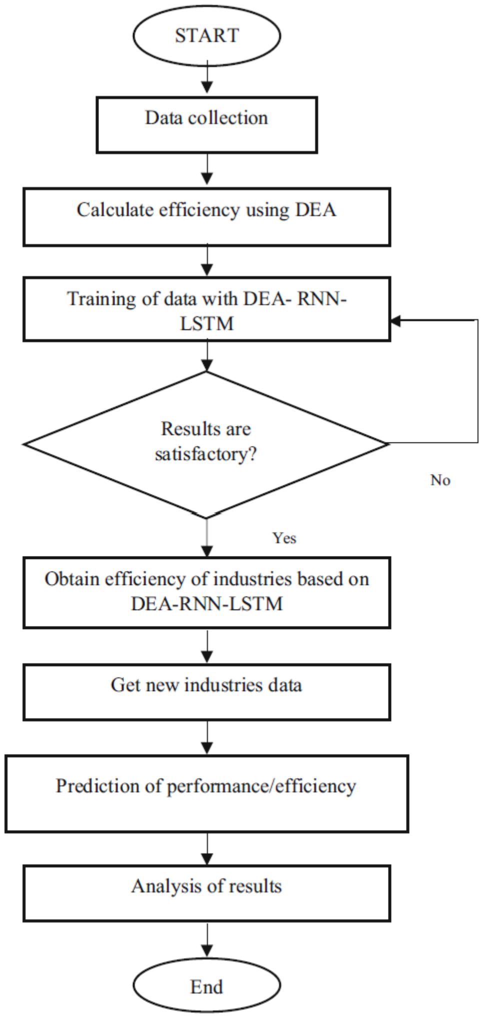

Figure 2. The integrated framework for ranking and prediction by DEA-DL (Jauhar et al., 2022)

To address these challenges, integrating predictive modelling with Data Envelopment Analysis (DEA) has emerged as a promising solution. This combination provides a comprehensive framework for both forecasting future performance and evaluating current efficiency. Predictive models, such as ARIMA and Random Forest, have been shown to be effective in predicting key dealership metrics like sales volumes and customer satisfaction (Chen et al., 2017; Zhu, 2014). When these predictions are used within DEA models, dealerships can assess how efficiently they are utilising their resources, enabling managers to pinpoint inefficiencies and make data-driven adjustments (Wang et al., 2018). This integrated approach is particularly valuable in markets with significant regional variations, such as the UK and Europe, where incorporating local economic conditions and consumer preferences into predictive models can help tailor strategies to specific market challenges (Cooper et al., 2011). By combining the strengths of predictive modelling and DEA, dealerships can make strategic adjustments that optimise resource allocation and improve overall performance.

2.6. Investigating Key Drivers in Predictive Analytics: A Review of Variable Importance and Sensitivity Analysis

The use of Variable Importance and Sensitivity Analysis in predictive analytics has become increasingly prominent in recent years, particularly in the automotive industry, where understanding the factors that drive performance is crucial. Studies by Breiman (2001) and Friedman (2001) have laid the groundwork for using methods like Random Forest and Gradient Boosting Machines (GBM) to assess the contribution of individual variables in predictive models. These methods have been widely adopted because they effectively handle complex, non-linear relationships and large datasets, making them suitable for identifying key performance drivers in industries with multifaceted operations, such as automotive dealerships.

Subsequent research has built upon these foundational studies, exploring how Variable Importance analysis can be applied specifically within the automotive context. For instance, Li et al. (2020) demonstrated that by focusing on critical variables, such as customer service quality and regional economic indicators, predictive models can significantly improve the accuracy of sales forecasts and customer satisfaction predictions. Other researchers, like García-Madariaga et al. (2017), have emphasized the importance of using Variable Importance to streamline operations by identifying the most impactful factors that dealerships should prioritize.

Sensitivity Analysis complements Variable Importance by providing a more nuanced understanding of how changes in key variables affect outcomes. This approach has been championed in the work of Saltelli et al. (2008), who emphasized its value in enhancing the robustness of predictive models. In the automotive sector, Sarıgöl and Katipoğlu (2023) have applied Sensitivity Analysis to examine how incremental changes in variables such as service times and the number of salespeople influence dealership performance. Their findings suggest that Sensitivity Analysis is not only crucial for risk management but also for optimizing resource allocation in a way that aligns with local market conditions.

The integration of these techniques with Data Envelopment Analysis (DEA) has also been explored in recent studies. Zhang et al. (2022) have highlighted how combining Variable Importance and Sensitivity Analysis with DEA provides a more comprehensive framework for evaluating dealership efficiency. This approach allows for a deeper understanding of the factors that drive both efficiency and performance, particularly in complex and dynamic markets like the automotive industry. Valkenborg et al. (2023) further emphasized that integrating these methods helps dealerships optimize resource allocation and improve overall operational efficiency, demonstrating the continued relevance of these analytical techniques in addressing contemporary challenges in dealership management.

2.7. Localisation Challenges for BYD in the UK and Europe

Localisation presents significant challenges for BYD's dealership network in the UK and Europe due to the diverse cultural, regulatory, and operational environments. Cultural differences across European countries, as explained by Hofstede's cultural dimensions theory, can complicate the standardisation of marketing strategies and customer engagement. For instance, varying consumer preferences and behaviours across countries require BYD to adapt its approach to meet the expectations of local markets (Hofstede, 1980). This cultural diversity introduces complexities in brand positioning and product offerings, making it difficult to create a unified strategy that resonates with all consumers.

In addition to cultural challenges, regulatory differences across Europe further complicate BYD’s localisation efforts. Compliance with a range of regional regulations, such as the European Union's emissions standards and data privacy laws (e.g., GDPR), is critical to avoid legal pitfalls and operational disruptions (European Commission, 2020). These regulations vary significantly across countries, demanding that BYD tailor its operations and adapt quickly to new legal requirements. The complexities of navigating different regulatory environments can strain resources and delay market entry, presenting substantial risks to BYD’s expansion strategy.

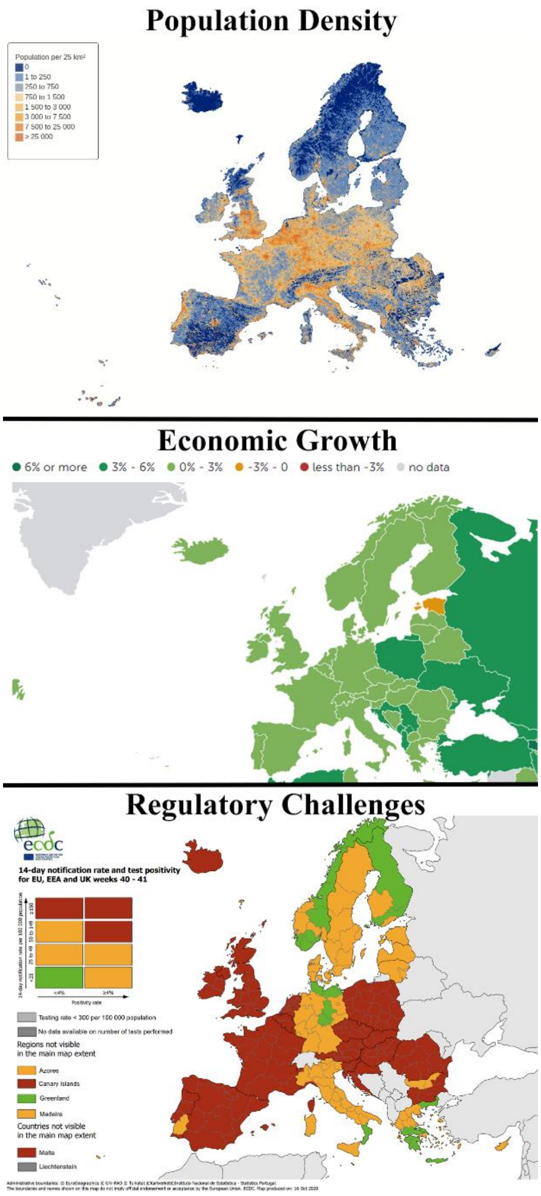

Figure 3. Europe Population Density, Economic Growth, and Regulatory Challenges (Eurostat, 2022; IMF, 2022; ECDC, 2020)

Operational differences, including infrastructure quality, logistics networks, and regional economic conditions, pose further challenges. In countries with advanced infrastructure like Germany, dealerships can benefit from faster delivery times and lower costs, whereas less developed regions, such as certain Eastern European countries, face higher operational costs and delays (Rodrigue et al., 2017). Additionally, regional economic factors such as population density and growth rates significantly influence dealership performance. Densely populated areas may offer greater customer volumes but also heightened competition, while less populated regions struggle with demand despite lower costs (Kotabe and Helsen, 2014). Understanding and addressing these diverse operational challenges is crucial for BYD's success in the European market.

2.8. Final Thoughts and Directions for Dissertation

Current research in predictive modelling and Data Envelopment Analysis (DEA) for dealership performance primarily centres on optimizing operational efficiency and forecasting key metrics like sales and resource utilization. However, many of these studies overlook the critical impact of localisation factors, particularly in diverse markets such as the UK and Europe. This dissertation seeks to address this gap by integrating localisation challenges into the existing frameworks, offering a more nuanced approach that accounts for regional variations such as population density and economic growth.

By combining predictive modelling, DEA, and localisation strategies, this research aims to provide actionable insights for optimizing dealership operations and enhancing customer satisfaction across different European regions. This approach not only builds upon existing research but also extends it by emphasizing the importance of adapting strategies to meet the specific needs of local markets. As the dissertation advances, the insights from this literature review will guide the strategic recommendations for BYD’s dealership network, ensuring that the company can effectively navigate the complexities of operating in diverse European markets.

Chapter 3: Methodology

This chapter outlines the methodological framework used to analyse dealership efficiency and the impact of localisation factors on key performance metrics. The study is guided by the primary research question: *What are the key factors influencing the performance of BYD dealerships in Europe, and how can predictive models and DEA optimize sales volume, customer satisfaction, and operational efficiency?*

To address this research question, the following objectives are established:

1. Assess BYD dealership efficiency using Data Envelopment Analysis (DEA).
2. Develop predictive models to forecast performance metrics, including Monthly Sales Volume per Dealer, Net Promoter Score (NPS), and DEA Efficiency.
3. Identify key internal and external factors impacting dealership performance.
4. Provide strategic recommendations to optimise operations and improve customer satisfaction.

The study integrates traditional statistical techniques with modern machine learning approaches. RStudio (version 2024.04.2 Build 764) is employed for data processing, ensuring reproducibility and facilitating effective data manipulation and modelling. This combination enables a comprehensive analysis of dealership performance and provides insights to guide strategic decisions (Zhang et al., 2022).

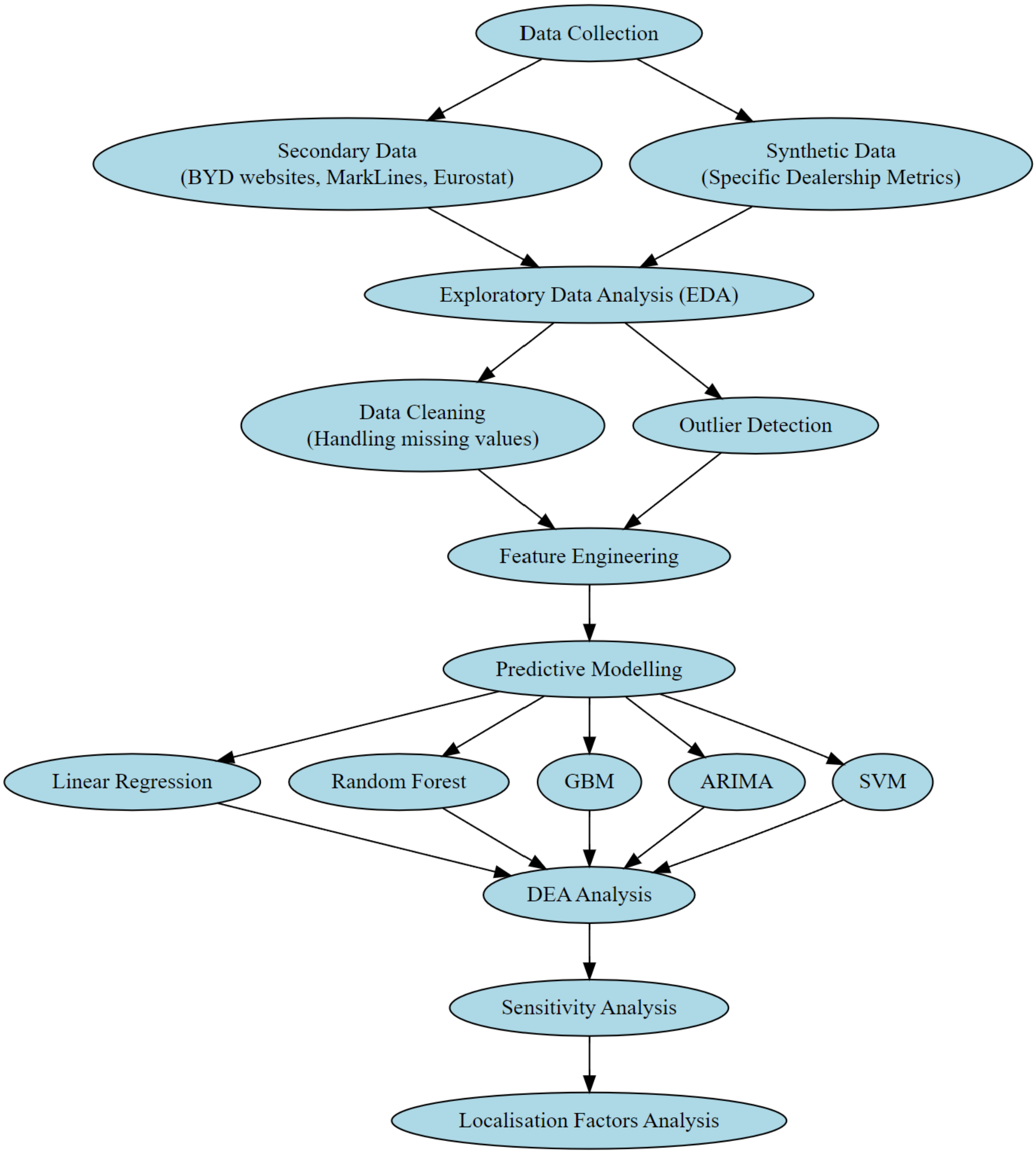

Figure 4. Summary of the Methodology

3.1. Data Collection

The dataset for this study integrates secondary data from authoritative sources and synthetic data to model dealership performance metrics. Comprising 2,197 observations from May 2023 to May 2024 across European dealerships, the dataset includes the following variables:

1. *Dealership_Name, Country, Region, Number_of_Outlets:* Information about dealership names, locations, and outlets is sourced from BYD's official websites. These variables

are vital for understanding the geographical distribution and scale of BYD’s network across Europe.

2. *Monthly_Sales_Volume_per_Country:* Sales volume data, sourced from MarkLines, provides monthly sales figures for various markets. This variable is essential for analysing sales trends and dealership performance over time, covering 2,197 records.

3. *Regional_Population_Density:* Population density figures, obtained from national and European statistical bodies like the UK Office for National Statistics and Eurostat, measure the number of people per square kilometer. This variable helps assess how densely populated areas influence dealership performance and market reach.

4. *Local_Economic_Growth:* Economic growth indicators, including GDP growth, are derived from reports such as those from the UK Office for National Statistics and Eurostat. Expressed as a percentage change, this variable captures the broader economic environment affecting dealership performance.

5. *Cultural_Difference_Score:* Sourced from the World Population Review, this score measures cultural diversity on a scale from 0 to 1, with higher values indicating greater diversity. It provides insights into how regional differences affect consumer behaviour and dealership success.

6. *Regulatory_Environment_Score:* Scores reflecting business conditions, measured on a 0-100 scale, are obtained from the World Bank’s Doing Business reports. This variable assesses the regulatory challenges and advantages impacting dealership operations.

7. *Monthly_Sales_Volume_per_Dealer:* Generated synthetically by proportionally distributing total sales volume across dealerships based on the number of outlets in each region, this variable reflects dealership capacity and performance.

8. *Number_of_Salespeople:* Estimated using a model that scales with the number of outlets and sales volume, this variable is synthetically generated by assuming a base of two salespeople per outlet, adjusted for specific dealership sales volume.

9. *Service_Completion_Time:* Modelled using a Weibull distribution to reflect varying service times across dealerships, this variable is essential for analysing the relationship between service efficiency and customer satisfaction.

10. *NPS_Score:* The Net Promoter Score (NPS) is synthetically generated, considering factors like service completion time, economic growth, cultural diversity, and regulatory

environment. The NPS is adjusted to reflect a realistic range of customer satisfaction levels.

3.2. Exploratory Data Analysis and Pre-Analysis

Variables	Missing Values
Dealership_Name	0
Country	0
Region	0
Number_of_Outlets	0
Year	0
Month	0
Monthly_Sales_Volume_per_Country	3
Regional_Population_Density	0
Local_Economic_Growth	0
Cultural_Difference_Score	0
Regulatory_Environment_Score	0

Table 1. Missing Values

The Exploratory Data Analysis (EDA) process ensures data quality and relevance, forming the foundation for subsequent analysis. Initially, data cleaning trims whitespace from column names, ensuring consistency and preventing errors. The dataset is then examined for missing values, with mean imputation applied to maintain distribution (Maheswari et al., 2019). For example, *Monthly_Sales_Volume_per_Country* has three missing values, representing less than 0.05% of the data, which are filled using mean imputation (Table 1).

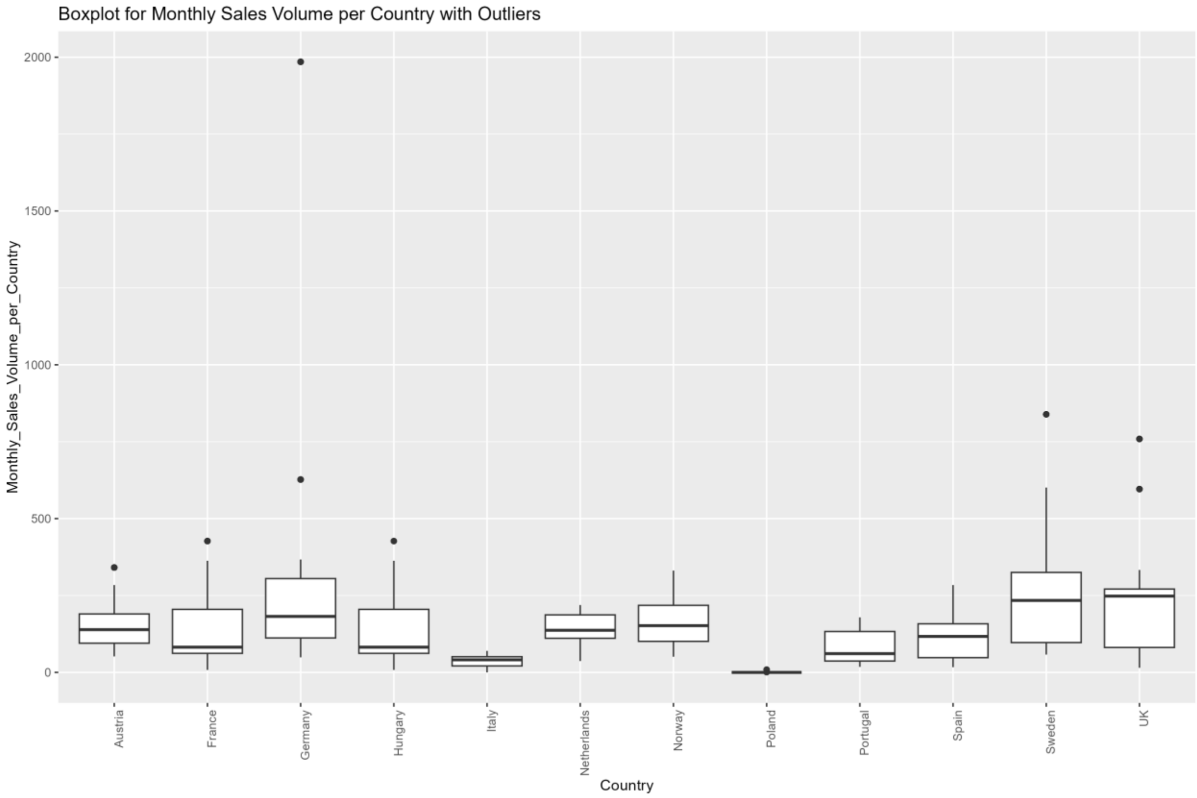

Figure 5. Boxplot for Monthly Sales Volume per Country

After addressing missing values, the focus shifts to identifying outliers in *Monthly_Sales_Volume_per_Country*. Significant outliers, particularly in Germany, Sweden, and the UK, reveal much higher sales volumes compared to other countries. Germany shows outliers exceeding 2,000 units, while Sweden and the UK have outliers between 500 and 1,000 units, as illustrated in Figure 5. These outliers are retained as they reflect real-world performance variations essential for comprehensive analysis (Dastjerdy et al., 2023).

Due to challenges in obtaining certain data from BYD, synthetic data generation is incorporated. Synthetic data are created for variables like *Monthly_Sales_Volume_per_Dealer*, *Number_of_Salespeople*, *Service_Completion_Time*, and *NPS_Score*. Dealer-level sales volumes are derived from country-level data and adjusted based on the number of outlets. This synthetic data is validated against known distributions and real-world scenarios, ensuring robustness for analysis (D'Amico et al., 2023).

With the dataset enriched, pre-analysis methods are employed to uncover preliminary insights into dealership performance and localisation factors. Trend analysis examines temporal changes in variables like *Monthly_Sales_Volume_per_Country* and *NPS_Score*, identifying patterns such as seasonal fluctuations (Parray et al., 2020). Movement analysis tracks changes in metrics like *Service_Completion_Time* and *Number_of_Salespeople*, using scatter plots and smoothing lines to highlight trends (Starr and Goldfarb, 2020). Comparison plots contrast *Average_Monthly_Sales_Volume_per_Dealer* across regions and aggregate *NPS_Scores* across dealerships, highlighting performance disparities (Subba and Das, 2023).

The final step in EDA is efficiency analysis, conducted using Data Envelopment Analysis (DEA) to assess dealership efficiency. The DEA model uses inputs like *Number_of_Salespeople*, *Number_of_Outlets*, *Local_Economic_Growth*, and *Service_Completion_Time*, with outputs like *Monthly_Sales_Volume_per_Dealer*, *NPS_Score*, and *Monthly_Sales_Volume_per_Country*. By normalising these variables, the DEA model produces efficiency scores, providing benchmarks for evaluating dealership performance (Chitnis and Mishra, 2019).

In summary, EDA and pre-analysis establish a strong, enriched dataset, ready for comprehensive dealership performance evaluation.

3.3. Predictive Modelling

Building on the foundational steps of data preparation and exploratory analysis, the predictive modelling is conducted to accurately forecast key dealership performance metrics in this research: *Monthly_Sales_Volume_per_Dealer*, *NPS_Score*, and *DEA_Efficiency*, which are essential for understanding and improving dealership operations. The chosen modelling approaches—Linear Regression, Random Forest, Support Vector Machines (SVM), Gradient Boosting Machines (GBM), and ARIMA—are selected based on their ability to handle diverse data patterns and complexities (Kuhn and Johnson, 2013; Kontopoulou et al., 2023). This section details the methodology behind feature engineering, model training, and evaluation, ensuring that the predictions are both accurate and aligned with the objectives of analysing dealership efficiency and performance across various contexts.

3.3.1. Predictive Modelling Preparation

The modelling process begins with feature engineering to improve predictive capabilities. New features, such as *Interaction_Term* (the product of *Number_of_Salespeople* and *Number_of_Outlets*) and *Polynomial_Term* (the square of *Number_of_Salespeople*), are generated (Hollmann et al., 2023). These features enhance the models' ability to capture complex relationships, especially for models assuming linear relationships (Maulud and Abdulazeez, 2020). The dataset is then split into training (80%) and testing (20%) subsets, with 1,758 observations for training and 439 for testing across the target variables: sales volume, NPS, and DEA efficiency. This partitioning ensures models are evaluated on unseen data, preventing overfitting and allowing for a fair comparison of their predictive performance (Vehtari et al., 2015).

3.3.2. Linear Regression

Linear Regression is initially implemented for its simplicity and interpretability (Bartlett et al., 2019). Feature selection is performed using the information gain criterion, which reduces entropy for the target variable, ensuring only the most relevant predictors are included (Karmitsa et al., 2022). The model is then built using these selected features, with hyperparameter tuning conducted through a grid search and 10-fold cross-validation. This optimises the regularization parameters, *alpha* (which controls the mix of *L1* and *L2* regularization) and *lambda* (which controls the strength of regularization), to balance bias and variance, thereby enhancing the model's accuracy and generalisability (Friedman et al., 2009).

3.3.3. Random Forest

Random Forest, an ensemble learning method, is used for its ability to handle numerous predictors and model complex interactions (Biau and Scornet, 2015). A preliminary model assesses variable importance via the IncNodePurity metric, which measures a variable's contribution to node purity. Significant features are then used to train a refined model. Hyperparameter tuning, focusing on the mtry parameter—the number of variables sampled at each split—optimises model performance, ensuring each tree in the forest uses the most informative variables (Belgiu and Draguţ, 2016; Hu and Szymczak, 2022).

3.3.4. ARIMA

Given the temporal nature of the dataset, ARIMA (AutoRegressive Integrated Moving Average) models are employed to forecast the time series data for Monthly Sales Volume, NPS Score, and DEA Efficiency (Tarmanini et al., 2023). The *auto.arima* function is used to automatically select the optimal order of autoregression, differencing, and moving average terms (Ospina et al., 2023). The selection is based on the Akaike Information Criterion (AIC), which balances model fit and complexity, thereby preventing overfitting. ARIMA is particularly suited for capturing underlying temporal patterns in the data, such as seasonality and trends, which other models might not fully exploit (Chodakowska et al., 2023).

3.3.5. Support Vector Machines (SVM)

Support Vector Machines (SVM) are utilised to model high-dimensional, potentially non-linear relationships in the dataset (Brereton and Lloyd, 2010). Recursive Feature Elimination (RFE) performs feature selection, iteratively removing less significant features to identify the optimal subset, enhancing model focus and predictive performance (Chang and Lin, 2011). Post-selection, SVM models undergo hyperparameter tuning via grid search, optimising the regularisation parameter *C*, which balances the trade-off between training accuracy and model complexity. A linear *kernel* is selected for computational efficiency, critical given the dataset size (Brereton and Lloyd, 2010).

3.3.6. Gradient Boosting Machines (GBM)

Gradient Boosting Machines (GBM) are employed for their ability to handle both linear and non-linear relationships, as well as their robustness to outliers and missing data (Natekin and Knoll, 2013). The GBM models are trained following feature selection using RFE, which identifies the most impactful features for each target variable.

Hyperparameter tuning for the GBM models involves optimizing several parameters, including the number of trees (*n.trees*), interaction depth (*interaction.depth*), learning rate (*shrinkage*), and the minimum number of observations required in terminal nodes (*n.minobsinnode*), as described by Hussien et al. (2023). This thorough tuning process ensures that the models are well-calibrated to achieve high predictive accuracy while controlling for overfitting.

3.3.7. Model Evaluation and Comparison

All models are evaluated using Mean Absolute Error (MAE) and Root Mean Squared Error (RMSE), which provide comprehensive measures of accuracy (Chai and Draxler, 2014). MAE reflects the average absolute difference between predicted and actual values, offering a clear interpretation of prediction errors (Iong et al., 2022). RMSE squares errors before averaging, giving more weight to larger errors, useful for identifying poor performance on outliers (Reddy and Kumar, 2022). These metrics are calculated for both training and test datasets to ensure fair comparison (James et al., 2013). Errors are also contextualized as percentages of the test set mean values, assessing their significance. Performance metrics are visualized using bar plots, highlighting models with the lowest MAE and RMSE as the most reliable (Provost and Fawcett, 2013). This rigorous approach ensures robust and generalizable findings, providing valuable insights into dealership performance metrics.

3.4. DEA (Data Envelopment Analysis) Process

The Data Envelopment Analysis (DEA) process is a critical step in evaluating the performance of dealerships. It involves several stages, from data preparation to efficiency scoring and variable importance analysis, to understand the factors influencing dealership performance. DEA is performed both pre- and post-predictive modelling to calculate efficiency scores for each dealership (Gonzalez-Padron et al., 2014). The pre-modelling DEA uses current data to assess the existing efficiency levels of dealerships, while the post-modelling DEA utilizes predicted values generated from the predictive models. This dual application of DEA allows for a comparison between actual and predicted efficiency, providing insights into how future changes in key variables may impact dealership performance (Biondi et al., 2013).

3.4.1. Data Preparation and Normalization

Prior to conducting DEA, the dataset undergoes normalization using the min-max scaling method. Normalization is critical to ensure that all variables are on a comparable scale, preventing any single variable from disproportionately influencing the DEA results due to differences in magnitude (Herwanto et al., 2021). The normalization is performed using a custom *normalize* function. This function rescales each variable to a range of [0, 1], which is then applied to all input and output variables, including the *Number_of_Salespeople*, *Number_of_Outlets*, *Service_Completion_Time*, *Regional_Population_Density*, *Local_Economic_Growth*, and the predicted outcomes (sales volume, NPS, efficiency).

3.4.2. DEA Model Execution

The DEA model is executed using the prepared and normalised data to assess the relative efficiency of decision-making units (DMUs), here represented by dealerships (Das and Kundu, 2019). DEA compares the weighted sum of outputs (sales volume, NPS, and efficiency score) to the weighted sum of inputs (number of salespeople, number of outlets, and service completion time). The *dea* function is employed, treating each dealership as a DMU (Sharma, 2018). The input-oriented DEA model assumes Variable Returns to Scale (VRS), acknowledging that dealerships may operate at varying scales, not necessarily at optimal efficiency (Ikeagwuani and Nwonu, 2021).

```
# Conduct DEA Analysis
dea_model <- dea(X = inputs, Y = outputs, RTS = "vrs", ORIENTATION = "in")
efficiency_scores <- dea_model$eff
```

Figure 6. A snapshot of code for DEA from RStudio

Inputs include *Number of Salespeople*, *Number of Outlets*, and *Service Completion Time*, while outputs encompass *Predicted Sales Volume*, *Predicted NPS*, and *Predicted DEA Efficiency Scores*. The model, depicted in Figure 6, uses X for inputs, Y for outputs, RTS = "vrs" for Variable Returns to Scale, and ORIENTATION = "in" for an input-focused approach (Alidrisi, 2021). Efficiency scores, obtained via *dea_model$eff*, reflect each dealership's efficiency relative to the most efficient one. A score of 1 denotes maximum efficiency, while scores below 1 indicate inefficiency (Biondi et al., 2013).

3.4.3. Visualization and Categorization of DEA Scores

To interpret the DEA results, efficiency scores are visualized using histograms, and dealerships are categorized into performance levels based on these scores. Specifically:

- High Performance: DEA Efficiency Score ≥ 0.7
- Medium Performance: DEA Efficiency Score ≥ 0.5 but < 0.7

- Low Performance: DEA Efficiency Score < 0.5

These categories allow for a clear differentiation between dealerships that are operating efficiently and those that require improvement. The histogram of DEA efficiency scores is generated using base R and then converted to a *ggplot* object for enhanced visualization (Cooper et al., 2007).

3.4.4. Variable Importance Analysis

To assess the influence of input factors on DEA efficiency scores, two methods are employed. First, a linear regression model is constructed using the *lm* function to quantify the impact of each variable. The model's coefficients indicate the expected change in efficiency for a one-unit change in each input, holding other factors constant. The statistical significance of each coefficient is evaluated to ensure the reliability of the identified relationships (Ngo and Tsui, 2021).

Second, a Random Forest model, implemented with the *randomForest* function, explores non-linear relationships and interactions among input variables such as *Number_of_Salespeople* and *Number_of_Outlets*. This approach constructs decision trees and aggregates their predictions to provide efficiency estimates. The model calculates variable importance using Gini importance, highlighting key factors influencing DEA efficiency and capturing complex patterns often overlooked by linear models (Bou-Hamad et al., 2021).

3.5. Sensitivity Analysis

The sensitivity analysis assesses how variations in key input variables influence the predicted outcomes of the Data Envelopment Analysis (DEA) model. This involves systematically adjusting inputs—*Number of Salespeople*, *Number of Outlets*, and *Service Completion Time*—by a specified percentage and observing changes in predicted *Sales Volume*, *Net Promoter Score (NPS)*, and *Efficiency* (Shi and Zhao, 2023). A custom function facilitates this process, taking the original dataset, trained models, and the variable to be adjusted as inputs. The function creates a modified dataset by scaling the selected variable according to the specified percentage.

The modelling technique is then applied to this modified data to generate new predictions, with differences from the original predictions quantifying the impact of the adjustments (Cinaroglu, 2021). Both positive and negative adjustments are tested (e.g., increasing the number of salespeople or outlets by 10% and decreasing service completion time by 10%), revealing the sensitivity of DEA efficiency scores to changes in input variables. This analysis provides insights into which factors most significantly influence dealership performance and identifies leverage points for operational optimisation (Nguyen et al., 2015). The results enhance the strength of DEA model predictions and guide performance improvements.

3.6. Localisation Factors

The impact of localisation factors on *DEA Efficiency* is assessed using three predictive modelling techniques: Generalized Additive Model (GAM), Random Forest, and Gradient Boosting Machine (GBM). Each method captures both linear and non-linear relationships between localisation factors and *DEA Efficiency*.

1. **Generalized Additive Model (GAM) Analysis**

   GAM is applied to model non-linear relationships between factors such as *Regional Population Density*, *Local Economic Growth*, *Cultural Difference Score*, and *Regulatory Environment Score* with *DEA Efficiency*. The *gam* function fits smooth, non-linear relationships, offering flexible insights into each factor's impact, assessed using smooth term estimates and diagnostics (Wood, 2017).

2. **Random Forest Analysis**

   To account for non-linear interactions, the *randomForest* function constructs multiple decision trees and aggregates predictions. Variable importance is calculated to identify the most influential localisation factors on *DEA Efficiency* (Thaker et al., 2021).

3. **Gradient Boosting Machine (GBM) Analysis**

   The *gbm* function is used to iteratively build trees, focusing on correcting previous errors. Cross-validation determines the optimal number of trees, quantifying the relative influence of each factor on *DEA Efficiency* (Friedman, 2001).

These models are evaluated using RMSE, MAE, and R-squared metrics, which compare their strengths and weaknesses. This comprehensive analysis not only identifies the best-performing model but also deepens the understanding of how localisation factors influence dealership efficiency. The insights gained are valuable for optimizing dealership performance across different regional contexts, ensuring that strategies are tailored effectively to local conditions.

3.7. Limitations on Methodology

This study acknowledges several limitations:

- Data Limitations: Reliance on secondary data may introduce biases, as it might not fully align with the study's needs. Synthetic data for variables like *Monthly_Sales_Volume_per_Dealer* and *Number_of_Salespeople* may not entirely reflect real-world conditions.
- Model Limitations: Predictive models, including Linear Regression, Random Forest, GBM, SVM, and ARIMA, have inherent limitations, such as interpretability issues and high computational demands.
- Scope Limitations: The focus on BYD dealerships in Europe limits the generalisability of findings to other regions. The analysis is also confined to a single year, potentially missing long-term trends.
- Time Frame Limitations: The short data collection period restricts the ability to account for seasonal fluctuations and long-term economic trends affecting dealership performance.

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Chapter 4: Findings and Discussions

This chapter discusses the results of analyses evaluating the predictive accuracy of models for forecasting key dealership performance metrics, including sales volume, Net Promoter Score (NPS), and operational efficiency. It also explores post-prediction Data Envelopment Analysis (DEA) to categorise dealerships by efficiency levels, examining variable importance, sensitivity analysis, and localisation factors' impact. The chapter assesses the models' effectiveness and interprets results, focusing on dealership-specific and localisation factors that influence performance, offering a nuanced understanding of dealership performance and broader contextual influences.

4.1. Data Pre-Analysis

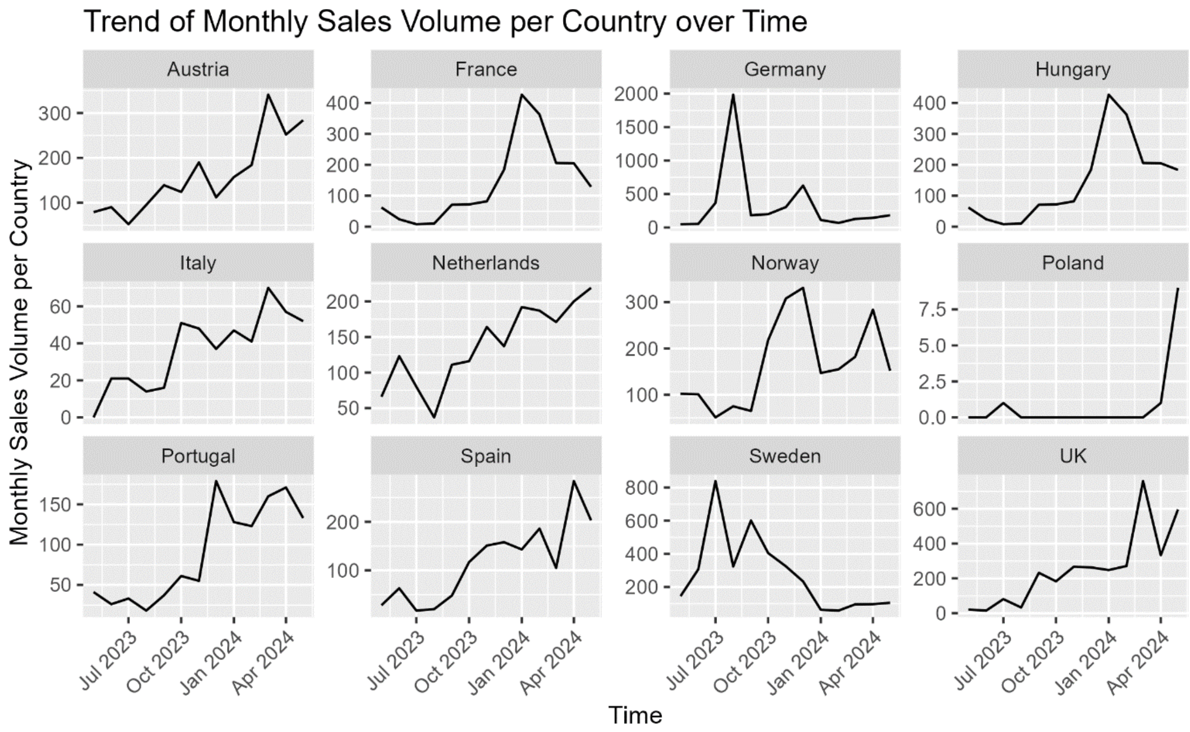

Figure 7. Trend of Monthly Sales Volume per Country over Time

In the data pre-analysis phase, as shown in Figure 7, notable trends emerge in BYD dealership performance across Europe. Germany and Sweden show significant volatility in monthly sales, with Germany peaking over 2,000 units before declining, likely due to market disruptions. Austria and Italy demonstrate steady growth, reflecting stable market conditions. These patterns highlight the need for region-specific strategies to optimise performance in response to local economic and regulatory conditions.

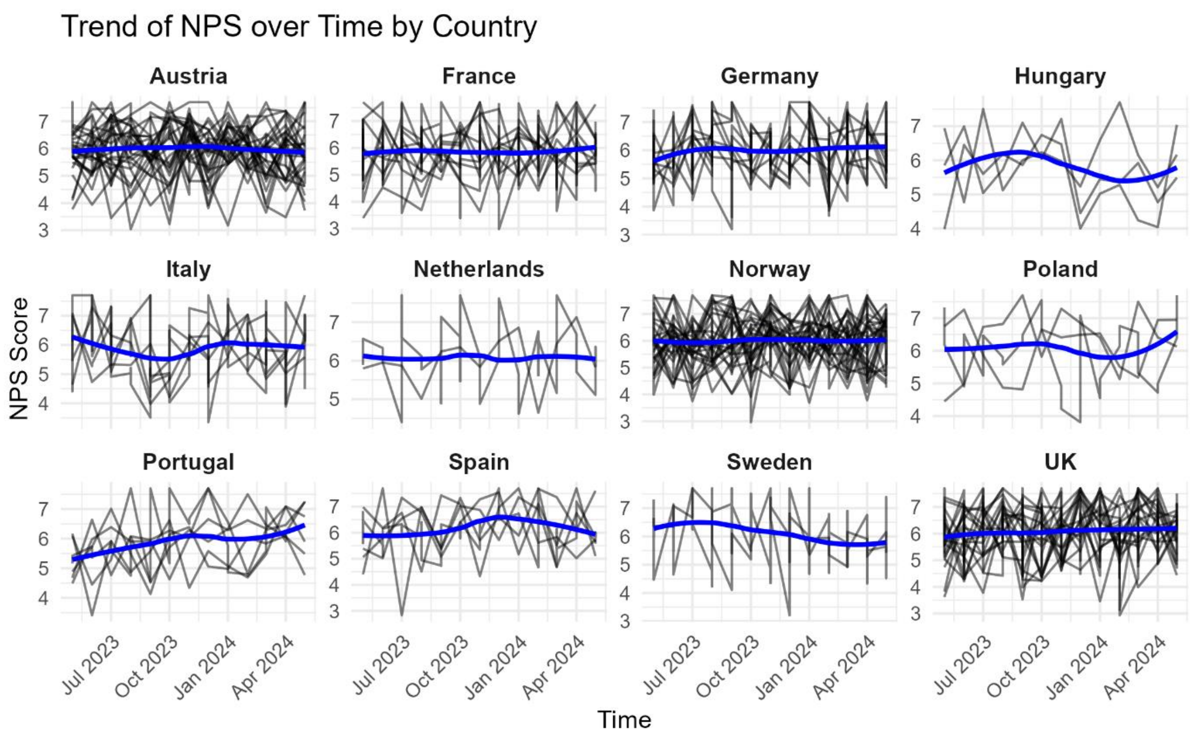

Figure 8. Trend of NPS per Country over Time

Customer satisfaction trends in Figure 8 show stable average NPS across most countries but with notable variability at individual BYD dealerships. Germany's NPS averages around 7 but varies widely between dealerships, indicating inconsistent service quality. Hungary shows a slight decline, while Italy and Portugal exhibit upward trends, possibly due to improved service efficiency. These findings highlight the importance of factors like service completion time and dealership size in influencing customer satisfaction and enhancing overall dealership performance.

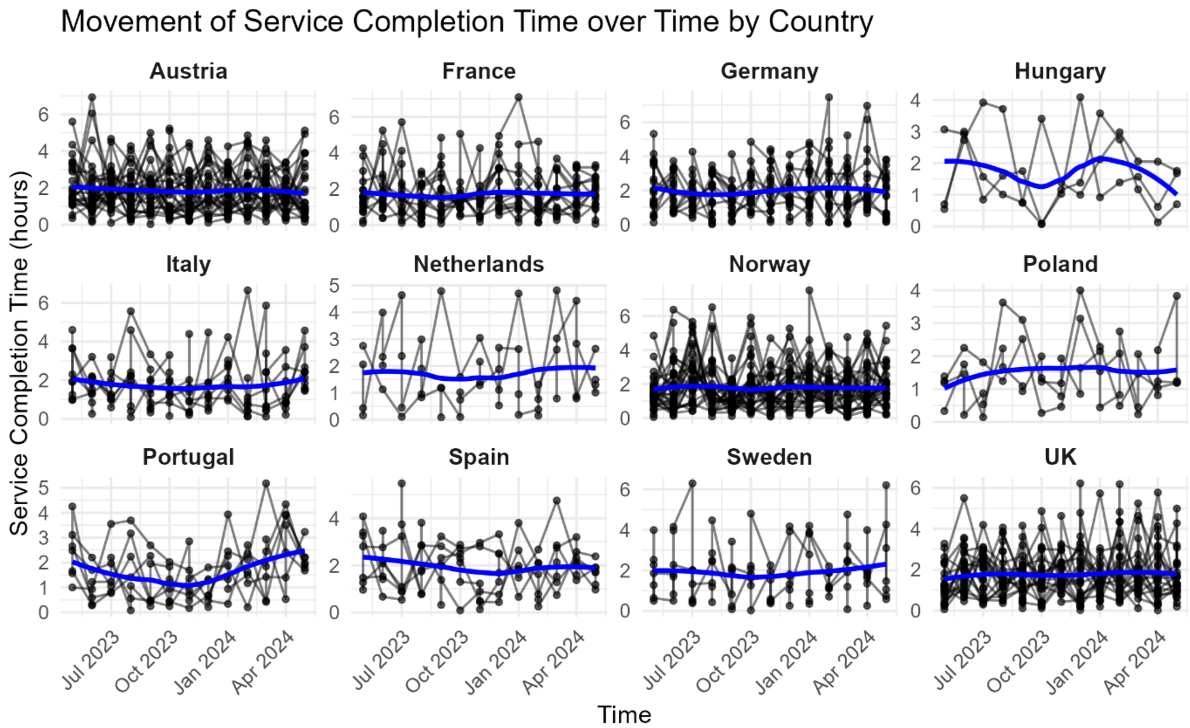

Figure 9. Movement of Service Completion Time over Time by Country

Building on earlier analyses, Figure 9 reveals insights into *Service_Completion_Time* across BYD dealerships. In Hungary, the trend line shows a reduction from 2 hours to 1.5 hours, indicating improved operational efficiency. In contrast, Poland maintains a stable service time just above 1 hour, reflecting steady but unchanged efficiency. These findings underscore the varying levels of operational effectiveness across regions and the need for continuous optimisation. The trends may also correlate with earlier NPS findings, highlighting operational efficiency's role in customer satisfaction.

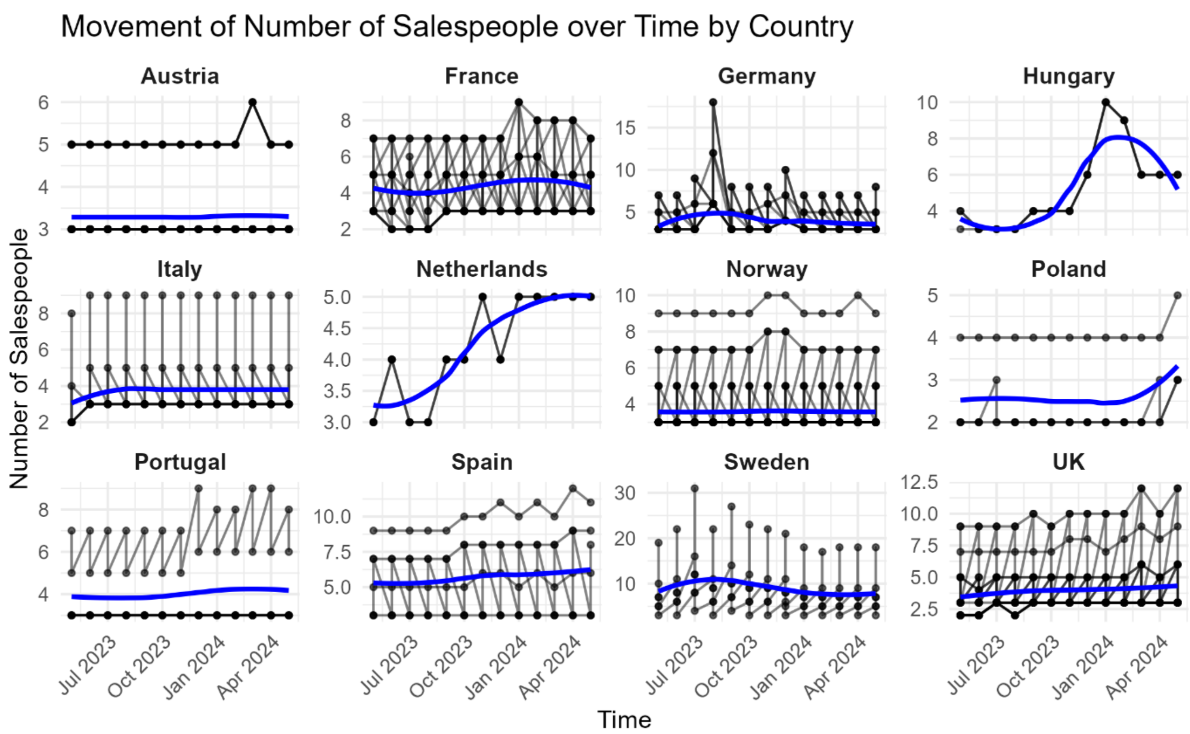

Figure 10. Movement of Number of Salespeople over Time by Country

Figure 10 examines the *Number_of_Salespeople* across BYD dealerships, revealing staffing dynamics that support operational changes. The Netherlands shows a steady increase from about 3 to nearly 5 salespeople, reflecting dealership expansion and rising sales capacity. Spain experiences modest growth, with staffing increasing from 5 to 6 per dealership. These adjustments suggest BYD is expanding its workforce in response to growing demand. In contrast, Austria maintains stable staffing levels, possibly indicating a more mature market or different strategic priorities.

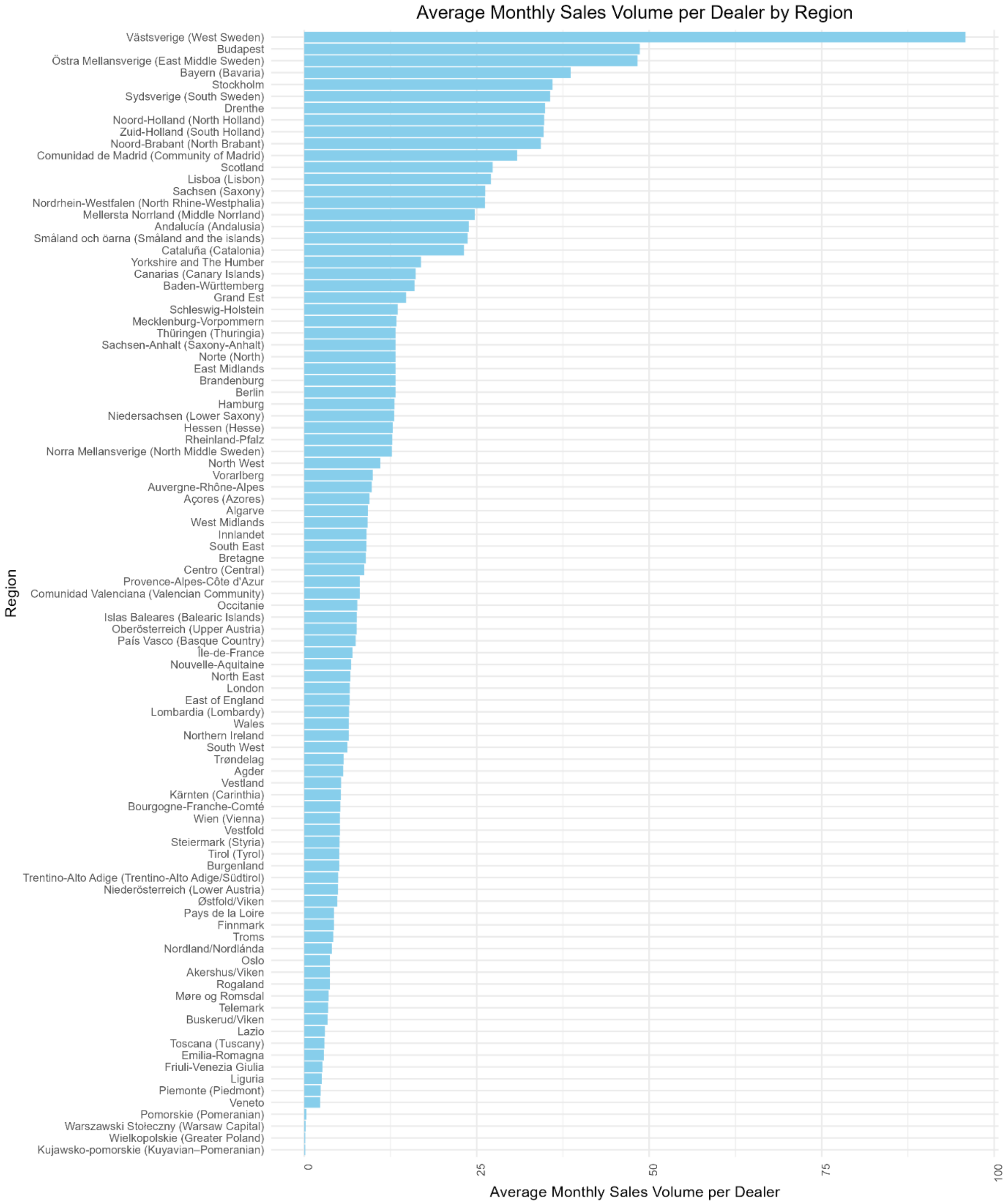

Figure 11. Average Monthly Sales Volume per Region

Disparities in *Monthly_Sales_Volume_per_Dealer* by region, as shown in Figure 11, underscore the significant impact of regional factors on BYD's dealership performance. Västsverige (West Sweden) leads with dealerships averaging over 100 units per month, outperforming other regions. Similarly, Östra Mellansverige and Sydsverige also show strong performance. In contrast, regions in Poland average below 10 units per month, highlighting stark differences in market conditions and dealership capacity. These findings reinforce the importance of tailoring BYD's strategies to address specific regional challenges, particularly in underperforming areas. For further insights, the complete visualization of average NPS per dealership is available in Appendix III, offering a detailed view of customer satisfaction across various dealerships.

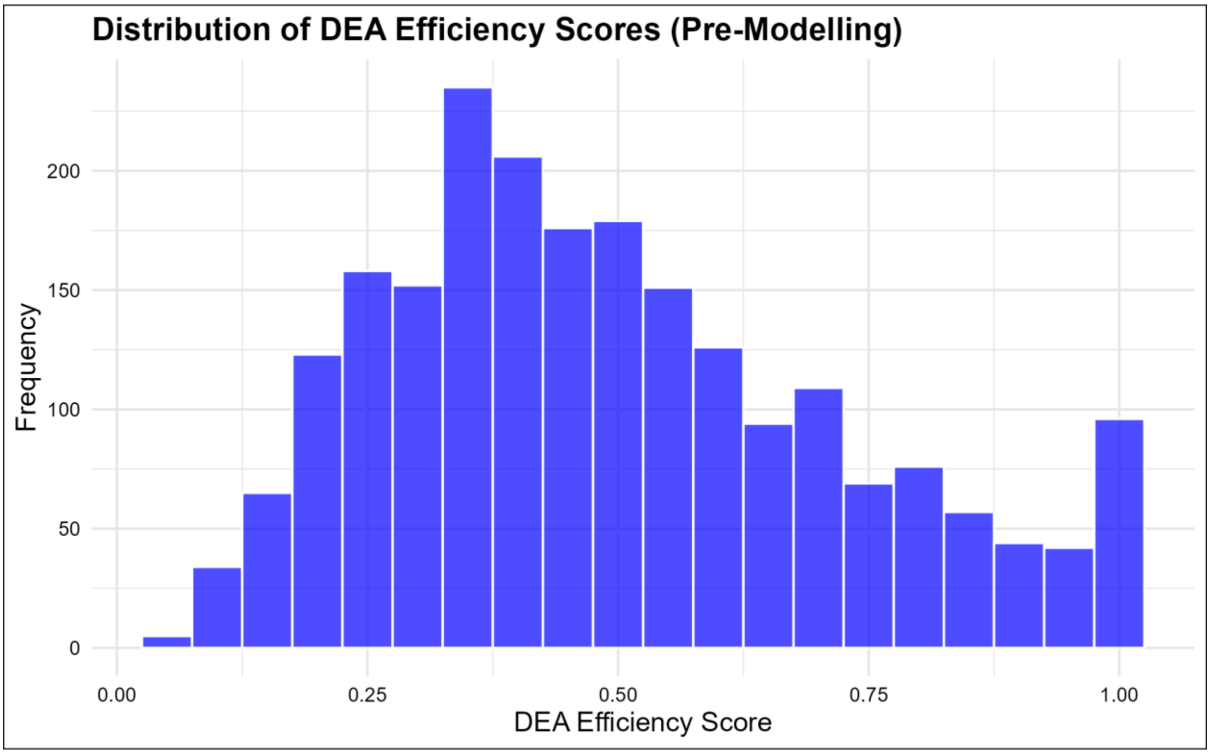

Figure 12. Distribution of DEA Efficiency Scores (Pre-Modelling)

The pre-modelling DEA (Data Envelopment Analysis) efficiency scores provide an initial evaluation of BYD dealership performance, highlighting how effectively resources are utilized relative to sales and customer satisfaction outputs. As shown in Figure 12, the distribution of DEA scores indicates that most BYD dealerships operate below full efficiency, with the majority scoring between 0.25 and 0.5, while a subset achieves near-optimal efficiency with scores close to 1.0. This variation in efficiency levels reveals substantial differences in how BYD dealerships manage their resources, which will be further examined in subsequent predictive analyses.

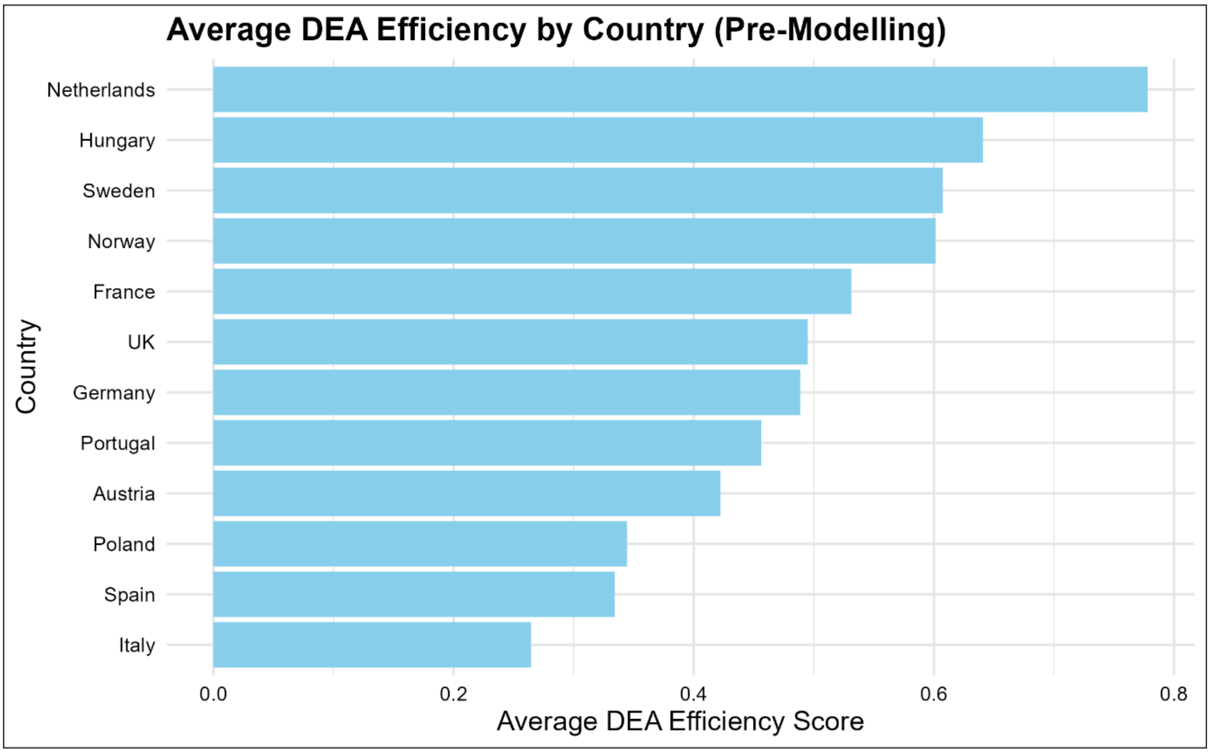

Figure 13. Average DEA Efficiency by Country (Pre-Modelling)

Figure 13 illustrates regional differences in BYD dealership efficiency, with the Netherlands, Hungary, and Sweden leading in average DEA scores. For instance, BYD dealerships in the Netherlands achieve an average DEA efficiency score of approximately 0.75, reflecting relatively efficient operations. In contrast, regions like Spain and Italy show lower average scores, with dealerships averaging below 0.4, indicating potential inefficiencies. These preliminary scores offer valuable insights into the operational efficiency of BYD dealerships across different regions, underscoring the importance of tailored strategies to improve performance where needed.

4.2. Prediction Modelling

This study employs five machine learning techniques to predict three key metrics: monthly sales volume per dealer, NPS, and DEA efficiency scores. The models are applied to training and test datasets, split at an 80:20 ratio, with 1,758 records for training and 439 for testing. Significant features are identified using information gain, with details in Appendix IV. Individual model results, including visual plots, are in Appendix V, while this section compares the five models to identify the best-performing one for each metric. Evaluating model performance on the test set, rather than training data alone, ensures the models generalise well and avoid overfitting, providing more reliable predictions for real-world applications.

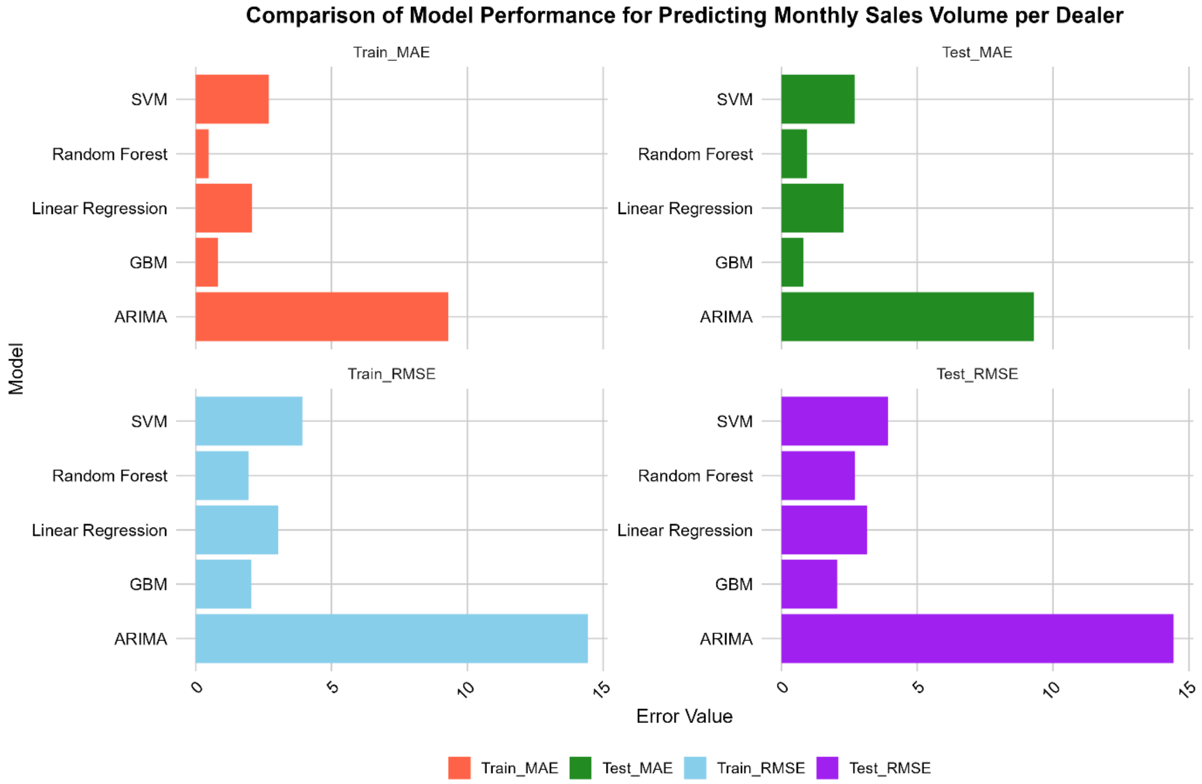

Figure 14. Model Comparison for Predicting Sales Volume

Evaluation Results for Models Predicting Sales Volume				
Model	Train_MAE	Test_MAE	Train_RMSE	Test_RMSE
Linear Regression	2.08	2.29	3.03	3.15
Random Forest	0.48	0.95	1.95	2.71
ARIMA	9.30	9.30	14.44	14.44
SVM	2.70	2.70	3.92	3.92
GBM	0.82	0.82	2.05	2.05

Table 2. Evaluation Results for Models Predicting Sales Volume

As seen in Figure 14 and detailed in Table 2, Random Forest demonstrates strong training performance but falls short on the test set. In contrast, the GBM outperforms other models on the test set, achieving the lowest Test MAE of 0.82 and Test RMSE of 2.05. These metrics indicate that, on average, the GBM model's predictions deviate from the actual sales volume by approximately 0.82 units, with a typical error of about 2.05 units of sales volume. This suggests that the GBM model exhibits better generalization capability, making it more suitable for predicting sales volume in practical applications. The test set results effectively serve as a proxy for future data, ensuring that the selected model is robust and not overly tailored to the training data's specific nuances.

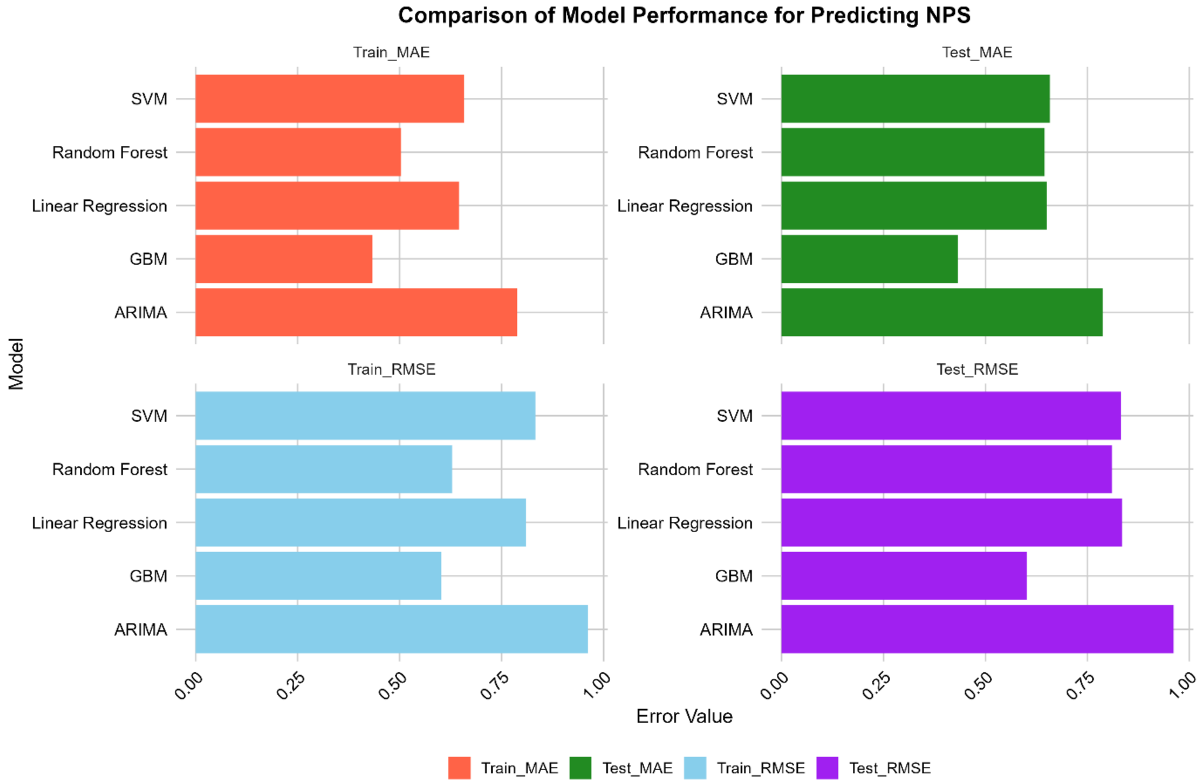

Figure 15. Model Comparison for Predicting NPS

Evaluation Results for Models Predicting NPS				
Model	Train_MAE	Test_MAE	Train_RMSE	Test_RMSE
Linear Regression	0.65	0.65	0.81	0.84
Random Forest	0.50	0.65	0.63	0.81
ARIMA	0.79	0.79	0.96	0.96
SVM	0.66	0.66	0.83	0.83
GBM	0.43	0.43	0.60	0.60

Table 3. Evaluation Results for Models Predicting NPS

When predicting NPS, the GBM model emerges as the top performer. As shown in the comparison Figure 15 and Table 3, GBM achieves the lowest Test MAE (0.43) and Test RMSE (0.60), outperforming alternative models such as Random Forest, SVM, and ARIMA. Given that NPS scores typically range from 0 to 10, the MAE of 0.43 indicates that, on average, the model's predictions deviate from the actual scores by around 0.43 points. Meanwhile, the RMSE of 0.60 suggests an average deviation of approximately 0.60 points on the NPS scale. These results highlight GBM's accuracy in predicting NPS, making it a strong model for gauging customer satisfaction trends.

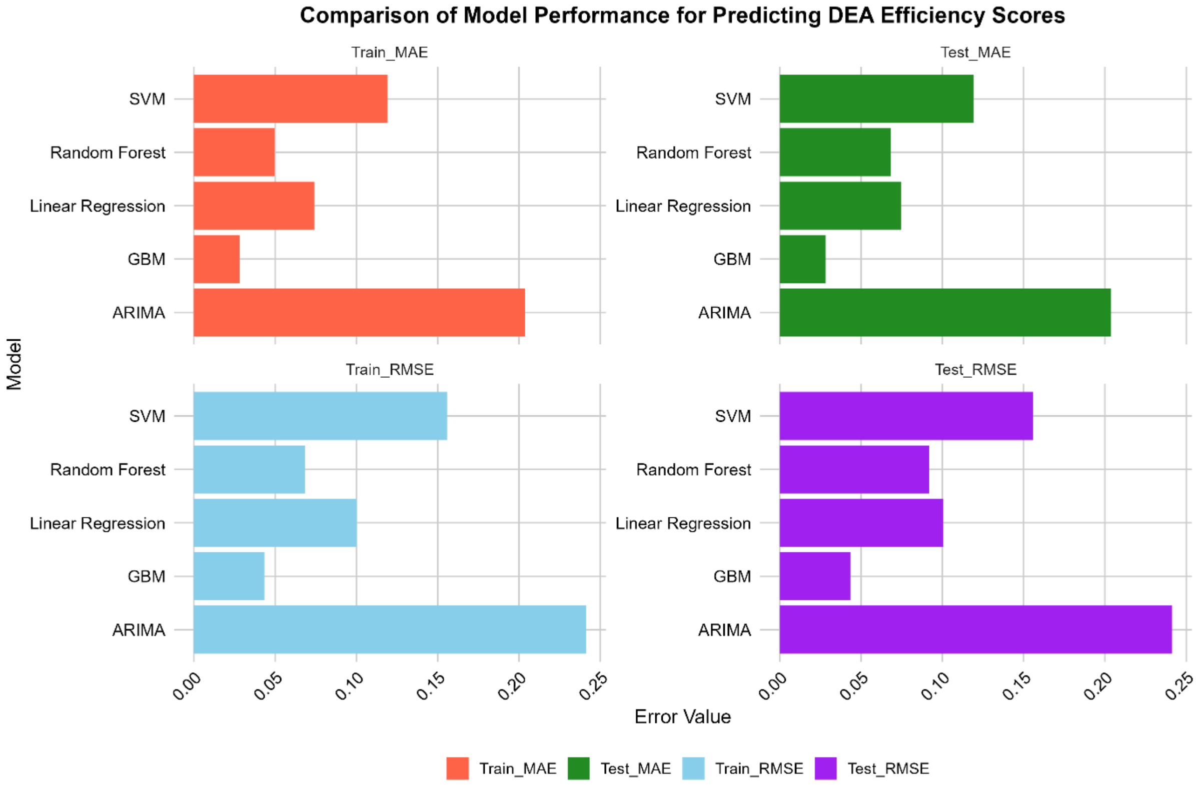

Figure 16. Model Comparison for Predicting DEA Efficiency

Evaluation Results for Models Predicting DEA Efficiency Scores				
Model	Train_MAE	Test_MAE	Train_RMSE	Test_RMSE
Linear Regression	0.07	0.07	0.10	0.10
Random Forest	0.05	0.07	0.07	0.09
ARIMA	0.20	0.20	0.24	0.24
SVM	0.12	0.12	0.16	0.16
GBM	0.03	0.03	0.04	0.04

Table 4. Evaluation Results for Models Predicting DEA Efficiency

Turning to DEA efficiency predictions, the GBM model also demonstrates the highest predictive performance, recording the lowest Test MAE (0.03) and Test RMSE (0.04), as shown in Figure 16 and Table 4. Since DEA efficiency is measured on a scale from 0 to 1, where 1 represents maximum efficiency, the MAE of 0.03 shows that GBM's predictions deviate from actual efficiency scores by an average of approximately 0.03 points. The RMSE of 0.04 suggests a typical deviation of about 0.04 points from the true efficiency values. This high level of precision confirms GBM as the most suitable model for predicting DEA efficiency in this analysis.

4.3. DEA Post-Modelling

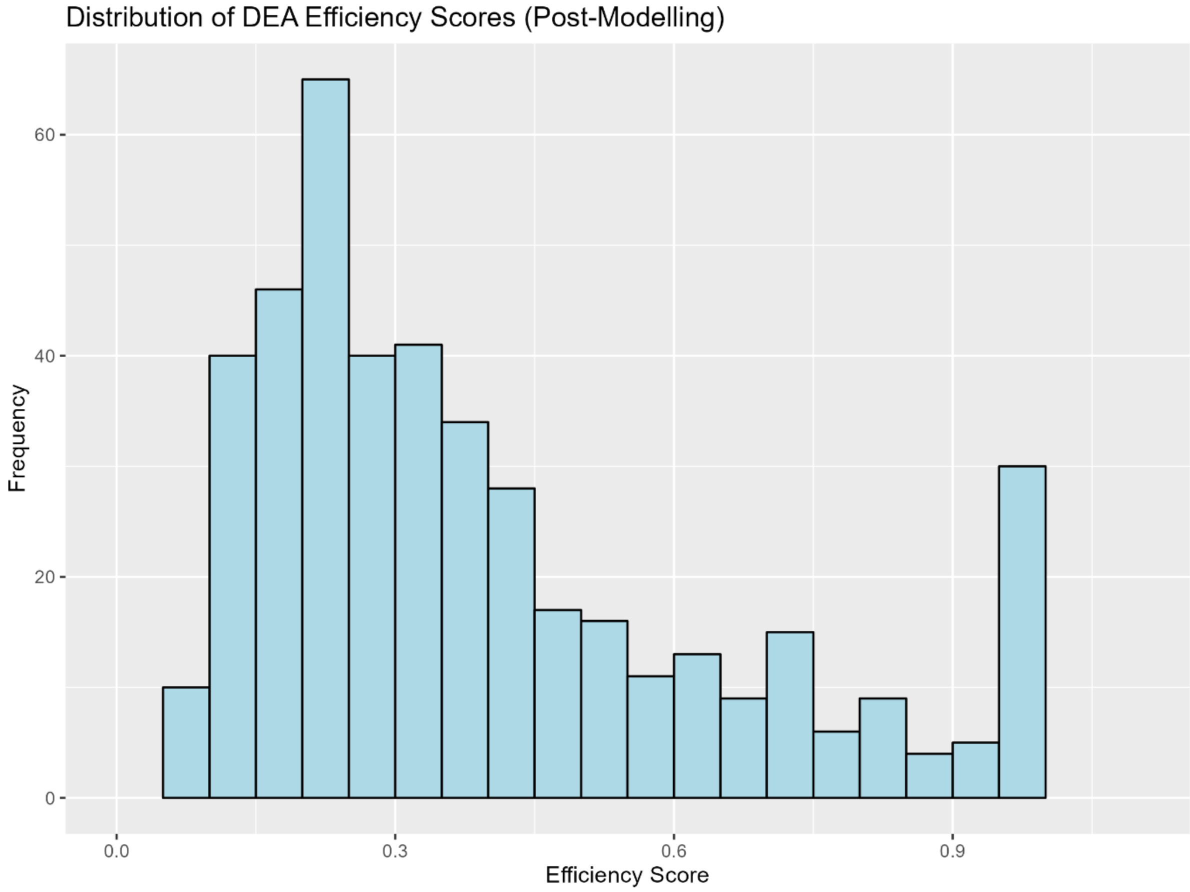

Figure 17. Distribution of DEA Efficiency Scores (Post-Modelling)

Statistical Summary of DEA Efficiency Scores Post-Modelling					
Min.	**1st Qu.**	**Median**	**Mean**	**3rd Qu.**	**Max.**
0.07	0.21	0.33	0.40	0.53	1.00

Table 5. Statistical Summary of DEA Efficiency Scores Post-Modelling

The DEA efficiency scores are recalculated using predicted values from the Gradient Boosting Machine (GBM) model, which estimates sales volume, NPS, and operational efficiency. This recalculation integrates predictions with key inputs like the number of salespeople, outlets, and service completion time, providing a more accurate reflection of potential future performance. As shown in Figure 17 and Table 5, efficiency scores range from 0.07 to 1.00, with a median of 0.33 and a mean of 0.40. These results reveal significant efficiency variations across BYD dealerships, with many scoring below 0.50, indicating room for improvement. A small group achieves near-optimal scores close to 1.00, setting benchmarks for excellence. This analysis can support a strategic approach to enhancing dealership efficiency, emphasizing resource allocation and process optimization.

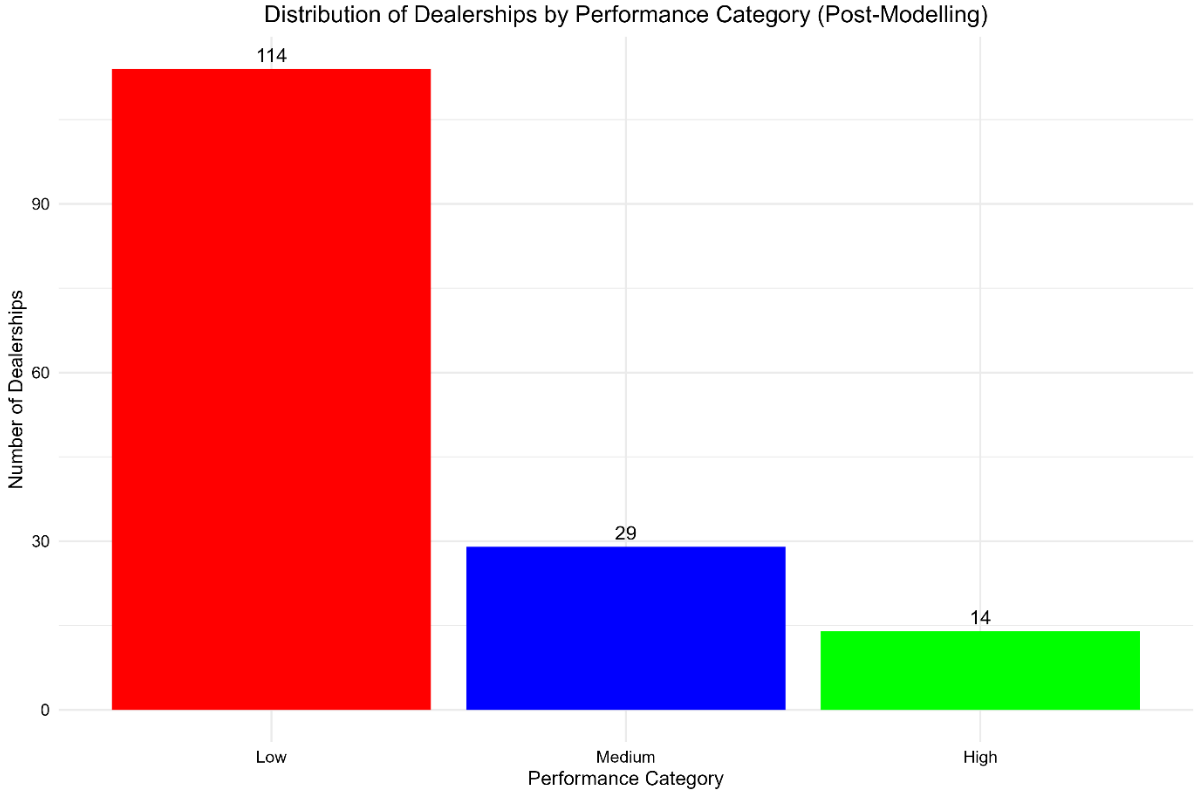

Figure 18. Distribution of Dealerships by Performance Category (Post-Modelling)

The analysis of dealership performance in Figure 18 classifies dealerships into three categories based on their DEA efficiency scores: low, medium, and high. A significant 114 dealerships are identified as low performers, with DEA scores below 0.5, indicating widespread inefficiencies. In contrast, only 14 dealerships achieve high efficiency, with scores above 0.7, serving as operational benchmarks. The medium category, with 29 dealerships scoring between 0.5 and 0.7, shows moderate efficiency with room for improvement. This distribution highlights the need for strategic interventions to enhance the lower-tier dealerships' performance. A detailed visualization of the DEA efficiency scores for each dealership and dealership groupings by performance, along with additional variables, are available in Appendices VI and VII.

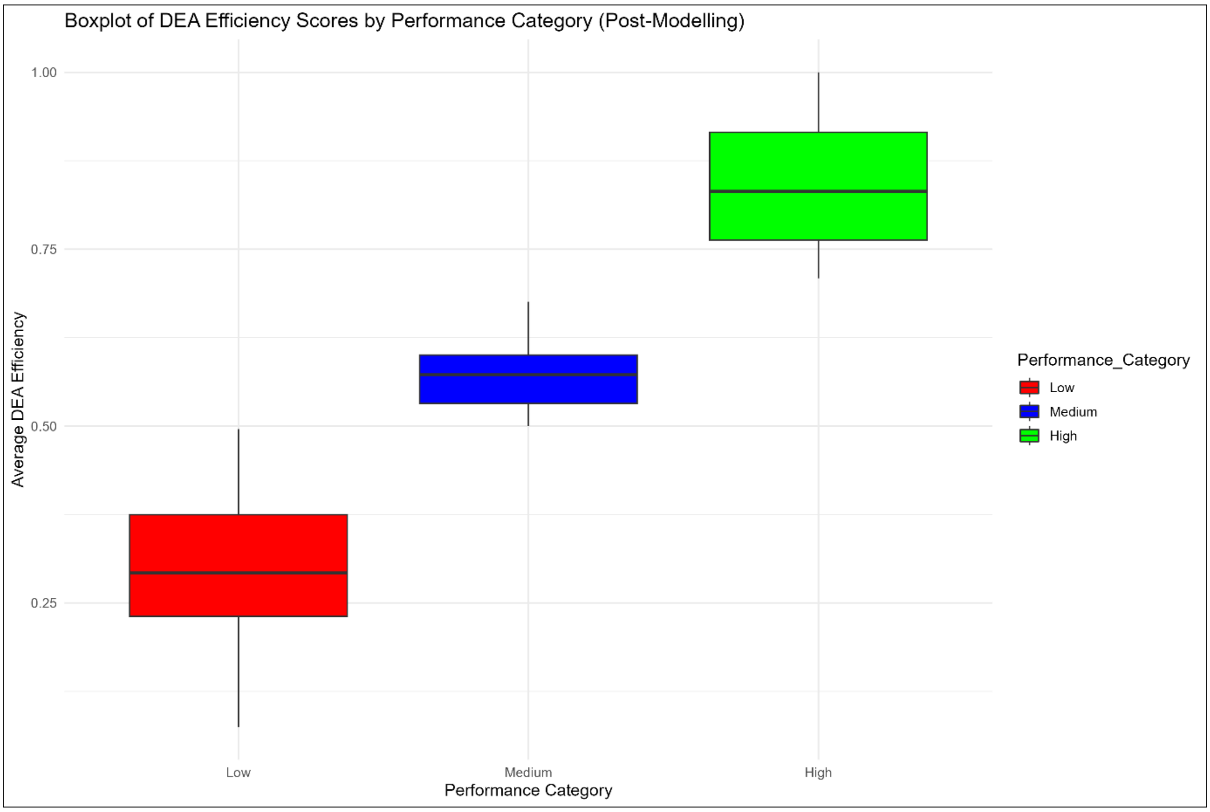

Figure 19. Boxplot of DEA Efficiency Scores by Performance Category (Post-Modelling)

Further exploration of dealerships' efficiency variation is depicted in the box plot in Figure 19, which illustrates the distribution of efficiency scores within each performance category. High-performing dealerships exhibit tight clustering near the upper limit of 1.00, indicating consistent high efficiency, while low-performing dealerships show a wider dispersion of scores, with many clustered around 0.25. Medium performers lie in between, but also display less variability than the low performers. This analysis indicates that while high performers have achieved operational optimization, low-performing dealerships suffer from inconsistencies that likely stem from operational inefficiencies, thus providing a clear pathway for targeted interventions to enhance their productivity.

4.4. Variable Importance for Dealership Performance

Linear Model Coefficients and Random Forest Importance			
Variable	**Estimate**	**Pr(>|t|)**	**Variable_Importance**
Service_Completion_Time	-0.49	4.86133E-18	5.54
Number_of_Salespeople	2.67	1.97051E-17	3.28
Number_of_Outlets	-2.78	1.27854E-22	3.09
(Intercept)	0.42	4.20052E-50	N/A

Table 6. Key Predictors of Dealership Performance: Linear Model Coefficients and Random Forest Importance

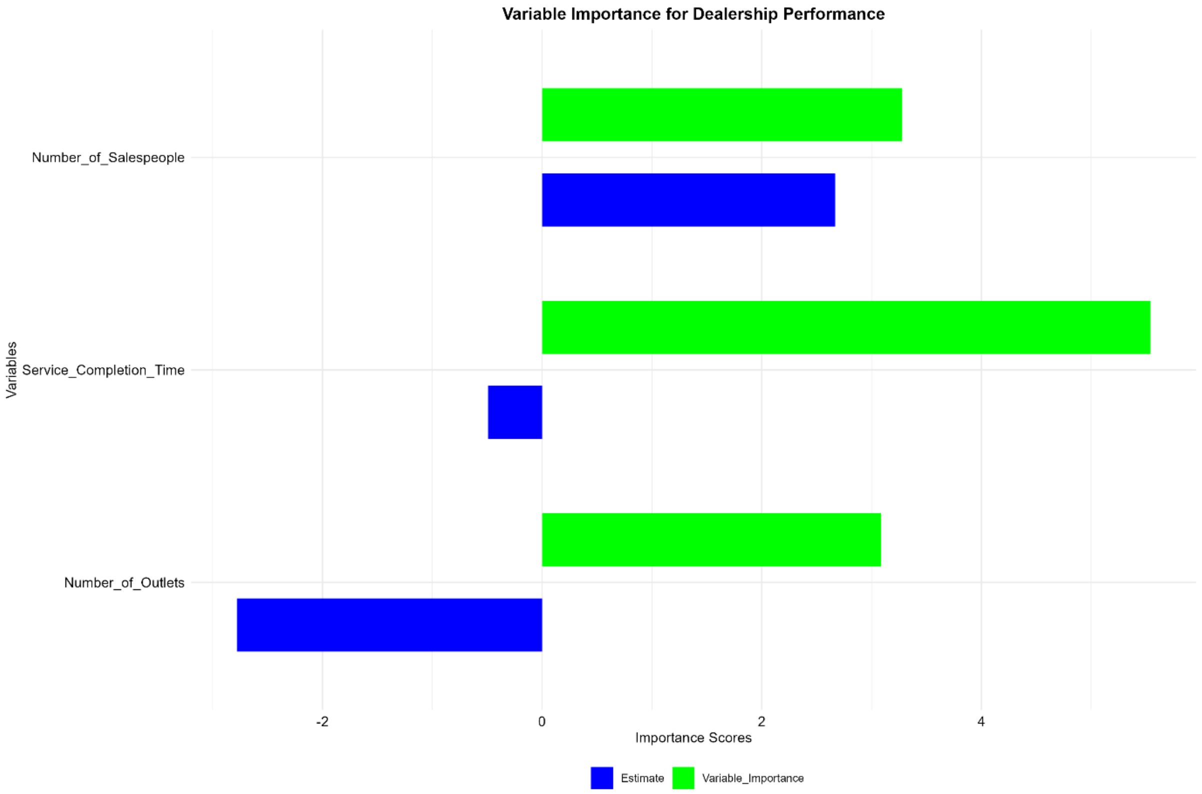

Figure 20. Variable Importance for Dealership Performance

The analysis of variable importance for dealership performance, detailed in Table 6 and visualised in Figure 20, reveals key factors influencing DEA efficiency scores post-modelling. Linear regression results show that the number of salespeople significantly enhances dealership efficiency, with a positive estimate of 2.67, suggesting that a larger workforce correlates with higher efficiency. Conversely, service completion time has a negative estimate of -0.49, indicating that shorter service times improve efficiency, likely due to better resource management and faster customer turnover. The number of outlets shows a negative coefficient of -2.78, suggesting that while expanding outlets may increase market reach, it can strain operational efficiency, possibly due to challenges in maintaining consistent service levels across multiple locations. All variables are statistically significant, with p-values well below 0.05, confirming their strong predictive influence on DEA efficiency.

The Random Forest model offers a complementary perspective by ranking the importance of each variable based on its contribution to the model's predictive performance. Service completion time emerges as the most important factor, with an importance score of 5.54, reinforcing its dominant role in driving DEA efficiency. The number of salespeople follows with an importance score of 3.28, further supporting the idea that a larger workforce contributes positively to operational efficiency. Although the number of outlets is negatively associated with efficiency in the linear model, it still holds a notable importance score of 3.09 in the Random Forest model, indicating its considerable effect on overall dealership performance. This combined analysis provides a comprehensive view, as both statistical significance (from linear regression) and practical relevance (from Random Forest importance) highlight the critical variables impacting DEA efficiency. Figure 4.12 visually illustrates this dual perspective, offering a clear comparison of each variable's contribution to dealership efficiency in terms of both direction and magnitude across the two analytical approaches.

4.5. Sensitivity Analysis on Key Variables Impacting Model Predictions

Scenario	Sales Volume Difference	NPS Difference	Efficiency Difference
Increase Number of Salespeople by 10%	49.21	1.91	0.51
Increase Number of Outlets by 10%	46.41	2.70	0.51
Decrease Service Completion Time by 10%	40.72	2.88	0.45

Table 7. Impact of Changes in Key Input Variables

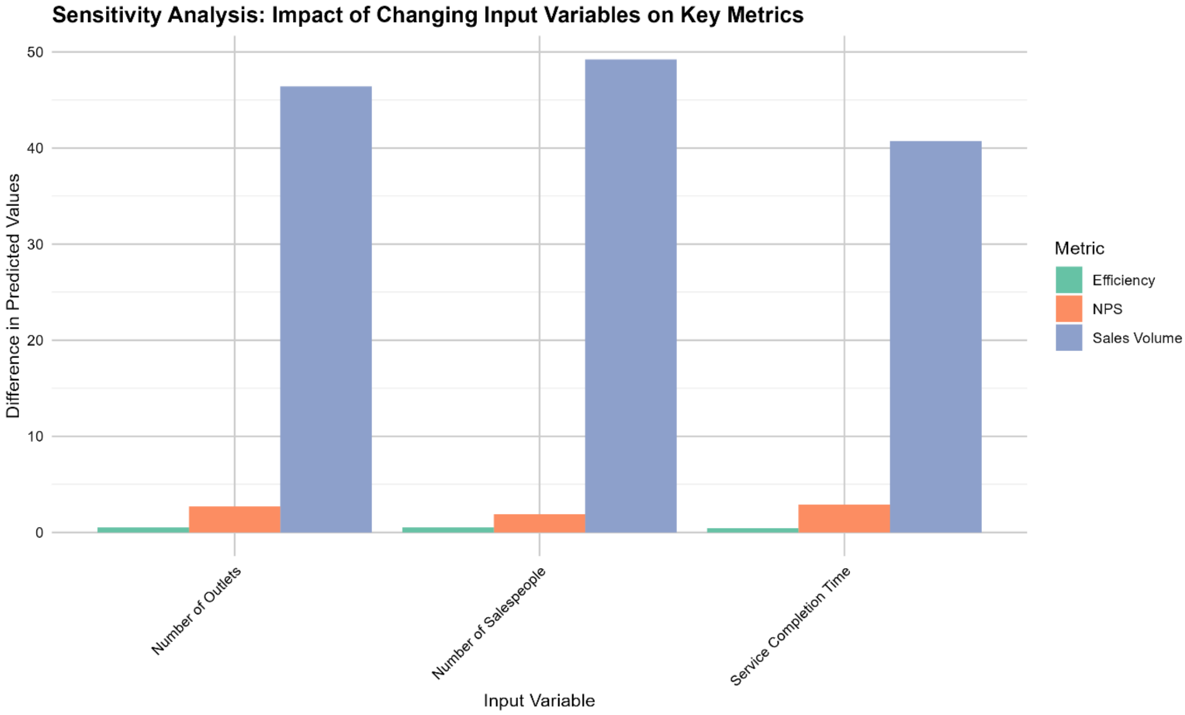

Figure 21. Sensitivity Analysis Plot

The sensitivity analysis conducted reveals the impact of varying key input variables—specifically, the number of outlets, the number of salespeople, and service completion time—on the predicted outcomes for sales volume, Net Promoter Score (NPS), and DEA efficiency scores. As shown in Table 7 and illustrated in Figure 21, a 10% average increase in the number of salespeople (measured in total headcount) leads to a rise in average sales volume by 49.21 units. This suggests that increasing the number of salespeople has a substantial effect on driving sales growth. Similarly, increasing the number of outlets (measured in total outlet count) by 10% results in an average increase of 46.41 units in sales volume, along with a 2.70-point average improvement in NPS, reflecting enhanced customer satisfaction. However, the impact on DEA efficiency is minimal, with only a slight increase of 0.51 in the efficiency score, indicating that while these changes positively influence sales and customer satisfaction, they do not significantly alter operational efficiency as measured by DEA.

Furthermore, the analysis shows that reducing service completion time (measured in hours) by 10% yields an average increase of 40.72 units in sales volume, coupled with an average improvement of 2.88 points in NPS. Once again, the DEA efficiency score shows only a modest average increase of 0.45. These findings underscore the importance of optimising service completion time alongside scaling the number of outlets and salespeople, as these factors collectively contribute to substantial gains in both sales' performance and customer satisfaction. However, given the limited impact on efficiency, further exploration into other potential drivers of operational efficiency is warranted. This indicates that while strategic adjustments to these key variables can lead to significant improvements in sales and customer satisfaction, they do not address all aspects of operational efficiency, suggesting the need for additional strategies to enhance DEA efficiency scores.

4.6. The Impact of Localisation Factors

Model Performance Metrics for Localisation Factors Analysis			
Model	**RMSE**	**MAE**	**R_squared**
GAM	0.17	0.13	0.22
Random Forest	0.20	0.17	0.02
GBM	0.20	0.17	0.004

Table 8. Model Performance Metrics for Localisation Factors Analysis

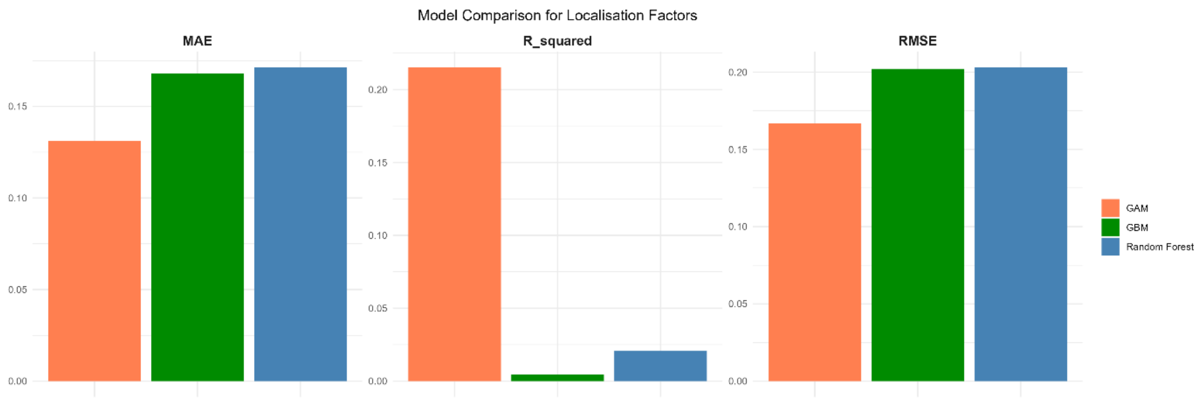

Figure 22. Model Comparison for Localisation Factors

In evaluating the impact of localisation factors on DEA efficiency scores for dealerships, three models—Generalised Additive Model (GAM), Random Forest, and Gradient Boosting Machine (GBM)—are compared. As indicated by the performance metrics in Table 8 and Figure 22, the GAM model outperforms the other methods, achieving the lowest RMSE (0.17) and MAE (0.13) alongside a higher R-squared value (0.22). This suggests that GAM offers superior predictive accuracy and is more effective in capturing the complex, non-linear relationships between localisation factors and dealership efficiency.

Smooth Terms	edf	Ref.df	F	p-value
s(Regional_Population_Density)	2.13	2.57	1.64	0.322
s(Local_Economic_Growth)	1.00	1.00	0.26	0.608
s(Cultural_Difference_Score)	1.00	1.00	1.47	0.227
s(Regulatory_Environment_Score)	6.87	7.60	4.95	3.38E-05

Table 9. Smooth Terms of Localisation Factors with GAM Model

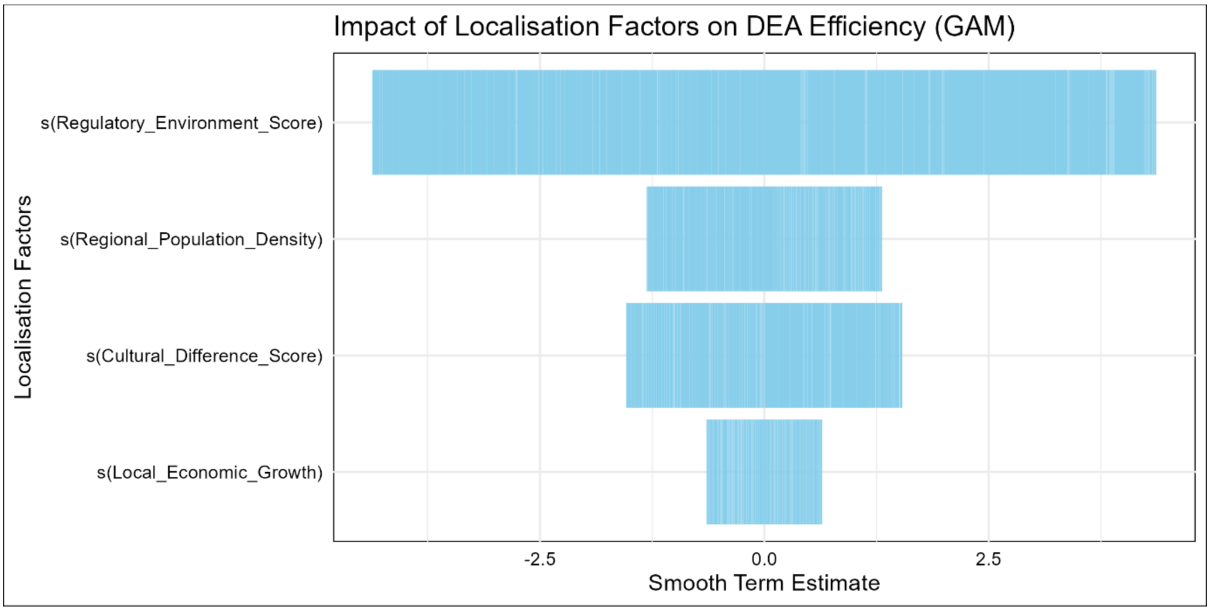

Figure 23. Influence of Localisation Factors on Dealership Performance (GAM)

The analysis highlights the Regulatory Environment Score as the most significant determinant of DEA efficiency, with an F-value of 4.95 and a p-value of 3.38e-05 (Table 9 and Figure 23), underscoring its substantial influence on dealership performance. While other factors—such as Regional Population Density, Cultural Difference Score, and Local Economic Growth—also contribute to efficiency, their effects are statistically less significant compared to the regulatory environment.

Overall, the GAM model not only outperforms Random Forest and GBM but also provides a robust framework for understanding the intricate interactions between localisation factors and dealership performance. By effectively capturing these dynamics, particularly the pivotal role of the regulatory environment, GAM offers valuable insights for optimising operations across diverse European markets. For further reference and comparison, detailed results of the Random Forest and GBM models are available in Appendix IX.

4.7. Summary, Recommendations, and Contributions of the Research

This research evaluates the performance of BYD dealerships across Europe using a combination of predictive modelling techniques and Data Envelopment Analysis (DEA). The study employs five advanced machine learning models—Gradient Boosting Machine (GBM), Random Forest, Support Vector Machine (SVM), ARIMA, and Linear Regression—to predict key performance metrics: monthly sales volume per dealer, Net Promoter Score (NPS), and DEA efficiency scores. Among these models, the GBM consistently demonstrates superior predictive accuracy across all metrics, yielding the lowest Test Mean Absolute Error (MAE) and Root Mean Squared Error (RMSE) for sales volume (0.82 and 2.05, respectively), NPS (0.43 and 0.60), and DEA efficiency scores (0.03 and 0.04). These results affirm GBM in capturing the complex interactions between variables, making it the most reliable model for forecasting dealership performance.

The DEA analysis uncovers significant disparities in dealership efficiency across various regions, revealing that a substantial number of dealerships operate below optimal efficiency levels. The analysis further identifies key determinants of operational efficiency: dealerships located in regions with higher *Regional Population Density* and more stringent *Regulatory Environment Scores* generally perform more efficiently. Additionally, *Service Completion Time* and the *Number of Salespeople* emerge as critical internal factors influencing operational efficiency, as corroborated by both the Linear Regression and Random Forest analysis. Sensitivity analysis highlights that increasing the number of sales staff and reducing service times positively impact sales performance and customer satisfaction, though these adjustments exhibit a limited effect on improving overall DEA efficiency scores. These findings underscore the importance of both internal operational metrics and external localisation factors in driving dealership efficiency and performance across Europe.

To enhance dealership efficiency, BYD should focus on region-specific strategies that address operational inefficiencies, particularly in areas with lower DEA scores. Key actions include optimising staffing levels, reducing service times, and ensuring compliance with local regulations. Additionally, dealerships in underperforming regions should implement targeted interventions to improve customer satisfaction, closely linked to operational efficiency.

This research advances the academic understanding of dealership performance by integrating machine learning with DEA, providing a framework for evaluating efficiency across different markets. It highlights the critical role of localisation factors—such as regulatory environments and regional economic conditions—in influencing dealership success. Practically, the findings offer BYD actionable insights to optimise operations across its European network, while the methodological approach serves as a replicable model for efficiency analysis in other industries.

In summary, the study identifies key performance drivers and provides a comprehensive framework for strategic decision-making, enabling BYD to enhance dealership performance in diverse regional contexts.

Chapter 5: Conclusions

5.1. Conclusions

This research investigates the performance of BYD dealerships across Europe, focusing on key metrics such as Monthly Sales Volume per Dealer, Net Promoter Score (NPS), and DEA Efficiency. By integrating Data Envelopment Analysis (DEA) with advanced predictive modelling techniques, including GBM, Random Forest, SVM, Linear regression, and ARIMA, the study provides a comprehensive evaluation of dealership efficiency and identifies key performance drivers.

The findings reveal that dealerships in regions with higher *Regional Population Density* and more favourable *Regulatory Environment Scores* generally achieve superior efficiency. The *Regulatory Environment Score* significantly impacts DEA efficiency, while other factors, such as *Cultural Difference Score* and *Local Economic Growth*, have less influence. Internally, *Service Completion Time* and the *Number of Salespeople* play crucial roles in operational efficiency, with shorter service times and increased staffing positively affecting performance. The GBM model consistently provides the most accurate predictions for Monthly Sales Volume, NPS, and DEA Efficiency, making it a valuable tool for BYD to optimise operations, particularly in underperforming regions.

5.2. Addressing Research Objectives

This study successfully addresses the following research objectives:

1. Assess BYD dealership efficiency using Data Envelopment Analysis (DEA) - DEA effectively assesses the efficiency of BYD dealerships across Europe, revealing significant variations. Regions like the Netherlands and Sweden perform efficiently, while Spain and Italy exhibit notable inefficiencies.

2. Develop predictive models to forecast performance metrics, including Monthly Sales Volume per Dealer, Net Promoter Score (NPS), and DEA Efficiency - The GBM model emerges as the most accurate across all metrics, making it a reliable tool for predicting sales volume, NPS, and DEA efficiency.

3. Identify key internal and external factors impacting dealership performance - Internal factors, such as *Service Completion Time* and the *Number of Salespeople*, significantly impact efficiency, while external factors like *Regional Population Density* and *Regulatory Environment Score* are also critical.

4. Provide strategic recommendations to optimise operations and improve customer satisfaction - The research offers recommendations to optimise staffing levels, reduce service completion times, and tailor operations to local regulations, aiming to improve both efficiency and customer satisfaction, especially in lower-performing regions.

5.3. Practical Recommendations and Limitations

To enhance dealership performance, the study recommends optimising staffing levels by increasing the number of salespeople in regions with high sales potential but low staffing, ensuring customer demand is met efficiently. Reducing service completion times by streamlining processes is crucial, particularly where delays are negatively impacting customer satisfaction. Aligning dealership operations with local regulatory environments can significantly improve efficiency, and focusing on underperforming regions like Spain and Italy will address specific inefficiencies, improving overall network performance.

However, this research has several limitations. The reliance on secondary and synthetic data introduces potential biases, and while synthetic data is validated, it may not fully capture real-world conditions. The predictive models, despite their robustness, face challenges like potential overfitting and limited interpretability, especially in complex models such as GBM. Additionally, the focus on BYD dealerships in Europe limits the generalisability of the findings to other regions, and the short data collection period restricts capturing long-term trends.

5.4. Future Research and Concluding Remarks

Future research could expand on this study by collecting long-term data to improve model accuracy and capture broader trends. Investigating additional variables, such as digitalisation, customer demographics, and marketing strategies, would provide further insights into dealership performance. Expanding the study to include other regions could offer a global perspective, and incorporating qualitative research, such as interviews with dealership managers, would enhance the understanding of operational drivers.

In conclusion, this dissertation contributes to academic literature by integrating DEA with predictive modelling to assess dealership performance. It provides BYD with practical insights for optimising operations across Europe. The findings lay a foundation for improving dealership efficiency and customer satisfaction while guiding future research to enhance dealership performance in other regions and industries.

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Appendices

Appendix I. Dataset Sources

Variables		Sources
Dealership Names, Country, Regions, Number of Outlets	UK	https://www.byd.com/uk/find-store.html
	Austria	https://www.bydauto.at/haendler
	France	https://www.byd.com/fr/reseau
	Germany	https://www.byd.com/de/find-store
	Hungary	https://www.byd.com/hu/find-store
	Italy	https://www.byd.com/it/find-store
	Netherlands	https://www.byd.com/nl/find-store
	Norway	https://www.byd.com/no/find-store
	Portugal	https://www.byd.com/pt/find-store
	Poland	https://www.byd.com/pl/find-store
	Spain	https://www.byd.com/es-es/find-store
	Sweden	https://www.byd.com/se/find-store
Monthly Sales Volume	2024 January - May	https://www.marklines.com/en/vehicle_sales/member
	2023 May - December	https://www.marklines.com/en/vehicle_sales/search_country/search/?searchID=3095978
Regional Population Density	UK	https://www.ons.gov.uk/peoplepopulationandcommunity/populationandmigration/populationestimates/datasets/populationestimatesforukenglandandwalesscotlandandnorthernireland
	France	https://www.insee.fr/fr/statistiques/5039951
	EU	https://ec.europa.eu/eurostat/databrowser/view/demo_r_d3dens__custom_12072967/default/table?lang=en
Local Economic Growth	UK	https://www.ons.gov.uk/economy/grossdomesticproductgdp/bulletins/gdpukregionsandcountries/julytoseptember2022
	France	https://economy-finance.ec.europa.eu/system/files/2023-06/ip234_en.pdf
	Norway	https://www.ssb.no/en/nasjonalregnskap-og-konjunkturer/nasjonalregnskap/statistikk/fylkesfordelt-nasjonalregnskap
	Germany	https://economy-finance.ec.europa.eu/system/files/2023-06/ip229_en.pdf
	EU	https://ec.europa.eu/eurostat/web/products-eurostat-news/w/ddn-20240220-2
Cultural Difference Score		https://worldpopulationreview.com/country-rankings/most-diverse-countries
Regulatory Environment Score		https://archive.doingbusiness.org/en/data/doing-business-score
Monthly_Sales_Volume_per_Dealer		Syntethic data
Number_of_Salespeople		Syntethic data
Service_Completion_Time		Syntethic data
NPS_Score		Syntethic data

Appendix II. Dealership Dataset

Dealership_Name	Country	Region	Number_of_Outlets	Year	Month	Monthly_Sales_Volume_per_Country	Regional_Population_Density	Local_Economic_Growth	Cultural_Difference_Score	Regulatory_Environment_Score
Arnold Clark	UK	Scotland	4	2023	May	21	70.0	-0.003	0.1211	83.5
Arnold Clark	UK	Scotland	4	2023	June	15	70.0	-0.003	0.1211	83.5
Arnold Clark	UK	Scotland	4	2023	July	81	70.0	-0.003	0.1211	83.5
Arnold Clark	UK	Scotland	4	2023	August	33	70.0	-0.003	0.1211	83.5
Arnold Clark	UK	Scotland	4	2023	September	232	70.0	-0.003	0.1211	83.5
Arnold Clark	UK	Scotland	4	2023	October	183	70.0	-0.003	0.1211	83.5
Arnold Clark	UK	Scotland	4	2023	November	267	70.0	-0.003	0.1211	83.5
Arnold Clark	UK	Scotland	4	2023	December	263	70.0	-0.003	0.1211	83.5
Arnold Clark	UK	Scotland	4	2024	January	248	70.0	-0.003	0.1211	83.5
Arnold Clark	UK	Scotland	4	2024	February	271	70.0	-0.003	0.1211	83.5
Arnold Clark	UK	Scotland	4	2024	March	759	70.0	-0.003	0.1211	83.5
Arnold Clark	UK	Scotland	4	2024	April	333	70.0	-0.003	0.1211	83.5
Arnold Clark	UK	Scotland	4	2024	May	596	70.0	-0.003	0.1211	83.5
Arnold Clark	UK	North East	1	2023	May	21	313.0	0.007	0.1211	83.5
Arnold Clark	UK	North East	1	2023	June	15	313.0	0.007	0.1211	83.5
Arnold Clark	UK	North East	1	2023	July	81	313.0	0.007	0.1211	83.5
Arnold Clark	UK	North East	1	2023	August	33	313.0	0.007	0.1211	83.5
Arnold Clark	UK	North East	1	2023	September	232	313.0	0.007	0.1211	83.5
Arnold Clark	UK	North East	1	2023	October	183	313.0	0.007	0.1211	83.5
Arnold Clark	UK	North East	1	2023	November	267	313.0	0.007	0.1211	83.5
Arnold Clark	UK	North East	1	2023	December	263	313.0	0.007	0.1211	83.5
Arnold Clark	UK	North East	1	2024	January	248	313.0	0.007	0.1211	83.5
Arnold Clark	UK	North East	1	2024	February	271	313.0	0.007	0.1211	83.5
Arnold Clark	UK	North East	1	2024	March	759	313.0	0.007	0.1211	83.5
Arnold Clark	UK	North East	1	2024	April	333	313.0	0.007	0.1211	83.5
Arnold Clark	UK	North East	1	2024	May	596	313.0	0.007	0.1211	83.5
DM Keith	UK	Yorkshire and The	4	2023	May	21	360.0	-0.002	0.1211	83.5
DM Keith	UK	Yorkshire and The Humber	4	2023	June	15	360.0	-0.002	0.1211	83.5
DM Keith	UK	Yorkshire and The Humber	4	2023	July	81	360.0	-0.002	0.1211	83.5
DM Keith	UK	Yorkshire and The Humber	4	2023	August	33	360.0	-0.002	0.1211	83.5
DM Keith	UK	Yorkshire and The Humber	4	2023	September	232	360.0	-0.002	0.1211	83.5
DM Keith	UK	Yorkshire and The Humber	4	2023	October	183	360.0	-0.002	0.1211	83.5
DM Keith	UK	Yorkshire and The Humber	4	2023	November	267	360.0	-0.002	0.1211	83.5
DM Keith	UK	Yorkshire and The Humber	4	2023	December	263	360.0	-0.002	0.1211	83.5
DM Keith	UK	Yorkshire and The Humber	4	2024	January	248	360.0	-0.002	0.1211	83.5
DM Keith	UK	Yorkshire and The Humber	4	2024	February	271	360.0	-0.002	0.1211	83.5
DM Keith	UK	Yorkshire and The Humber	4	2024	March	759	360.0	-0.002	0.1211	83.5
DM Keith	UK	Yorkshire and The Humber	4	2024	April	333	360.0	-0.002	0.1211	83.5
DM Keith	UK	Yorkshire and The Humber	4	2024	May	596	360.0	-0.002	0.1211	83.5
Stratstone	UK	West Midlands	2	2023	May	21	463.0	-0.006	0.1211	83.5
Stratstone	UK	West Midlands	2	2023	June	15	463.0	-0.006	0.1211	83.5
Stratstone	UK	West Midlands	2	2023	July	81	463.0	-0.006	0.1211	83.5
Stratstone	UK	West Midlands	2	2023	August	33	463.0	-0.006	0.1211	83.5
Stratstone	UK	West Midlands	2	2023	September	232	463.0	-0.006	0.1211	83.5
Stratstone	UK	West Midlands	2	2023	October	183	463.0	-0.006	0.1211	83.5
Stratstone	UK	West Midlands	2	2023	November	267	463.0	-0.006	0.1211	83.5
Stratstone	UK	West Midlands	2	2023	December	263	463.0	-0.006	0.1211	83.5
Stratstone	UK	West Midlands	2	2024	January	248	463.0	-0.006	0.1211	83.5
Stratstone	UK	West Midlands	2	2024	February	271	463.0	-0.006	0.1211	83.5
Stratstone	UK	West Midlands	2	2024	March	759	463.0	-0.006	0.1211	83.5
Stratstone	UK	West Midlands	2	2024	April	333	463.0	-0.006	0.1211	83.5
Stratstone	UK	West Midlands	2	2024	May	596	463.0	-0.006	0.1211	83.5
Stratstone	UK	London	1	2023	May	21	5,640.0	0.009	0.1211	83.5
Stratstone	UK	London	1	2023	June	15	5,640.0	0.009	0.1211	83.5
Stratstone	UK	London	1	2023	July	81	5,640.0	0.009	0.1211	83.5
Stratstone	UK	London	1	2023	August	33	5,640.0	0.009	0.1211	83.5
Stratstone	UK	London	1	2023	September	232	5,640.0	0.009	0.1211	83.5
Stratstone	UK	London	1	2023	October	183	5,640.0	0.009	0.1211	83.5
Stratstone	UK	London	1	2023	November	267	5,640.0	0.009	0.1211	83.5
Stratstone	UK	London	1	2023	December	263	5,640.0	0.009	0.1211	83.5
Stratstone	UK	London	1	2024	January	248	5,640.0	0.009	0.1211	83.5
Stratstone	UK	London	1	2024	February	271	5,640.0	0.009	0.1211	83.5
Stratstone	UK	London	1	2024	March	759	5,640.0	0.009	0.1211	83.5
Stratstone	UK	London	1	2024	April	333	5,640.0	0.009	0.1211	83.5
Stratstone	UK	London	1	2024	May	596	5,640.0	0.009	0.1211	83.5
Stratstone	UK	South East	1	2023	May	21	492.0	-0.001	0.1211	83.5
Stratstone	UK	South East	1	2023	June	15	492.0	-0.001	0.1211	83.5
Stratstone	UK	South East	1	2023	July	81	492.0	-0.001	0.1211	83.5
Stratstone	UK	South East	1	2023	August	33	492.0	-0.001	0.1211	83.5
Stratstone	UK	South East	1	2023	September	232	492.0	-0.001	0.1211	83.5
Stratstone	UK	South East	1	2023	October	183	492.0	-0.001	0.1211	83.5
Stratstone	UK	South East	1	2023	November	267	492.0	-0.001	0.1211	83.5
Stratstone	UK	South East	1	2023	December	263	492.0	-0.001	0.1211	83.5
Stratstone	UK	South East	1	2024	January	248	492.0	-0.001	0.1211	83.5
Stratstone	UK	South East	1	2024	February	271	492.0	-0.001	0.1211	83.5
Stratstone	UK	South East	1	2024	March	759	492.0	-0.001	0.1211	83.5
Stratstone	UK	South East	1	2024	April	333	492.0	-0.001	0.1211	83.5
Stratstone	UK	South East	1	2024	May	596	492.0	-0.001	0.1211	83.5

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Dealership_Name	Country	Region	Number_of_Outlets	Year	Month	Monthly_Sales_Volume_per_Country	Regional_Population_Density	Local_Economic_Growth	Cultural_Difference_Score	Regulatory_Environment_Score
LSH Auto	UK	North West	2	2023	May	21	533.0	-0.001	0.1211	83.5
LSH Auto	UK	North West	2	2023	June	15	533.0	-0.001	0.1211	83.5
LSH Auto	UK	North West	2	2023	July	81	533.0	-0.001	0.1211	83.5
LSH Auto	UK	North West	2	2023	August	33	533.0	-0.001	0.1211	83.5
LSH Auto	UK	North West	2	2023	September	232	533.0	-0.001	0.1211	83.5
LSH Auto	UK	North West	2	2023	October	183	533.0	-0.001	0.1211	83.5
LSH Auto	UK	North West	2	2023	November	267	533.0	-0.001	0.1211	83.5
LSH Auto	UK	North West	2	2023	December	263	533.0	-0.001	0.1211	83.5
LSH Auto	UK	North West	2	2024	January	248	533.0	-0.001	0.1211	83.5
LSH Auto	UK	North West	2	2024	February	271	533.0	-0.001	0.1211	83.5
LSH Auto	UK	North West	2	2024	March	759	533.0	-0.001	0.1211	83.5
LSH Auto	UK	North West	2	2024	April	333	533.0	-0.001	0.1211	83.5
LSH Auto	UK	North West	2	2024	May	596	533.0	-0.001	0.1211	83.5
LSH Auto	UK	West Midlands	1	2023	May	21	463.0	-0.006	0.1211	83.5
LSH Auto	UK	West Midlands	1	2023	June	15	463.0	-0.006	0.1211	83.5
LSH Auto	UK	West Midlands	1	2023	July	81	463.0	-0.006	0.1211	83.5
LSH Auto	UK	West Midlands	1	2023	August	33	463.0	-0.006	0.1211	83.5
LSH Auto	UK	West Midlands	1	2023	September	232	463.0	-0.006	0.1211	83.5
LSH Auto	UK	West Midlands	1	2023	October	183	463.0	-0.006	0.1211	83.5
LSH Auto	UK	West Midlands	1	2023	November	267	463.0	-0.006	0.1211	83.5
LSH Auto	UK	West Midlands	1	2023	December	263	463.0	-0.006	0.1211	83.5
LSH Auto	UK	West Midlands	1	2024	January	248	463.0	-0.006	0.1211	83.5
LSH Auto	UK	West Midlands	1	2024	February	271	463.0	-0.006	0.1211	83.5
LSH Auto	UK	West Midlands	1	2024	March	759	463.0	-0.006	0.1211	83.5
LSH Auto	UK	West Midlands	1	2024	April	333	463.0	-0.006	0.1211	83.5
LSH Auto	UK	West Midlands	1	2024	May	596	463.0	-0.006	0.1211	83.5
LSH Auto	UK	London	1	2023	May	21	5,640.0	0.009	0.1211	83.5
LSH Auto	UK	London	1	2023	June	15	5,640.0	0.009	0.1211	83.5
LSH Auto	UK	London	1	2023	July	81	5,640.0	0.009	0.1211	83.5
LSH Auto	UK	London	1	2023	August	33	5,640.0	0.009	0.1211	83.5
LSH Auto	UK	London	1	2023	September	232	5,640.0	0.009	0.1211	83.5
LSH Auto	UK	London	1	2023	October	183	5,640.0	0.009	0.1211	83.5
LSH Auto	UK	London	1	2023	November	267	5,640.0	0.009	0.1211	83.5
LSH Auto	UK	London	1	2023	December	263	5,640.0	0.009	0.1211	83.5
LSH Auto	UK	London	1	2024	January	248	5,640.0	0.009	0.1211	83.5
LSH Auto	UK	London	1	2024	February	271	5,640.0	0.009	0.1211	83.5
LSH Auto	UK	London	1	2024	March	759	5,640.0	0.009	0.1211	83.5
LSH Auto	UK	London	1	2024	April	333	5,640.0	0.009	0.1211	83.5
LSH Auto	UK	London	1	2024	May	596	5,640.0	0.009	0.1211	83.5
Hartwell	UK	East of England	1	2023	May	21	335.0	-0.007	0.1211	83.5
Hartwell	UK	East of England	1	2023	June	15	335.0	-0.007	0.1211	83.5
Hartwell	UK	East of England	1	2023	July	81	335.0	-0.007	0.1211	83.5
Hartwell	UK	East of England	1	2023	August	33	335.0	-0.007	0.1211	83.5
Hartwell	UK	East of England	1	2023	September	232	335.0	-0.007	0.1211	83.5
Hartwell	UK	East of England	1	2023	October	183	335.0	-0.007	0.1211	83.5
Hartwell	UK	East of England	1	2023	November	267	335.0	-0.007	0.1211	83.5
Hartwell	UK	East of England	1	2023	December	263	335.0	-0.007	0.1211	83.5
Hartwell	UK	East of England	1	2024	January	248	335.0	-0.007	0.1211	83.5
Hartwell	UK	East of England	1	2024	February	271	335.0	-0.007	0.1211	83.5
Hartwell	UK	East of England	1	2024	March	759	335.0	-0.007	0.1211	83.5
Hartwell	UK	East of England	1	2024	April	333	335.0	-0.007	0.1211	83.5
Hartwell	UK	East of England	1	2024	May	596	335.0	-0.007	0.1211	83.5
Hartwell	UK	West Midlands	1	2023	May	21	463.0	-0.006	0.1211	83.5
Hartwell	UK	West Midlands	1	2023	June	15	463.0	-0.006	0.1211	83.5
Hartwell	UK	West Midlands	1	2023	July	81	463.0	-0.006	0.1211	83.5
Hartwell	UK	West Midlands	1	2023	August	33	463.0	-0.006	0.1211	83.5
Hartwell	UK	West Midlands	1	2023	September	232	463.0	-0.006	0.1211	83.5
Hartwell	UK	West Midlands	1	2023	October	183	463.0	-0.006	0.1211	83.5
Hartwell	UK	West Midlands	1	2023	November	267	463.0	-0.006	0.1211	83.5
Hartwell	UK	West Midlands	1	2023	December	263	463.0	-0.006	0.1211	83.5
Hartwell	UK	West Midlands	1	2024	January	248	463.0	-0.006	0.1211	83.5
Hartwell	UK	West Midlands	1	2024	February	271	463.0	-0.006	0.1211	83.5
Hartwell	UK	West Midlands	1	2024	March	759	463.0	-0.006	0.1211	83.5
Hartwell	UK	West Midlands	1	2024	April	333	463.0	-0.006	0.1211	83.5
Hartwell	UK	West Midlands	1	2024	May	596	463.0	-0.006	0.1211	83.5
Hartwell	UK	South East	1	2023	May	21	492.0	-0.001	0.1211	83.5
Hartwell	UK	South East	1	2023	June	15	492.0	-0.001	0.1211	83.5
Hartwell	UK	South East	1	2023	July	81	492.0	-0.001	0.1211	83.5
Hartwell	UK	South East	1	2023	August	33	492.0	-0.001	0.1211	83.5
Hartwell	UK	South East	1	2023	September	232	492.0	-0.001	0.1211	83.5
Hartwell	UK	South East	1	2023	October	183	492.0	-0.001	0.1211	83.5
Hartwell	UK	South East	1	2023	November	267	492.0	-0.001	0.1211	83.5
Hartwell	UK	South East	1	2023	December	263	492.0	-0.001	0.1211	83.5
Hartwell	UK	South East	1	2024	January	248	492.0	-0.001	0.1211	83.5
Hartwell	UK	South East	1	2024	February	271	492.0	-0.001	0.1211	83.5
Hartwell	UK	South East	1	2024	March	759	492.0	-0.001	0.1211	83.5
Hartwell	UK	South East	1	2024	April	333	492.0	-0.001	0.1211	83.5
Hartwell	UK	South East	1	2024	May	596	492.0	-0.001	0.1211	83.5
Pentagon	UK	East Midlands	3	2023	May	21	316.0	-0.016	0.1211	83.5
Pentagon	UK	East Midlands	3	2023	June	15	316.0	-0.016	0.1211	83.5
Pentagon	UK	East Midlands	3	2023	July	81	316.0	-0.016	0.1211	83.5
Pentagon	UK	East Midlands	3	2023	August	33	316.0	-0.016	0.1211	83.5
Pentagon	UK	East Midlands	3	2023	September	232	316.0	-0.016	0.1211	83.5
Pentagon	UK	East Midlands	3	2023	October	183	316.0	-0.016	0.1211	83.5
Pentagon	UK	East Midlands	3	2023	November	267	316.0	-0.016	0.1211	83.5
Pentagon	UK	East Midlands	3	2023	December	263	316.0	-0.016	0.1211	83.5
Pentagon	UK	East Midlands	3	2024	January	248	316.0	-0.016	0.1211	83.5
Pentagon	UK	East Midlands	3	2024	February	271	316.0	-0.016	0.1211	83.5
Pentagon	UK	East Midlands	3	2024	March	759	316.0	-0.016	0.1211	83.5
Pentagon	UK	East Midlands	3	2024	April	333	316.0	-0.016	0.1211	83.5
Pentagon	UK	East Midlands	3	2024	May	596	316.0	-0.016	0.1211	83.5
Lookers	UK	Yorkshire and The	1	2023	May	21	360.0	-0.002	0.1211	83.5
Lookers	UK	Yorkshire and The Humber	1	2023	June	15	360.0	-0.002	0.1211	83.5
Lookers	UK	Yorkshire and The Humber	1	2023	July	81	360.0	-0.002	0.1211	83.5
Lookers	UK	Yorkshire and The Humber	1	2023	August	33	360.0	-0.002	0.1211	83.5
Lookers	UK	Yorkshire and The Humber	1	2023	September	232	360.0	-0.002	0.1211	83.5
Lookers	UK	Yorkshire and The Humber	1	2023	October	183	360.0	-0.002	0.1211	83.5
Lookers	UK	Yorkshire and The Humber	1	2023	November	267	360.0	-0.002	0.1211	83.5
Lookers	UK	Yorkshire and The Humber	1	2023	December	263	360.0	-0.002	0.1211	83.5
Lookers	UK	Yorkshire and The Humber	1	2024	January	248	360.0	-0.002	0.1211	83.5
Lookers	UK	Yorkshire and The Humber	1	2024	February	271	360.0	-0.002	0.1211	83.5
Lookers	UK	Yorkshire and The Humber	1	2024	March	759	360.0	-0.002	0.1211	83.5
Lookers	UK	Yorkshire and The Humber	1	2024	April	333	360.0	-0.002	0.1211	83.5
Lookers	UK	Yorkshire and The Humber	1	2024	May	596	360.0	-0.002	0.1211	83.5

Dealership_Name	Country	Region	Number_of_Outlets	Year	Month	Monthly_Sales_Volume_per_Country	Regional_Population_Density	Local_Economic_Growth	Cultural_Difference_Score	Regulatory_Environment_Score
Lookers	UK	Yorkshire and The Humber	1	2024	January	248	360.0	-0.002	0.1211	83.5
Lookers	UK	Yorkshire and The Humber	1	2024	February	271	360.0	-0.002	0.1211	83.5
Lookers	UK	Yorkshire and The Humber	1	2024	March	759	360.0	-0.002	0.1211	83.5
Lookers	UK	Yorkshire and The Humber	1	2024	April	333	360.0	-0.002	0.1211	83.5
Lookers	UK	Yorkshire and The Humber	1	2024	May	596	360.0	-0.002	0.1211	83.5
Lookers	UK	North East	1	2023	May	21	313.0	0.007	0.1211	83.5
Lookers	UK	North East	1	2023	June	15	313.0	0.007	0.1211	83.5
Lookers	UK	North East	1	2023	July	81	313.0	0.007	0.1211	83.5
Lookers	UK	North East	1	2023	August	33	313.0	0.007	0.1211	83.5
Lookers	UK	North East	1	2023	September	232	313.0	0.007	0.1211	83.5
Lookers	UK	North East	1	2023	October	183	313.0	0.007	0.1211	83.5
Lookers	UK	North East	1	2023	November	267	313.0	0.007	0.1211	83.5
Lookers	UK	North East	1	2023	December	263	313.0	0.007	0.1211	83.5
Lookers	UK	North East	1	2024	January	248	313.0	0.007	0.1211	83.5
Lookers	UK	North East	1	2024	February	271	313.0	0.007	0.1211	83.5
Lookers	UK	North East	1	2024	March	759	313.0	0.007	0.1211	83.5
Lookers	UK	North East	1	2024	April	333	313.0	0.007	0.1211	83.5
Lookers	UK	North East	1	2024	May	596	313.0	0.007	0.1211	83.5
Snows	UK	South East	2	2023	May	21	492.0	-0.001	0.1211	83.5
Snows	UK	South East	2	2023	June	15	492.0	-0.001	0.1211	83.5
Snows	UK	South East	2	2023	July	81	492.0	-0.001	0.1211	83.5
Snows	UK	South East	2	2023	August	33	492.0	-0.001	0.1211	83.5
Snows	UK	South East	2	2023	September	232	492.0	-0.001	0.1211	83.5
Snows	UK	South East	2	2023	October	183	492.0	-0.001	0.1211	83.5
Snows	UK	South East	2	2023	November	267	492.0	-0.001	0.1211	83.5
Snows	UK	South East	2	2023	December	263	492.0	-0.001	0.1211	83.5
Snows	UK	South East	2	2024	January	248	492.0	-0.001	0.1211	83.5
Snows	UK	South East	2	2024	February	271	492.0	-0.001	0.1211	83.5
Snows	UK	South East	2	2024	March	759	492.0	-0.001	0.1211	83.5
Snows	UK	South East	2	2024	April	333	492.0	-0.001	0.1211	83.5
Snows	UK	South East	2	2024	May	596	492.0	-0.001	0.1211	83.5
Swansway	UK	North West	2	2023	May	21	533.0	-0.001	0.1211	83.5
Swansway	UK	North West	2	2023	June	15	533.0	-0.001	0.1211	83.5
Swansway	UK	North West	2	2023	July	81	533.0	-0.001	0.1211	83.5
Swansway	UK	North West	2	2023	August	33	533.0	-0.001	0.1211	83.5
Swansway	UK	North West	2	2023	September	232	533.0	-0.001	0.1211	83.5
Swansway	UK	North West	2	2023	October	183	533.0	-0.001	0.1211	83.5
Swansway	UK	North West	2	2023	November	267	533.0	-0.001	0.1211	83.5
Swansway	UK	North West	2	2023	December	263	533.0	-0.001	0.1211	83.5
Swansway	UK	North West	2	2024	January	248	533.0	-0.001	0.1211	83.5
Swansway	UK	North West	2	2024	February	271	533.0	-0.001	0.1211	83.5
Swansway	UK	North West	2	2024	March	759	533.0	-0.001	0.1211	83.5
Swansway	UK	North West	2	2024	April	333	533.0	-0.001	0.1211	83.5
Swansway	UK	North West	2	2024	May	596	533.0	-0.001	0.1211	83.5
Sinclair Group	UK	Wales	1	2023	May	21	151.0	-0.020	0.1211	83.5
Sinclair Group	UK	Wales	1	2023	June	15	151.0	-0.020	0.1211	83.5
Sinclair Group	UK	Wales	1	2023	July	81	151.0	-0.020	0.1211	83.5
Sinclair Group	UK	Wales	1	2023	August	33	151.0	-0.020	0.1211	83.5
Sinclair Group	UK	Wales	1	2023	September	232	151.0	-0.020	0.1211	83.5
Sinclair Group	UK	Wales	1	2023	October	183	151.0	-0.020	0.1211	83.5
Sinclair Group	UK	Wales	1	2023	November	267	151.0	-0.020	0.1211	83.5
Sinclair Group	UK	Wales	1	2023	December	263	151.0	-0.020	0.1211	83.5
Sinclair Group	UK	Wales	1	2024	January	248	151.0	-0.020	0.1211	83.5
Sinclair Group	UK	Wales	1	2024	February	271	151.0	-0.020	0.1211	83.5
Sinclair Group	UK	Wales	1	2024	March	759	151.0	-0.020	0.1211	83.5
Sinclair Group	UK	Wales	1	2024	April	333	151.0	-0.020	0.1211	83.5
Sinclair Group	UK	Wales	1	2024	May	596	151.0	-0.020	0.1211	83.5
Charles Hurst	UK	Northern Ireland	1	2023	May	21	141.0	0.000	0.1211	83.5
Charles Hurst	UK	Northern Ireland	1	2023	June	15	141.0	0.000	0.1211	83.5
Charles Hurst	UK	Northern Ireland	1	2023	July	81	141.0	0.000	0.1211	83.5
Charles Hurst	UK	Northern Ireland	1	2023	August	33	141.0	0.000	0.1211	83.5
Charles Hurst	UK	Northern Ireland	1	2023	September	232	141.0	0.000	0.1211	83.5
Charles Hurst	UK	Northern Ireland	1	2023	October	183	141.0	0.000	0.1211	83.5
Charles Hurst	UK	Northern Ireland	1	2023	November	267	141.0	0.000	0.1211	83.5
Charles Hurst	UK	Northern Ireland	1	2023	December	263	141.0	0.000	0.1211	83.5
Charles Hurst	UK	Northern Ireland	1	2024	January	248	141.0	0.000	0.1211	83.5
Charles Hurst	UK	Northern Ireland	1	2024	February	271	141.0	0.000	0.1211	83.5
Charles Hurst	UK	Northern Ireland	1	2024	March	759	141.0	0.000	0.1211	83.5
Charles Hurst	UK	Northern Ireland	1	2024	April	333	141.0	0.000	0.1211	83.5
Charles Hurst	UK	Northern Ireland	1	2024	May	596	141.0	0.000	0.1211	83.5
Alan Day	UK	London	1	2023	May	21	5,640.0	0.009	0.1211	83.5
Alan Day	UK	London	1	2023	June	15	5,640.0	0.009	0.1211	83.5
Alan Day	UK	London	1	2023	July	81	5,640.0	0.009	0.1211	83.5
Alan Day	UK	London	1	2023	August	33	5,640.0	0.009	0.1211	83.5
Alan Day	UK	London	1	2023	September	232	5,640.0	0.009	0.1211	83.5
Alan Day	UK	London	1	2023	October	183	5,640.0	0.009	0.1211	83.5
Alan Day	UK	London	1	2023	November	267	5,640.0	0.009	0.1211	83.5
Alan Day	UK	London	1	2023	December	263	5,640.0	0.009	0.1211	83.5
Alan Day	UK	London	1	2024	January	248	5,640.0	0.009	0.1211	83.5
Alan Day	UK	London	1	2024	February	271	5,640.0	0.009	0.1211	83.5
Alan Day	UK	London	1	2024	March	759	5,640.0	0.009	0.1211	83.5
Alan Day	UK	London	1	2024	April	333	5,640.0	0.009	0.1211	83.5
Alan Day	UK	London	1	2024	May	596	5,640.0	0.009	0.1211	83.5
Sturgess	UK	East Midlands	1	2023	May	21	316.0	-0.016	0.1211	83.5
Sturgess	UK	East Midlands	1	2023	June	15	316.0	-0.016	0.1211	83.5
Sturgess	UK	East Midlands	1	2023	July	81	316.0	-0.016	0.1211	83.5
Sturgess	UK	East Midlands	1	2023	August	33	316.0	-0.016	0.1211	83.5
Sturgess	UK	East Midlands	1	2023	September	232	316.0	-0.016	0.1211	83.5
Sturgess	UK	East Midlands	1	2023	October	183	316.0	-0.016	0.1211	83.5
Sturgess	UK	East Midlands	1	2023	November	267	316.0	-0.016	0.1211	83.5
Sturgess	UK	East Midlands	1	2023	December	263	316.0	-0.016	0.1211	83.5
Sturgess	UK	East Midlands	1	2024	January	248	316.0	-0.016	0.1211	83.5
Sturgess	UK	East Midlands	1	2024	February	271	316.0	-0.016	0.1211	83.5
Sturgess	UK	East Midlands	1	2024	March	759	316.0	-0.016	0.1211	83.5
Sturgess	UK	East Midlands	1	2024	April	333	316.0	-0.016	0.1211	83.5
Sturgess	UK	East Midlands	1	2024	May	596	316.0	-0.016	0.1211	83.5

Dealership_Name	Country	Region	Number_of_Outlets	Year	Month	Monthly_Sales_Volume_per_Country	Regional_Population_Density	Local_Economic_Growth	Cultural_Difference_Score	Regulatory_Environment_Score
SG Petch	UK	North East	1	2023	May	21	313.0	0.007	0.1211	83.5
SG Petch	UK	North East	1	2023	June	15	313.0	0.007	0.1211	83.5
SG Petch	UK	North East	1	2023	July	81	313.0	0.007	0.1211	83.5
SG Petch	UK	North East	1	2023	August	33	313.0	0.007	0.1211	83.5
SG Petch	UK	North East	1	2023	September	232	313.0	0.007	0.1211	83.5
SG Petch	UK	North East	1	2023	October	183	313.0	0.007	0.1211	83.5
SG Petch	UK	North East	1	2023	November	267	313.0	0.007	0.1211	83.5
SG Petch	UK	North East	1	2023	December	263	313.0	0.007	0.1211	83.5
SG Petch	UK	North East	1	2024	January	248	313.0	0.007	0.1211	83.5
SG Petch	UK	North East	1	2024	February	271	313.0	0.007	0.1211	83.5
SG Petch	UK	North East	1	2024	March	759	313.0	0.007	0.1211	83.5
SG Petch	UK	North East	1	2024	April	333	313.0	0.007	0.1211	83.5
SG Petch	UK	North East	1	2024	May	596	313.0	0.007	0.1211	83.5
Busseys	UK	East of England	1	2023	May	21	335.0	-0.007	0.1211	83.5
Busseys	UK	East of England	1	2023	June	15	335.0	-0.007	0.1211	83.5
Busseys	UK	East of England	1	2023	July	81	335.0	-0.007	0.1211	83.5
Busseys	UK	East of England	1	2023	August	33	335.0	-0.007	0.1211	83.5
Busseys	UK	East of England	1	2023	September	232	335.0	-0.007	0.1211	83.5
Busseys	UK	East of England	1	2023	October	183	335.0	-0.007	0.1211	83.5
Busseys	UK	East of England	1	2023	November	267	335.0	-0.007	0.1211	83.5
Busseys	UK	East of England	1	2023	December	263	335.0	-0.007	0.1211	83.5
Busseys	UK	East of England	1	2024	January	248	335.0	-0.007	0.1211	83.5
Busseys	UK	East of England	1	2024	February	271	335.0	-0.007	0.1211	83.5
Busseys	UK	East of England	1	2024	March	759	335.0	-0.007	0.1211	83.5
Busseys	UK	East of England	1	2024	April	333	335.0	-0.007	0.1211	83.5
Busseys	UK	East of England	1	2024	May	596	335.0	-0.007	0.1211	83.5
Harmony Auto	UK	London	1	2023	May	21	5,640.0	0.009	0.1211	83.5
Harmony Auto	UK	London	1	2023	June	15	5,640.0	0.009	0.1211	83.5
Harmony Auto	UK	London	1	2023	July	81	5,640.0	0.009	0.1211	83.5
Harmony Auto	UK	London	1	2023	August	33	5,640.0	0.009	0.1211	83.5
Harmony Auto	UK	London	1	2023	September	232	5,640.0	0.009	0.1211	83.5
Harmony Auto	UK	London	1	2023	October	183	5,640.0	0.009	0.1211	83.5
Harmony Auto	UK	London	1	2023	November	267	5,640.0	0.009	0.1211	83.5
Harmony Auto	UK	London	1	2023	December	263	5,640.0	0.009	0.1211	83.5
Harmony Auto	UK	London	1	2024	January	248	5,640.0	0.009	0.1211	83.5
Harmony Auto	UK	London	1	2024	February	271	5,640.0	0.009	0.1211	83.5
Harmony Auto	UK	London	1	2024	March	759	5,640.0	0.009	0.1211	83.5
Harmony Auto	UK	London	1	2024	April	333	5,640.0	0.009	0.1211	83.5
Harmony Auto	UK	London	1	2024	May	596	5,640.0	0.009	0.1211	83.5
City West	UK	South West	1	2023	May	21	242.0	0.004	0.1211	83.5
City West Country	UK	South West	1	2023	June	15	242.0	0.004	0.1211	83.5
City West Country	UK	South West	1	2023	July	81	242.0	0.004	0.1211	83.5
City West Country	UK	South West	1	2023	August	33	242.0	0.004	0.1211	83.5
City West Country	UK	South West	1	2023	September	232	242.0	0.004	0.1211	83.5
City West Country	UK	South West	1	2023	October	183	242.0	0.004	0.1211	83.5
City West Country	UK	South West	1	2023	November	267	242.0	0.004	0.1211	83.5
City West Country	UK	South West	1	2023	December	263	242.0	0.004	0.1211	83.5
City West Country	UK	South West	1	2024	January	248	242.0	0.004	0.1211	83.5
City West Country	UK	South West	1	2024	February	271	242.0	0.004	0.1211	83.5
City West Country	UK	South West	1	2024	March	759	242.0	0.004	0.1211	83.5
City West Country	UK	South West	1	2024	April	333	242.0	0.004	0.1211	83.5
City West Country	UK	South West	1	2024	May	596	242.0	0.004	0.1211	83.5
Peoples	UK	North West	1	2023	May	21	533.0	-0.001	0.1211	83.5
Peoples	UK	North West	1	2023	June	15	533.0	-0.001	0.1211	83.5
Peoples	UK	North West	1	2023	July	81	533.0	-0.001	0.1211	83.5
Peoples	UK	North West	1	2023	August	33	533.0	-0.001	0.1211	83.5
Peoples	UK	North West	1	2023	September	232	533.0	-0.001	0.1211	83.5
Peoples	UK	North West	1	2023	October	183	533.0	-0.001	0.1211	83.5
Peoples	UK	North West	1	2023	November	267	533.0	-0.001	0.1211	83.5
Peoples	UK	North West	1	2023	December	263	533.0	-0.001	0.1211	83.5
Peoples	UK	North West	1	2024	January	248	533.0	-0.001	0.1211	83.5
Peoples	UK	North West	1	2024	February	271	533.0	-0.001	0.1211	83.5
Peoples	UK	North West	1	2024	March	759	533.0	-0.001	0.1211	83.5
Peoples	UK	North West	1	2024	April	333	533.0	-0.001	0.1211	83.5
Peoples	UK	North West	1	2024	May	596	533.0	-0.001	0.1211	83.5
Groupe Kroely	France	Grand Est	3	2023	May	62	96.6	0.002	0.1032	76.8
Groupe Kroely	France	Grand Est	3	2023	June	24	96.6	0.002	0.1032	76.8
Groupe Kroely	France	Grand Est	3	2023	July	8	96.6	0.002	0.1032	76.8
Groupe Kroely	France	Grand Est	3	2023	August	10	96.6	0.002	0.1032	76.8
Groupe Kroely	France	Grand Est	3	2023	September	71	96.6	0.002	0.1032	76.8
Groupe Kroely	France	Grand Est	3	2023	October	72	96.6	0.002	0.1032	76.8
Groupe Kroely	France	Grand Est	3	2023	November	82	96.6	0.002	0.1032	76.8
Groupe Kroely	France	Grand Est	3	2023	December	184	96.6	0.002	0.1032	76.8
Groupe Kroely	France	Grand Est	3	2024	January	427	96.6	0.002	0.1032	76.8
Groupe Kroely	France	Grand Est	3	2024	February	363	96.6	0.002	0.1032	76.8
Groupe Kroely	France	Grand Est	3	2024	March	206	96.6	0.002	0.1032	76.8
Groupe Kroely	France	Grand Est	3	2024	April	205	96.6	0.002	0.1032	76.8
Groupe Kroely	France	Grand Est	3	2024	May	129	96.6	0.002	0.1032	76.8

Dealership_Name	Country	Region	Number_of_Outlets	Year	Month	Monthly_Sales_Volume_per_Country	Regional_Population_Density	Local_Economic_Growth	Cultural_Difference_Score	Regulatory_Environment_Score
Groupe Chopard	France	Auvergne-Rhône-Alpes	2	2023	May	62	114.0	0.008	0.1032	76.8
Groupe Chopard	France	Auvergne-Rhône-Alpes	2	2023	June	24	114.0	0.008	0.1032	76.8
Groupe Chopard	France	Auvergne-Rhône-Alpes	2	2023	July	8	114.0	0.008	0.1032	76.8
Groupe Chopard	France	Auvergne-Rhône-Alpes	2	2023	August	10	114.0	0.008	0.1032	76.8
Groupe Chopard	France	Auvergne-Rhône-Alpes	2	2023	September	71	114.0	0.008	0.1032	76.8
Groupe Chopard	France	Auvergne-Rhône-Alpes	2	2023	October	72	114.0	0.008	0.1032	76.8
Groupe Chopard	France	Auvergne-Rhône-Alpes	2	2023	November	82	114.0	0.008	0.1032	76.8
Groupe Chopard	France	Auvergne-Rhône-Alpes	2	2023	December	184	114.0	0.008	0.1032	76.8
Groupe Chopard	France	Auvergne-Rhône-Alpes	2	2024	January	427	114.0	0.008	0.1032	76.8
Groupe Chopard	France	Auvergne-Rhône-Alpes	2	2024	February	363	114.0	0.008	0.1032	76.8
Groupe Chopard	France	Auvergne-Rhône-Alpes	2	2024	March	206	114.0	0.008	0.1032	76.8
Groupe Chopard	France	Auvergne-Rhône-Alpes	2	2024	April	205	114.0	0.008	0.1032	76.8
Groupe Chopard	France	Auvergne-Rhône-Alpes	2	2024	May	129	114.0	0.008	0.1032	76.8
Groupe Chopard	France	Bourgogne-Franche-Comté	1	2023	May	62	59.0	-0.003	0.1032	76.8
Groupe Chopard	France	Bourgogne-Franche-Comté	1	2023	June	24	59.0	-0.003	0.1032	76.8
Groupe Chopard	France	Bourgogne-Franche-Comté	1	2023	July	8	59.0	-0.003	0.1032	76.8
Groupe Chopard	France	Bourgogne-Franche-Comté	1	2023	August	10	59.0	-0.003	0.1032	76.8
Groupe Chopard	France	Bourgogne-Franche-Comté	1	2023	September	71	59.0	-0.003	0.1032	76.8
Groupe Chopard	France	Bourgogne-Franche-Comté	1	2023	October	72	59.0	-0.003	0.1032	76.8
Groupe Chopard	France	Bourgogne-Franche-Comté	1	2023	November	82	59.0	-0.003	0.1032	76.8
Groupe Chopard	France	Bourgogne-Franche-Comté	1	2023	December	184	59.0	-0.003	0.1032	76.8
Groupe Chopard	France	Bourgogne-Franche-Comté	1	2024	January	427	59.0	-0.003	0.1032	76.8
Groupe Chopard	France	Bourgogne-Franche-Comté	1	2024	February	363	59.0	-0.003	0.1032	76.8
Groupe Chopard	France	Bourgogne-Franche-Comté	1	2024	March	206	59.0	-0.003	0.1032	76.8
Groupe Chopard	France	Bourgogne-Franche-Comté	1	2024	April	205	59.0	-0.003	0.1032	76.8
Groupe Chopard	France	Bourgogne-Franche-Comté	1	2024	May	129	59.0	-0.003	0.1032	76.8
Groupe	France	Provence-Alpes-Côte	1	2023	May	62	162.0	0.002	0.1032	76.8
Groupe Chopard	France	Provence-Alpes-Côte d'Azur	1	2023	June	24	162.0	0.002	0.1032	76.8
Groupe Chopard	France	Provence-Alpes-Côte d'Azur	1	2023	July	8	162.0	0.002	0.1032	76.8
Groupe Chopard	France	Provence-Alpes-Côte d'Azur	1	2023	August	10	162.0	0.002	0.1032	76.8
Groupe Chopard	France	Provence-Alpes-Côte d'Azur	1	2023	September	71	162.0	0.002	0.1032	76.8
Groupe Chopard	France	Provence-Alpes-Côte d'Azur	1	2023	October	72	162.0	0.002	0.1032	76.8
Groupe Chopard	France	Provence-Alpes-Côte d'Azur	1	2023	November	82	162.0	0.002	0.1032	76.8
Groupe Chopard	France	Provence-Alpes-Côte d'Azur	1	2023	December	184	162.0	0.002	0.1032	76.8
Groupe Chopard	France	Provence-Alpes-Côte d'Azur	1	2024	January	427	162.0	0.002	0.1032	76.8
Groupe Chopard	France	Provence-Alpes-Côte d'Azur	1	2024	February	363	162.0	0.002	0.1032	76.8
Groupe Chopard	France	Provence-Alpes-Côte d'Azur	1	2024	March	206	162.0	0.002	0.1032	76.8
Groupe Chopard	France	Provence-Alpes-Côte d'Azur	1	2024	April	205	162.0	0.002	0.1032	76.8
Groupe Chopard	France	Provence-Alpes-Côte d'Azur	1	2024	May	129	162.0	0.002	0.1032	76.8
BYmyCAR	France	Auvergne-Rhône-	3	2023	May	62	114.0	0.008	0.1032	76.8
BYmyCAR	France	Auvergne-Rhône-Alpes	3	2023	June	24	114.0	0.008	0.1032	76.8
BYmyCAR	France	Auvergne-Rhône-Alpes	3	2023	July	8	114.0	0.008	0.1032	76.8
BYmyCAR	France	Auvergne-Rhône-Alpes	3	2023	August	10	114.0	0.008	0.1032	76.8
BYmyCAR	France	Auvergne-Rhône-Alpes	3	2023	September	71	114.0	0.008	0.1032	76.8
BYmyCAR	France	Auvergne-Rhône-Alpes	3	2023	October	72	114.0	0.008	0.1032	76.8
BYmyCAR	France	Auvergne-Rhône-Alpes	3	2023	November	82	114.0	0.008	0.1032	76.8
BYmyCAR	France	Auvergne-Rhône-Alpes	3	2023	December	184	114.0	0.008	0.1032	76.8
BYmyCAR	France	Auvergne-Rhône-Alpes	3	2024	January	427	114.0	0.008	0.1032	76.8
BYmyCAR	France	Auvergne-Rhône-Alpes	3	2024	February	363	114.0	0.008	0.1032	76.8
BYmyCAR	France	Auvergne-Rhône-Alpes	3	2024	March	206	114.0	0.008	0.1032	76.8
BYmyCAR	France	Auvergne-Rhône-Alpes	3	2024	April	205	114.0	0.008	0.1032	76.8
BYmyCAR	France	Auvergne-Rhône-Alpes	3	2024	May	129	114.0	0.008	0.1032	76.8
BYmyCAR	France	Île-de-France	2	2023	May	62	1,063.0	0.005	0.1032	76.8
BYmyCAR	France	Île-de-France	2	2023	June	24	1,063.0	0.005	0.1032	76.8
BYmyCAR	France	Île-de-France	2	2023	July	8	1,063.0	0.005	0.1032	76.8
BYmyCAR	France	Île-de-France	2	2023	August	10	1,063.0	0.005	0.1032	76.8
BYmyCAR	France	Île-de-France	2	2023	September	71	1,063.0	0.005	0.1032	76.8
BYmyCAR	France	Île-de-France	2	2023	October	72	1,063.0	0.005	0.1032	76.8
BYmyCAR	France	Île-de-France	2	2023	November	82	1,063.0	0.005	0.1032	76.8
BYmyCAR	France	Île-de-France	2	2023	December	184	1,063.0	0.005	0.1032	76.8
BYmyCAR	France	Île-de-France	2	2024	January	427	1,063.0	0.005	0.1032	76.8
BYmyCAR	France	Île-de-France	2	2024	February	363	1,063.0	0.005	0.1032	76.8
BYmyCAR	France	Île-de-France	2	2024	March	206	1,063.0	0.005	0.1032	76.8
BYmyCAR	France	Île-de-France	2	2024	April	205	1,063.0	0.005	0.1032	76.8
BYmyCAR	France	Île-de-France	2	2024	May	129	1,063.0	0.005	0.1032	76.8

Dealership_Name	Country	Region	Number_of_Outlets	Year	Month	Monthly_Sales_Volume_per_Country	Regional_Population_Density	Local_Economic_Growth	Cultural_Difference_Score	Regulatory_Environment_Score
BYmyCAR	France	Provence-Alpes-Côte d'Azur	2	2023	May	62	162.0	0.002	0.1032	76.8
BYmyCAR	France	Provence-Alpes-Côte d'Azur	2	2023	June	24	162.0	0.002	0.1032	76.8
BYmyCAR	France	Provence-Alpes-Côte d'Azur	2	2023	July	8	162.0	0.002	0.1032	76.8
BYmyCAR	France	Provence-Alpes-Côte d'Azur	2	2023	August	10	162.0	0.002	0.1032	76.8
BYmyCAR	France	Provence-Alpes-Côte d'Azur	2	2023	September	71	162.0	0.002	0.1032	76.8
BYmyCAR	France	Provence-Alpes-Côte d'Azur	2	2023	October	72	162.0	0.002	0.1032	76.8
BYmyCAR	France	Provence-Alpes-Côte d'Azur	2	2023	November	82	162.0	0.002	0.1032	76.8
BYmyCAR	France	Provence-Alpes-Côte d'Azur	2	2023	December	184	162.0	0.002	0.1032	76.8
BYmyCAR	France	Provence-Alpes-Côte d'Azur	2	2024	January	427	162.0	0.002	0.1032	76.8
BYmyCAR	France	Provence-Alpes-Côte d'Azur	2	2024	February	363	162.0	0.002	0.1032	76.8
BYmyCAR	France	Provence-Alpes-Côte d'Azur	2	2024	March	206	162.0	0.002	0.1032	76.8
BYmyCAR	France	Provence-Alpes-Côte d'Azur	2	2024	April	205	162.0	0.002	0.1032	76.8
BYmyCAR	France	Provence-Alpes-Côte d'Azur	2	2024	May	129	162.0	0.002	0.1032	76.8
Groupe Maurin	France	Auvergne-Rhône-Alpes	1	2023	May	62	114.0	0.008	0.1032	76.8
Groupe Maurin	France	Auvergne-Rhône-Alpes	1	2023	June	24	114.0	0.008	0.1032	76.8
Groupe Maurin	France	Auvergne-Rhône-Alpes	1	2023	July	8	114.0	0.008	0.1032	76.8
Groupe Maurin	France	Auvergne-Rhône-Alpes	1	2023	August	10	114.0	0.008	0.1032	76.8
Groupe Maurin	France	Auvergne-Rhône-Alpes	1	2023	September	71	114.0	0.008	0.1032	76.8
Groupe Maurin	France	Auvergne-Rhône-Alpes	1	2023	October	72	114.0	0.008	0.1032	76.8
Groupe Maurin	France	Auvergne-Rhône-Alpes	1	2023	November	82	114.0	0.008	0.1032	76.8
Groupe Maurin	France	Auvergne-Rhône-Alpes	1	2023	December	184	114.0	0.008	0.1032	76.8
Groupe Maurin	France	Auvergne-Rhône-Alpes	1	2024	January	427	114.0	0.008	0.1032	76.8
Groupe Maurin	France	Auvergne-Rhône-Alpes	1	2024	February	363	114.0	0.008	0.1032	76.8
Groupe Maurin	France	Auvergne-Rhône-Alpes	1	2024	March	206	114.0	0.008	0.1032	76.8
Groupe Maurin	France	Auvergne-Rhône-Alpes	1	2024	April	205	114.0	0.008	0.1032	76.8
Groupe Maurin	France	Auvergne-Rhône-Alpes	1	2024	May	129	114.0	0.008	0.1032	76.8
Groupe Maurin	France	Provence-Alpes-Côte d'Azur	2	2023	May	62	162.0	0.002	0.1032	76.8
Groupe Maurin	France	Provence-Alpes-Côte d'Azur	2	2023	June	24	162.0	0.002	0.1032	76.8
Groupe Maurin	France	Provence-Alpes-Côte d'Azur	2	2023	July	8	162.0	0.002	0.1032	76.8
Groupe Maurin	France	Provence-Alpes-Côte d'Azur	2	2023	August	10	162.0	0.002	0.1032	76.8
Groupe Maurin	France	Provence-Alpes-Côte d'Azur	2	2023	September	71	162.0	0.002	0.1032	76.8
Groupe Maurin	France	Provence-Alpes-Côte d'Azur	2	2023	October	72	162.0	0.002	0.1032	76.8
Groupe Maurin	France	Provence-Alpes-Côte d'Azur	2	2023	November	82	162.0	0.002	0.1032	76.8
Groupe Maurin	France	Provence-Alpes-Côte d'Azur	2	2023	December	184	162.0	0.002	0.1032	76.8
Groupe Maurin	France	Provence-Alpes-Côte d'Azur	2	2024	January	427	162.0	0.002	0.1032	76.8
Groupe Maurin	France	Provence-Alpes-Côte d'Azur	2	2024	February	363	162.0	0.002	0.1032	76.8
Groupe Maurin	France	Provence-Alpes-Côte d'Azur	2	2024	March	206	162.0	0.002	0.1032	76.8
Groupe Maurin	France	Provence-Alpes-Côte d'Azur	2	2024	April	205	162.0	0.002	0.1032	76.8
Groupe Maurin	France	Provence-Alpes-Côte d'Azur	2	2024	May	129	162.0	0.002	0.1032	76.8
Groupe Maurin	France	Occitanie	3	2023	May	62	82.0	0.010	0.1032	76.8
Groupe Maurin	France	Occitanie	3	2023	June	24	82.0	0.010	0.1032	76.8
Groupe Maurin	France	Occitanie	3	2023	July	8	82.0	0.010	0.1032	76.8
Groupe Maurin	France	Occitanie	3	2023	August	10	82.0	0.010	0.1032	76.8
Groupe Maurin	France	Occitanie	3	2023	September	71	82.0	0.010	0.1032	76.8
Groupe Maurin	France	Occitanie	3	2023	October	72	82.0	0.010	0.1032	76.8
Groupe Maurin	France	Occitanie	3	2023	November	82	82.0	0.010	0.1032	76.8
Groupe Maurin	France	Occitanie	3	2023	December	184	82.0	0.010	0.1032	76.8
Groupe Maurin	France	Occitanie	3	2024	January	427	82.0	0.010	0.1032	76.8
Groupe Maurin	France	Occitanie	3	2024	February	363	82.0	0.010	0.1032	76.8
Groupe Maurin	France	Occitanie	3	2024	March	206	82.0	0.010	0.1032	76.8
Groupe Maurin	France	Occitanie	3	2024	April	205	82.0	0.010	0.1032	76.8
Groupe Maurin	France	Occitanie	3	2024	May	129	82.0	0.010	0.1032	76.8

Dealership_Name	Country	Region	Number_of_Outlets	Year	Month	Monthly_Sales_Volume_per_Country	Regional_Population_Density	Local_Economic_Growth	Cultural_Difference_Score	Regulatory_Environment_Score
Sipa Automobiles	France	Occitanie	1	2023	May	62	82.0	0.010	0.1032	76.8
Sipa Automobiles	France	Occitanie	1	2023	June	24	82.0	0.010	0.1032	76.8
Sipa Automobiles	France	Occitanie	1	2023	July	8	82.0	0.010	0.1032	76.8
Sipa Automobiles	France	Occitanie	1	2023	August	10	82.0	0.010	0.1032	76.8
Sipa Automobiles	France	Occitanie	1	2023	September	71	82.0	0.010	0.1032	76.8
Sipa Automobiles	France	Occitanie	1	2023	October	72	82.0	0.010	0.1032	76.8
Sipa Automobiles	France	Occitanie	1	2023	November	82	82.0	0.010	0.1032	76.8
Sipa Automobiles	France	Occitanie	1	2023	December	184	82.0	0.010	0.1032	76.8
Sipa Automobiles	France	Occitanie	1	2024	January	427	82.0	0.010	0.1032	76.8
Sipa Automobiles	France	Occitanie	1	2024	February	363	82.0	0.010	0.1032	76.8
Sipa Automobiles	France	Occitanie	1	2024	March	206	82.0	0.010	0.1032	76.8
Sipa Automobiles	France	Occitanie	1	2024	April	205	82.0	0.010	0.1032	76.8
Sipa Automobiles	France	Occitanie	1	2024	May	129	82.0	0.010	0.1032	76.8
Sipa Automobiles	France	Nouvelle-Aquitaine	1	2023	May	62	71.0	0.006	0.1032	76.8
Sipa Automobiles	France	Nouvelle-Aquitaine	1	2023	June	24	71.0	0.006	0.1032	76.8
Sipa Automobiles	France	Nouvelle-Aquitaine	1	2023	July	8	71.0	0.006	0.1032	76.8
Sipa Automobiles	France	Nouvelle-Aquitaine	1	2023	August	10	71.0	0.006	0.1032	76.8
Sipa Automobiles	France	Nouvelle-Aquitaine	1	2023	September	71	71.0	0.006	0.1032	76.8
Sipa Automobiles	France	Nouvelle-Aquitaine	1	2023	October	72	71.0	0.006	0.1032	76.8
Sipa Automobiles	France	Nouvelle-Aquitaine	1	2023	November	82	71.0	0.006	0.1032	76.8
Sipa Automobiles	France	Nouvelle-Aquitaine	1	2023	December	184	71.0	0.006	0.1032	76.8
Sipa Automobiles	France	Nouvelle-Aquitaine	1	2024	January	427	71.0	0.006	0.1032	76.8
Sipa Automobiles	France	Nouvelle-Aquitaine	1	2024	February	363	71.0	0.006	0.1032	76.8
Sipa Automobiles	France	Nouvelle-Aquitaine	1	2024	March	206	71.0	0.006	0.1032	76.8
Sipa Automobiles	France	Nouvelle-Aquitaine	1	2024	April	205	71.0	0.006	0.1032	76.8
Sipa Automobiles	France	Nouvelle-Aquitaine	1	2024	May	129	71.0	0.006	0.1032	76.8
Groupe Fabre	France	Occitanie	1	2023	May	62	82.0	0.010	0.1032	76.8
Groupe Fabre	France	Occitanie	1	2023	June	24	82.0	0.010	0.1032	76.8
Groupe Fabre	France	Occitanie	1	2023	July	8	82.0	0.010	0.1032	76.8
Groupe Fabre	France	Occitanie	1	2023	August	10	82.0	0.010	0.1032	76.8
Groupe Fabre	France	Occitanie	1	2023	September	71	82.0	0.010	0.1032	76.8
Groupe Fabre	France	Occitanie	1	2023	October	72	82.0	0.010	0.1032	76.8
Groupe Fabre	France	Occitanie	1	2023	November	82	82.0	0.010	0.1032	76.8
Groupe Fabre	France	Occitanie	1	2023	December	184	82.0	0.010	0.1032	76.8
Groupe Fabre	France	Occitanie	1	2024	January	427	82.0	0.010	0.1032	76.8
Groupe Fabre	France	Occitanie	1	2024	February	363	82.0	0.010	0.1032	76.8
Groupe Fabre	France	Occitanie	1	2024	March	206	82.0	0.010	0.1032	76.8
Groupe Fabre	France	Occitanie	1	2024	April	205	82.0	0.010	0.1032	76.8
Groupe Fabre	France	Occitanie	1	2024	May	129	82.0	0.010	0.1032	76.8
Autoshphere	France	Nouvelle-Aquitaine	2	2023	May	62	71.0	0.006	0.1032	76.8
Autoshphere	France	Nouvelle-Aquitaine	2	2023	June	24	71.0	0.006	0.1032	76.8
Autoshphere	France	Nouvelle-Aquitaine	2	2023	July	8	71.0	0.006	0.1032	76.8
Autoshphere	France	Nouvelle-Aquitaine	2	2023	August	10	71.0	0.006	0.1032	76.8
Autoshphere	France	Nouvelle-Aquitaine	2	2023	September	71	71.0	0.006	0.1032	76.8
Autoshphere	France	Nouvelle-Aquitaine	2	2023	October	72	71.0	0.006	0.1032	76.8
Autoshphere	France	Nouvelle-Aquitaine	2	2023	November	82	71.0	0.006	0.1032	76.8
Autoshphere	France	Nouvelle-Aquitaine	2	2023	December	184	71.0	0.006	0.1032	76.8
Autoshphere	France	Nouvelle-Aquitaine	2	2024	January	427	71.0	0.006	0.1032	76.8
Autoshphere	France	Nouvelle-Aquitaine	2	2024	February	363	71.0	0.006	0.1032	76.8
Autoshphere	France	Nouvelle-Aquitaine	2	2024	March	206	71.0	0.006	0.1032	76.8
Autoshphere	France	Nouvelle-Aquitaine	2	2024	April	205	71.0	0.006	0.1032	76.8
Autoshphere	France	Nouvelle-Aquitaine	2	2024	May	129	71.0	0.006	0.1032	76.8
Groupe Bodemer	France	Pays de la Loire	1	2023	May	62	118.0	0.009	0.1032	76.8
Groupe Bodemer	France	Pays de la Loire	1	2023	June	24	118.0	0.009	0.1032	76.8
Groupe Bodemer	France	Pays de la Loire	1	2023	July	8	118.0	0.009	0.1032	76.8
Groupe Bodemer	France	Pays de la Loire	1	2023	August	10	118.0	0.009	0.1032	76.8
Groupe Bodemer	France	Pays de la Loire	1	2023	September	71	118.0	0.009	0.1032	76.8
Groupe Bodemer	France	Pays de la Loire	1	2023	October	72	118.0	0.009	0.1032	76.8
Groupe Bodemer	France	Pays de la Loire	1	2023	November	82	118.0	0.009	0.1032	76.8
Groupe Bodemer	France	Pays de la Loire	1	2023	December	184	118.0	0.009	0.1032	76.8
Groupe Bodemer	France	Pays de la Loire	1	2024	January	427	118.0	0.009	0.1032	76.8
Groupe Bodemer	France	Pays de la Loire	1	2024	February	363	118.0	0.009	0.1032	76.8
Groupe Bodemer	France	Pays de la Loire	1	2024	March	206	118.0	0.009	0.1032	76.8
Groupe Bodemer	France	Pays de la Loire	1	2024	April	205	118.0	0.009	0.1032	76.8
Groupe Bodemer	France	Pays de la Loire	1	2024	May	129	118.0	0.009	0.1032	76.8

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Dealership_Name	Country	Region	Number_of_Outlets	Year	Month	Monthly_Sales_Volume_per_Country	Regional_Population_Density	Local_Economic_Growth	Cultural_Difference_Score	Regulatory_Environment_Score
Electrik Automobile	France	Pays de la Loire	1	2023	May	62	118.0	0.009	0.1032	76.8
Electrik Automobile	France	Pays de la Loire	1	2023	June	24	118.0	0.009	0.1032	76.8
Electrik Automobile	France	Pays de la Loire	1	2023	July	8	118.0	0.009	0.1032	76.8
Electrik Automobile	France	Pays de la Loire	1	2023	August	10	118.0	0.009	0.1032	76.8
Electrik Automobile	France	Pays de la Loire	1	2023	September	71	118.0	0.009	0.1032	76.8
Electrik Automobile	France	Pays de la Loire	1	2023	October	72	118.0	0.009	0.1032	76.8
Electrik Automobile	France	Pays de la Loire	1	2023	November	82	118.0	0.009	0.1032	76.8
Electrik Automobile	France	Pays de la Loire	1	2023	December	184	118.0	0.009	0.1032	76.8
Electrik Automobile	France	Pays de la Loire	1	2024	January	427	118.0	0.009	0.1032	76.8
Electrik Automobile	France	Pays de la Loire	1	2024	February	363	118.0	0.009	0.1032	76.8
Electrik Automobile	France	Pays de la Loire	1	2024	March	206	118.0	0.009	0.1032	76.8
Electrik Automobile	France	Pays de la Loire	1	2024	April	205	118.0	0.009	0.1032	76.8
Electrik Automobile	France	Pays de la Loire	1	2024	May	129	118.0	0.009	0.1032	76.8
Electrik Automobile	France	Bretagne	2	2023	May	62	122.0	0.011	0.1032	76.8
Electrik Automobile	France	Bretagne	2	2023	June	24	122.0	0.011	0.1032	76.8
Electrik Automobile	France	Bretagne	2	2023	July	8	122.0	0.011	0.1032	76.8
Electrik Automobile	France	Bretagne	2	2023	August	10	122.0	0.011	0.1032	76.8
Electrik Automobile	France	Bretagne	2	2023	September	71	122.0	0.011	0.1032	76.8
Electrik Automobile	France	Bretagne	2	2023	October	72	122.0	0.011	0.1032	76.8
Electrik Automobile	France	Bretagne	2	2023	November	82	122.0	0.011	0.1032	76.8
Electrik Automobile	France	Bretagne	2	2023	December	184	122.0	0.011	0.1032	76.8
Electrik Automobile	France	Bretagne	2	2024	January	427	122.0	0.011	0.1032	76.8
Electrik Automobile	France	Bretagne	2	2024	February	363	122.0	0.011	0.1032	76.8
Electrik Automobile	France	Bretagne	2	2024	March	206	122.0	0.011	0.1032	76.8
Electrik Automobile	France	Bretagne	2	2024	April	205	122.0	0.011	0.1032	76.8
Electrik Automobile	France	Bretagne	2	2024	May	129	122.0	0.011	0.1032	76.8
Harmony Auto	France	Île-de-France	1	2023	May	62	1,063.0	0.005	0.1032	76.8
Harmony Auto	France	Île-de-France	1	2023	June	24	1,063.0	0.005	0.1032	76.8
Harmony Auto	France	Île-de-France	1	2023	July	8	1,063.0	0.005	0.1032	76.8
Harmony Auto	France	Île-de-France	1	2023	August	10	1,063.0	0.005	0.1032	76.8
Harmony Auto	France	Île-de-France	1	2023	September	71	1,063.0	0.005	0.1032	76.8
Harmony Auto	France	Île-de-France	1	2023	October	72	1,063.0	0.005	0.1032	76.8
Harmony Auto	France	Île-de-France	1	2023	November	82	1,063.0	0.005	0.1032	76.8
Harmony Auto	France	Île-de-France	1	2023	December	184	1,063.0	0.005	0.1032	76.8
Harmony Auto	France	Île-de-France	1	2024	January	427	1,063.0	0.005	0.1032	76.8
Harmony Auto	France	Île-de-France	1	2024	February	363	1,063.0	0.005	0.1032	76.8
Harmony Auto	France	Île-de-France	1	2024	March	206	1,063.0	0.005	0.1032	76.8
Harmony Auto	France	Île-de-France	1	2024	April	205	1,063.0	0.005	0.1032	76.8
Harmony Auto	France	Île-de-France	1	2024	May	129	1,063.0	0.005	0.1032	76.8
Schiller Autó Család	Hungary	Budapest	1	2023	May	62	3,405.9	0.057	0.1522	73.4
Schiller Autó Család	Hungary	Budapest	1	2023	June	24	3,405.9	0.057	0.1522	73.4
Schiller Autó Család	Hungary	Budapest	1	2023	July	8	3,405.9	0.057	0.1522	73.4
Schiller Autó Család	Hungary	Budapest	1	2023	August	10	3,405.9	0.057	0.1522	73.4
Schiller Autó Család	Hungary	Budapest	1	2023	September	71	3,405.9	0.057	0.1522	73.4
Schiller Autó Család	Hungary	Budapest	1	2023	October	72	3,405.9	0.057	0.1522	73.4
Schiller Autó Család	Hungary	Budapest	1	2023	November	82	3,405.9	0.057	0.1522	73.4
Schiller Autó Család	Hungary	Budapest	1	2023	December	184	3,405.9	0.057	0.1522	73.4
Schiller Autó Család	Hungary	Budapest	1	2024	January	427	3,405.9	0.057	0.1522	73.4
Schiller Autó Család	Hungary	Budapest	1	2024	February	363	3,405.9	0.057	0.1522	73.4
Schiller Autó Család	Hungary	Budapest	1	2024	March	206	3,405.9	0.057	0.1522	73.4
Schiller Autó Család	Hungary	Budapest	1	2024	April	205	3,405.9	0.057	0.1522	73.4
Schiller Autó Család	Hungary	Budapest	1	2024	May	n/a	3,405.9	0.057	0.1522	73.4
Duna Autó	Hungary	Budapest	1	2023	May	62	3,405.9	0.057	0.1522	73.4
Duna Autó	Hungary	Budapest	1	2023	June	24	3,405.9	0.057	0.1522	73.4
Duna Autó	Hungary	Budapest	1	2023	July	8	3,405.9	0.057	0.1522	73.4
Duna Autó	Hungary	Budapest	1	2023	August	10	3,405.9	0.057	0.1522	73.4
Duna Autó	Hungary	Budapest	1	2023	September	71	3,405.9	0.057	0.1522	73.4
Duna Autó	Hungary	Budapest	1	2023	October	72	3,405.9	0.057	0.1522	73.4
Duna Autó	Hungary	Budapest	1	2023	November	82	3,405.9	0.057	0.1522	73.4
Duna Autó	Hungary	Budapest	1	2023	December	184	3,405.9	0.057	0.1522	73.4
Duna Autó	Hungary	Budapest	1	2024	January	427	3,405.9	0.057	0.1522	73.4
Duna Autó	Hungary	Budapest	1	2024	February	363	3,405.9	0.057	0.1522	73.4
Duna Autó	Hungary	Budapest	1	2024	March	206	3,405.9	0.057	0.1522	73.4
Duna Autó	Hungary	Budapest	1	2024	April	205	3,405.9	0.057	0.1522	73.4
Duna Autó	Hungary	Budapest	1	2024	May	n/a	3,405.9	0.057	0.1522	73.4

Dealership_Name	Country	Region	Number_of_Outlets	Year	Month	Monthly_Sales_Volume_per_Country	Regional_Population_Density	Local_Economic_Growth	Cultural_Difference_Score	Regulatory_Environment_Score
Wallis Motor	Hungary	Budapest	1	2023	May	62	3,405.9	0.057	0.1522	73.4
Wallis Motor	Hungary	Budapest	1	2023	June	24	3,405.9	0.057	0.1522	73.4
Wallis Motor	Hungary	Budapest	1	2023	July	8	3,405.9	0.057	0.1522	73.4
Wallis Motor	Hungary	Budapest	1	2023	August	10	3,405.9	0.057	0.1522	73.4
Wallis Motor	Hungary	Budapest	1	2023	September	71	3,405.9	0.057	0.1522	73.4
Wallis Motor	Hungary	Budapest	1	2023	October	72	3,405.9	0.057	0.1522	73.4
Wallis Motor	Hungary	Budapest	1	2023	November	82	3,405.9	0.057	0.1522	73.4
Wallis Motor	Hungary	Budapest	1	2023	December	184	3,405.9	0.057	0.1522	73.4
Wallis Motor	Hungary	Budapest	1	2024	January	427	3,405.9	0.057	0.1522	73.4
Wallis Motor	Hungary	Budapest	1	2024	February	363	3,405.9	0.057	0.1522	73.4
Wallis Motor	Hungary	Budapest	1	2024	March	206	3,405.9	0.057	0.1522	73.4
Wallis Motor	Hungary	Budapest	1	2024	April	205	3,405.9	0.057	0.1522	73.4
Wallis Motor	Hungary	Budapest	1	2024	May	n/a	3,405.9	0.057	0.1522	73.4
ADG Groep	Netherlands	Drenthe	1	2023	May	66	187.2	0.028	0.1054	76.1
ADG Groep	Netherlands	Drenthe	1	2023	June	123	187.2	0.028	0.1054	76.1
ADG Groep	Netherlands	Drenthe	1	2023	July	80	187.2	0.028	0.1054	76.1
ADG Groep	Netherlands	Drenthe	1	2023	August	37	187.2	0.028	0.1054	76.1
ADG Groep	Netherlands	Drenthe	1	2023	September	111	187.2	0.028	0.1054	76.1
ADG Groep	Netherlands	Drenthe	1	2023	October	116	187.2	0.028	0.1054	76.1
ADG Groep	Netherlands	Drenthe	1	2023	November	164	187.2	0.028	0.1054	76.1
ADG Groep	Netherlands	Drenthe	1	2023	December	137	187.2	0.028	0.1054	76.1
ADG Groep	Netherlands	Drenthe	1	2024	January	192	187.2	0.028	0.1054	76.1
ADG Groep	Netherlands	Drenthe	1	2024	February	187	187.2	0.028	0.1054	76.1
ADG Groep	Netherlands	Drenthe	1	2024	March	171	187.2	0.028	0.1054	76.1
ADG Groep	Netherlands	Drenthe	1	2024	April	200	187.2	0.028	0.1054	76.1
ADG Groep	Netherlands	Drenthe	1	2024	May	219	187.2	0.028	0.1054	76.1
Louwman	Netherlands	Noord-Holland (North Holland)	1	2023	May	66	1,064.4	0.067	0.1054	76.1
Louwman	Netherlands	Noord-Holland (North Holland)	1	2023	June	123	1,064.4	0.067	0.1054	76.1
Louwman	Netherlands	Noord-Holland (North Holland)	1	2023	July	80	1,064.4	0.067	0.1054	76.1
Louwman	Netherlands	Noord-Holland (North Holland)	1	2023	August	37	1,064.4	0.067	0.1054	76.1
Louwman	Netherlands	Noord-Holland (North Holland)	1	2023	September	111	1,064.4	0.067	0.1054	76.1
Louwman	Netherlands	Noord-Holland (North Holland)	1	2023	October	116	1,064.4	0.067	0.1054	76.1
Louwman	Netherlands	Noord-Holland (North Holland)	1	2023	November	164	1,064.4	0.067	0.1054	76.1
Louwman	Netherlands	Noord-Holland (North Holland)	1	2023	December	137	1,064.4	0.067	0.1054	76.1
Louwman	Netherlands	Noord-Holland (North Holland)	1	2024	January	192	1,064.4	0.067	0.1054	76.1
Louwman	Netherlands	Noord-Holland (North Holland)	1	2024	February	187	1,064.4	0.067	0.1054	76.1
Louwman	Netherlands	Noord-Holland (North Holland)	1	2024	March	171	1,064.4	0.067	0.1054	76.1
Louwman	Netherlands	Noord-Holland (North Holland)	1	2024	April	200	1,064.4	0.067	0.1054	76.1
Louwman	Netherlands	Noord-Holland (North Holland)	1	2024	May	219	1,064.4	0.067	0.1054	76.1
Louwman	Netherlands	Zuid-Holland (South Holland)	1	2023	May	66	1,310.9	0.035	0.1054	76.1
Louwman	Netherlands	Zuid-Holland (South Holland)	1	2023	June	123	1,310.9	0.035	0.1054	76.1
Louwman	Netherlands	Zuid-Holland (South Holland)	1	2023	July	80	1,310.9	0.035	0.1054	76.1
Louwman	Netherlands	Zuid-Holland (South Holland)	1	2023	August	37	1,310.9	0.035	0.1054	76.1
Louwman	Netherlands	Zuid-Holland (South Holland)	1	2023	September	111	1,310.9	0.035	0.1054	76.1
Louwman	Netherlands	Zuid-Holland (South Holland)	1	2023	October	116	1,310.9	0.035	0.1054	76.1
Louwman	Netherlands	Zuid-Holland (South Holland)	1	2023	November	164	1,310.9	0.035	0.1054	76.1
Louwman	Netherlands	Zuid-Holland (South Holland)	1	2023	December	137	1,310.9	0.035	0.1054	76.1
Louwman	Netherlands	Zuid-Holland (South Holland)	1	2024	January	192	1,310.9	0.035	0.1054	76.1
Louwman	Netherlands	Zuid-Holland (South Holland)	1	2024	February	187	1,310.9	0.035	0.1054	76.1
Louwman	Netherlands	Zuid-Holland (South Holland)	1	2024	March	171	1,310.9	0.035	0.1054	76.1
Louwman	Netherlands	Zuid-Holland (South Holland)	1	2024	April	200	1,310.9	0.035	0.1054	76.1
Louwman	Netherlands	Zuid-Holland (South Holland)	1	2024	May	219	1,310.9	0.035	0.1054	76.1
Louwman	Netherlands	Noord-Brabant (North Brabant)	1	2023	May	66	526.1	0.044	0.1054	76.1
Louwman	Netherlands	Noord-Brabant (North Brabant)	1	2023	June	123	526.1	0.044	0.1054	76.1
Louwman	Netherlands	Noord-Brabant (North Brabant)	1	2023	July	80	526.1	0.044	0.1054	76.1
Louwman	Netherlands	Noord-Brabant (North Brabant)	1	2023	August	37	526.1	0.044	0.1054	76.1
Louwman	Netherlands	Noord-Brabant (North Brabant)	1	2023	September	111	526.1	0.044	0.1054	76.1
Louwman	Netherlands	Noord-Brabant (North Brabant)	1	2023	October	116	526.1	0.044	0.1054	76.1
Louwman	Netherlands	Noord-Brabant (North Brabant)	1	2023	November	164	526.1	0.044	0.1054	76.1
Louwman	Netherlands	Noord-Brabant (North Brabant)	1	2023	December	137	526.1	0.044	0.1054	76.1
Louwman	Netherlands	Noord-Brabant (North Brabant)	1	2024	January	192	526.1	0.044	0.1054	76.1
Louwman	Netherlands	Noord-Brabant (North Brabant)	1	2024	February	187	526.1	0.044	0.1054	76.1
Louwman	Netherlands	Noord-Brabant (North Brabant)	1	2024	March	171	526.1	0.044	0.1054	76.1
Louwman	Netherlands	Noord-Brabant (North Brabant)	1	2024	April	200	526.1	0.044	0.1054	76.1
Louwman	Netherlands	Noord-Brabant (North Brabant)	1	2024	May	219	526.1	0.044	0.1054	76.1

Dealership_Name	Country	Region	Number_of_Outlets	Year	Month	Monthly_Sales_Volume_per_Country	Regional_Population_Density	Local_Economic_Growth	Cultural_Difference_Score	Regulatory_Environment_Score
Leonori	Italy	Lazio	1	2023	May	0	337.1	0.037	0.1145	72.9
Leonori	Italy	Lazio	1	2023	June	21	337.1	0.037	0.1145	72.9
Leonori	Italy	Lazio	1	2023	July	21	337.1	0.037	0.1145	72.9
Leonori	Italy	Lazio	1	2023	August	14	337.1	0.037	0.1145	72.9
Leonori	Italy	Lazio	1	2023	September	16	337.1	0.037	0.1145	72.9
Leonori	Italy	Lazio	1	2023	October	51	337.1	0.037	0.1145	72.9
Leonori	Italy	Lazio	1	2023	November	48	337.1	0.037	0.1145	72.9
Leonori	Italy	Lazio	1	2023	December	37	337.1	0.037	0.1145	72.9
Leonori	Italy	Lazio	1	2024	January	47	337.1	0.037	0.1145	72.9
Leonori	Italy	Lazio	1	2024	February	41	337.1	0.037	0.1145	72.9
Leonori	Italy	Lazio	1	2024	March	70	337.1	0.037	0.1145	72.9
Leonori	Italy	Lazio	1	2024	April	57	337.1	0.037	0.1145	72.9
Leonori	Italy	Lazio	1	2024	May	52	337.1	0.037	0.1145	72.9
Car Village Firenze	Italy	Toscana (Tuscany)	1	2023	May	0	160.6	0.060	0.1145	72.9
Car Village Firenze	Italy	Toscana (Tuscany)	1	2023	June	21	160.6	0.060	0.1145	72.9
Car Village Firenze	Italy	Toscana (Tuscany)	1	2023	July	21	160.6	0.060	0.1145	72.9
Car Village Firenze	Italy	Toscana (Tuscany)	1	2023	August	14	160.6	0.060	0.1145	72.9
Car Village Firenze	Italy	Toscana (Tuscany)	1	2023	September	16	160.6	0.060	0.1145	72.9
Car Village Firenze	Italy	Toscana (Tuscany)	1	2023	October	51	160.6	0.060	0.1145	72.9
Car Village Firenze	Italy	Toscana (Tuscany)	1	2023	November	48	160.6	0.060	0.1145	72.9
Car Village Firenze	Italy	Toscana (Tuscany)	1	2023	December	37	160.6	0.060	0.1145	72.9
Car Village Firenze	Italy	Toscana (Tuscany)	1	2024	January	47	160.6	0.060	0.1145	72.9
Car Village Firenze	Italy	Toscana (Tuscany)	1	2024	February	41	160.6	0.060	0.1145	72.9
Car Village Firenze	Italy	Toscana (Tuscany)	1	2024	March	70	160.6	0.060	0.1145	72.9
Car Village Firenze	Italy	Toscana (Tuscany)	1	2024	April	57	160.6	0.060	0.1145	72.9
Car Village Firenze	Italy	Toscana (Tuscany)	1	2024	May	52	160.6	0.060	0.1145	72.9
Autotorino	Italy	Emilia-Romagna	1	2023	May	0	200.6	0.033	0.1145	72.9
Autotorino	Italy	Emilia-Romagna	1	2023	June	21	200.6	0.033	0.1145	72.9
Autotorino	Italy	Emilia-Romagna	1	2023	July	21	200.6	0.033	0.1145	72.9
Autotorino	Italy	Emilia-Romagna	1	2023	August	14	200.6	0.033	0.1145	72.9
Autotorino	Italy	Emilia-Romagna	1	2023	September	16	200.6	0.033	0.1145	72.9
Autotorino	Italy	Emilia-Romagna	1	2023	October	51	200.6	0.033	0.1145	72.9
Autotorino	Italy	Emilia-Romagna	1	2023	November	48	200.6	0.033	0.1145	72.9
Autotorino	Italy	Emilia-Romagna	1	2023	December	37	200.6	0.033	0.1145	72.9
Autotorino	Italy	Emilia-Romagna	1	2024	January	47	200.6	0.033	0.1145	72.9
Autotorino	Italy	Emilia-Romagna	1	2024	February	41	200.6	0.033	0.1145	72.9
Autotorino	Italy	Emilia-Romagna	1	2024	March	70	200.6	0.033	0.1145	72.9
Autotorino	Italy	Emilia-Romagna	1	2024	April	57	200.6	0.033	0.1145	72.9
Autotorino	Italy	Emilia-Romagna	1	2024	May	52	200.6	0.033	0.1145	72.9
Autotorino	Italy	Lombardia	4	2023	May	0	432.1	0.028	0.1145	72.9
Autotorino	Italy	Lombardia (Lombardy)	4	2023	June	21	432.1	0.028	0.1145	72.9
Autotorino	Italy	Lombardia (Lombardy)	4	2023	July	21	432.1	0.028	0.1145	72.9
Autotorino	Italy	Lombardia (Lombardy)	4	2023	August	14	432.1	0.028	0.1145	72.9
Autotorino	Italy	Lombardia (Lombardy)	4	2023	September	16	432.1	0.028	0.1145	72.9
Autotorino	Italy	Lombardia (Lombardy)	4	2023	October	51	432.1	0.028	0.1145	72.9
Autotorino	Italy	Lombardia (Lombardy)	4	2023	November	48	432.1	0.028	0.1145	72.9
Autotorino	Italy	Lombardia (Lombardy)	4	2023	December	37	432.1	0.028	0.1145	72.9
Autotorino	Italy	Lombardia (Lombardy)	4	2024	January	47	432.1	0.028	0.1145	72.9
Autotorino	Italy	Lombardia (Lombardy)	4	2024	February	41	432.1	0.028	0.1145	72.9
Autotorino	Italy	Lombardia (Lombardy)	4	2024	March	70	432.1	0.028	0.1145	72.9
Autotorino	Italy	Lombardia (Lombardy)	4	2024	April	57	432.1	0.028	0.1145	72.9
Autotorino	Italy	Lombardia (Lombardy)	4	2024	May	52	432.1	0.028	0.1145	72.9
Autotorino	Italy	Friuli-Venezia Giulia	1	2023	May	0	157.8	0.039	0.1145	72.9
Autotorino	Italy	Friuli-Venezia Giulia	1	2023	June	21	157.8	0.039	0.1145	72.9
Autotorino	Italy	Friuli-Venezia Giulia	1	2023	July	21	157.8	0.039	0.1145	72.9
Autotorino	Italy	Friuli-Venezia Giulia	1	2023	August	14	157.8	0.039	0.1145	72.9
Autotorino	Italy	Friuli-Venezia Giulia	1	2023	September	16	157.8	0.039	0.1145	72.9
Autotorino	Italy	Friuli-Venezia Giulia	1	2023	October	51	157.8	0.039	0.1145	72.9
Autotorino	Italy	Friuli-Venezia Giulia	1	2023	November	48	157.8	0.039	0.1145	72.9
Autotorino	Italy	Friuli-Venezia Giulia	1	2023	December	37	157.8	0.039	0.1145	72.9
Autotorino	Italy	Friuli-Venezia Giulia	1	2024	January	47	157.8	0.039	0.1145	72.9
Autotorino	Italy	Friuli-Venezia Giulia	1	2024	February	41	157.8	0.039	0.1145	72.9
Autotorino	Italy	Friuli-Venezia Giulia	1	2024	March	70	157.8	0.039	0.1145	72.9
Autotorino	Italy	Friuli-Venezia Giulia	1	2024	April	57	157.8	0.039	0.1145	72.9
Autotorino	Italy	Friuli-Venezia Giulia	1	2024	May	52	157.8	0.039	0.1145	72.9
Theorema	Italy	Liguria	1	2023	May	0	278.9	0.052	0.1145	72.9
Theorema	Italy	Liguria	1	2023	June	21	278.9	0.052	0.1145	72.9
Theorema	Italy	Liguria	1	2023	July	21	278.9	0.052	0.1145	72.9
Theorema	Italy	Liguria	1	2023	August	14	278.9	0.052	0.1145	72.9
Theorema	Italy	Liguria	1	2023	September	16	278.9	0.052	0.1145	72.9
Theorema	Italy	Liguria	1	2023	October	51	278.9	0.052	0.1145	72.9
Theorema	Italy	Liguria	1	2023	November	48	278.9	0.052	0.1145	72.9
Theorema	Italy	Liguria	1	2023	December	37	278.9	0.052	0.1145	72.9
Theorema	Italy	Liguria	1	2024	January	47	278.9	0.052	0.1145	72.9
Theorema	Italy	Liguria	1	2024	February	41	278.9	0.052	0.1145	72.9
Theorema	Italy	Liguria	1	2024	March	70	278.9	0.052	0.1145	72.9
Theorema	Italy	Liguria	1	2024	April	57	278.9	0.052	0.1145	72.9
Theorema	Italy	Liguria	1	2024	May	52	278.9	0.052	0.1145	72.9

Dealership_Name	Country	Region	Number_of_Outlets	Year	Month	Monthly_Sales_Volume_per_Country	Regional_Population_Density	Local_Economic_Growth	Cultural_Difference_Score	Regulatory_Environment_Score
Theorema	Italy	Piemonte (Piedmont)	1	2023	May	0	169.1	0.027	0.1145	72.9
Theorema	Italy	Piemonte (Piedmont)	1	2023	June	21	169.1	0.027	0.1145	72.9
Theorema	Italy	Piemonte (Piedmont)	1	2023	July	21	169.1	0.027	0.1145	72.9
Theorema	Italy	Piemonte (Piedmont)	1	2023	August	14	169.1	0.027	0.1145	72.9
Theorema	Italy	Piemonte (Piedmont)	1	2023	September	16	169.1	0.027	0.1145	72.9
Theorema	Italy	Piemonte (Piedmont)	1	2023	October	51	169.1	0.027	0.1145	72.9
Theorema	Italy	Piemonte (Piedmont)	1	2023	November	48	169.1	0.027	0.1145	72.9
Theorema	Italy	Piemonte (Piedmont)	1	2023	December	37	169.1	0.027	0.1145	72.9
Theorema	Italy	Piemonte (Piedmont)	1	2024	January	47	169.1	0.027	0.1145	72.9
Theorema	Italy	Piemonte (Piedmont)	1	2024	February	41	169.1	0.027	0.1145	72.9
Theorema	Italy	Piemonte (Piedmont)	1	2024	March	70	169.1	0.027	0.1145	72.9
Theorema	Italy	Piemonte (Piedmont)	1	2024	April	57	169.1	0.027	0.1145	72.9
Theorema	Italy	Piemonte (Piedmont)	1	2024	May	52	169.1	0.027	0.1145	72.9
Barchetti	Italy	Lombardia (Lombardy)	1	2023	May	0	432.1	0.028	0.1145	72.9
Barchetti	Italy	Lombardia (Lombardy)	1	2023	June	21	432.1	0.028	0.1145	72.9
Barchetti	Italy	Lombardia (Lombardy)	1	2023	July	21	432.1	0.028	0.1145	72.9
Barchetti	Italy	Lombardia (Lombardy)	1	2023	August	14	432.1	0.028	0.1145	72.9
Barchetti	Italy	Lombardia (Lombardy)	1	2023	September	16	432.1	0.028	0.1145	72.9
Barchetti	Italy	Lombardia (Lombardy)	1	2023	October	51	432.1	0.028	0.1145	72.9
Barchetti	Italy	Lombardia (Lombardy)	1	2023	November	48	432.1	0.028	0.1145	72.9
Barchetti	Italy	Lombardia (Lombardy)	1	2023	December	37	432.1	0.028	0.1145	72.9
Barchetti	Italy	Lombardia (Lombardy)	1	2024	January	47	432.1	0.028	0.1145	72.9
Barchetti	Italy	Lombardia (Lombardy)	1	2024	February	41	432.1	0.028	0.1145	72.9
Barchetti	Italy	Lombardia (Lombardy)	1	2024	March	70	432.1	0.028	0.1145	72.9
Barchetti	Italy	Lombardia (Lombardy)	1	2024	April	57	432.1	0.028	0.1145	72.9
Barchetti	Italy	Lombardia (Lombardy)	1	2024	May	52	432.1	0.028	0.1145	72.9
Barchetti	Italy	Veneto	1	2023	May	0	279.5	0.049	0.1145	72.9
Barchetti	Italy	Veneto	1	2023	June	21	279.5	0.049	0.1145	72.9
Barchetti	Italy	Veneto	1	2023	July	21	279.5	0.049	0.1145	72.9
Barchetti	Italy	Veneto	1	2023	August	14	279.5	0.049	0.1145	72.9
Barchetti	Italy	Veneto	1	2023	September	16	279.5	0.049	0.1145	72.9
Barchetti	Italy	Veneto	1	2023	October	51	279.5	0.049	0.1145	72.9
Barchetti	Italy	Veneto	1	2023	November	48	279.5	0.049	0.1145	72.9
Barchetti	Italy	Veneto	1	2023	December	37	279.5	0.049	0.1145	72.9
Barchetti	Italy	Veneto	1	2024	January	47	279.5	0.049	0.1145	72.9
Barchetti	Italy	Veneto	1	2024	February	41	279.5	0.049	0.1145	72.9
Barchetti	Italy	Veneto	1	2024	March	70	279.5	0.049	0.1145	72.9
Barchetti	Italy	Veneto	1	2024	April	57	279.5	0.049	0.1145	72.9
Barchetti	Italy	Veneto	1	2024	May	52	279.5	0.049	0.1145	72.9
Barchetti	Italy	Trentino-Alto Adige	2	2023	May	0	88.0	0.055	0.1145	72.9
Barchetti	Italy	Trentino-Alto Adige (Trentino-Alto Adige/Südtirol)	2	2023	June	21	88.0	0.055	0.1145	72.9
Barchetti	Italy	Trentino-Alto Adige (Trentino-Alto Adige/Südtirol)	2	2023	July	21	88.0	0.055	0.1145	72.9
Barchetti	Italy	Trentino-Alto Adige (Trentino-Alto Adige/Südtirol)	2	2023	August	14	88.0	0.055	0.1145	72.9
Barchetti	Italy	Trentino-Alto Adige (Trentino-Alto Adige/Südtirol)	2	2023	September	16	88.0	0.055	0.1145	72.9
Barchetti	Italy	Trentino-Alto Adige (Trentino-Alto Adige/Südtirol)	2	2023	October	51	88.0	0.055	0.1145	72.9
Barchetti	Italy	Trentino-Alto Adige (Trentino-Alto Adige/Südtirol)	2	2023	November	48	88.0	0.055	0.1145	72.9
Barchetti	Italy	Trentino-Alto Adige (Trentino-Alto Adige/Südtirol)	2	2023	December	37	88.0	0.055	0.1145	72.9
Barchetti	Italy	Trentino-Alto Adige (Trentino-Alto Adige/Südtirol)	2	2024	January	47	88.0	0.055	0.1145	72.9
Barchetti	Italy	Trentino-Alto Adige (Trentino-Alto Adige/Südtirol)	2	2024	February	41	88.0	0.055	0.1145	72.9
Barchetti	Italy	Trentino-Alto Adige (Trentino-Alto Adige/Südtirol)	2	2024	March	70	88.0	0.055	0.1145	72.9
Barchetti	Italy	Trentino-Alto Adige (Trentino-Alto Adige/Südtirol)	2	2024	April	57	88.0	0.055	0.1145	72.9
Barchetti	Italy	Trentino-Alto Adige (Trentino-Alto Adige/Südtirol)	2	2024	May	52	88.0	0.055	0.1145	72.9
Sør-Varanger	Norway	Finnmark	1	2023	May	102	1.6	0.058	0.0586	82.6
Sør-Varanger Bilteknikk AS	Norway	Finnmark	1	2023	June	101	1.6	0.058	0.0586	82.6
Sør-Varanger Bilteknikk AS	Norway	Finnmark	1	2023	July	51	1.6	0.058	0.0586	82.6
Sør-Varanger Bilteknikk AS	Norway	Finnmark	1	2023	August	75	1.6	0.058	0.0586	82.6
Sør-Varanger Bilteknikk AS	Norway	Finnmark	1	2023	September	65	1.6	0.058	0.0586	82.6
Sør-Varanger Bilteknikk AS	Norway	Finnmark	1	2023	October	218	1.6	0.058	0.0586	82.6
Sør-Varanger Bilteknikk AS	Norway	Finnmark	1	2023	November	308	1.6	0.058	0.0586	82.6
Sør-Varanger Bilteknikk AS	Norway	Finnmark	1	2023	December	331	1.6	0.058	0.0586	82.6
Sør-Varanger Bilteknikk AS	Norway	Finnmark	1	2024	January	147	1.6	0.058	0.0586	82.6
Sør-Varanger Bilteknikk AS	Norway	Finnmark	1	2024	February	155	1.6	0.058	0.0586	82.6
Sør-Varanger Bilteknikk AS	Norway	Finnmark	1	2024	March	182	1.6	0.058	0.0586	82.6
Sør-Varanger Bilteknikk AS	Norway	Finnmark	1	2024	April	284	1.6	0.058	0.0586	82.6
Sør-Varanger Bilteknikk AS	Norway	Finnmark	1	2024	May	152	1.6	0.058	0.0586	82.6

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Dealership_Name	Country	Region	Number_of_Outlets	Year	Month	Monthly_Sales_Volume_per_Country	Regional_Population_Density	Local_Economic_Growth	Cultural_Difference_Score	Regulatory_Environment_Score
RSA BIL	Norway	Troms	1	2023	May	102	6.6	0.058	0.0586	82.6
RSA BIL	Norway	Troms	1	2023	June	101	6.6	0.058	0.0586	82.6
RSA BIL	Norway	Troms	1	2023	July	51	6.6	0.058	0.0586	82.6
RSA BIL	Norway	Troms	1	2023	August	75	6.6	0.058	0.0586	82.6
RSA BIL	Norway	Troms	1	2023	September	65	6.6	0.058	0.0586	82.6
RSA BIL	Norway	Troms	1	2023	October	218	6.6	0.058	0.0586	82.6
RSA BIL	Norway	Troms	1	2023	November	308	6.6	0.058	0.0586	82.6
RSA BIL	Norway	Troms	1	2023	December	331	6.6	0.058	0.0586	82.6
RSA BIL	Norway	Troms	1	2024	January	147	6.6	0.058	0.0586	82.6
RSA BIL	Norway	Troms	1	2024	February	155	6.6	0.058	0.0586	82.6
RSA BIL	Norway	Troms	1	2024	March	182	6.6	0.058	0.0586	82.6
RSA BIL	Norway	Troms	1	2024	April	284	6.6	0.058	0.0586	82.6
RSA BIL	Norway	Troms	1	2024	May	152	6.6	0.058	0.0586	82.6
RSA BIL	Norway	Trøndelag	1	2023	May	102	12.0	0.045	0.0586	82.6
RSA BIL	Norway	Trøndelag	1	2023	June	101	12.0	0.045	0.0586	82.6
RSA BIL	Norway	Trøndelag	1	2023	July	51	12.0	0.045	0.0586	82.6
RSA BIL	Norway	Trøndelag	1	2023	August	75	12.0	0.045	0.0586	82.6
RSA BIL	Norway	Trøndelag	1	2023	September	65	12.0	0.045	0.0586	82.6
RSA BIL	Norway	Trøndelag	1	2023	October	218	12.0	0.045	0.0586	82.6
RSA BIL	Norway	Trøndelag	1	2023	November	308	12.0	0.045	0.0586	82.6
RSA BIL	Norway	Trøndelag	1	2023	December	331	12.0	0.045	0.0586	82.6
RSA BIL	Norway	Trøndelag	1	2024	January	147	12.0	0.045	0.0586	82.6
RSA BIL	Norway	Trøndelag	1	2024	February	155	12.0	0.045	0.0586	82.6
RSA BIL	Norway	Trøndelag	1	2024	March	182	12.0	0.045	0.0586	82.6
RSA BIL	Norway	Trøndelag	1	2024	April	284	12.0	0.045	0.0586	82.6
RSA BIL	Norway	Trøndelag	1	2024	May	152	12.0	0.045	0.0586	82.6
RSA BIL	Norway	Rogaland	1	2023	May	102	54.1	0.048	0.0586	82.6
RSA BIL	Norway	Rogaland	1	2023	June	101	54.1	0.048	0.0586	82.6
RSA BIL	Norway	Rogaland	1	2023	July	51	54.1	0.048	0.0586	82.6
RSA BIL	Norway	Rogaland	1	2023	August	75	54.1	0.048	0.0586	82.6
RSA BIL	Norway	Rogaland	1	2023	September	65	54.1	0.048	0.0586	82.6
RSA BIL	Norway	Rogaland	1	2023	October	218	54.1	0.048	0.0586	82.6
RSA BIL	Norway	Rogaland	1	2023	November	308	54.1	0.048	0.0586	82.6
RSA BIL	Norway	Rogaland	1	2023	December	331	54.1	0.048	0.0586	82.6
RSA BIL	Norway	Rogaland	1	2024	January	147	54.1	0.048	0.0586	82.6
RSA BIL	Norway	Rogaland	1	2024	February	155	54.1	0.048	0.0586	82.6
RSA BIL	Norway	Rogaland	1	2024	March	182	54.1	0.048	0.0586	82.6
RSA BIL	Norway	Rogaland	1	2024	April	284	54.1	0.048	0.0586	82.6
RSA BIL	Norway	Rogaland	1	2024	May	152	54.1	0.048	0.0586	82.6
RSA BIL	Norway	Agder	2	2023	May	102	27.3	0.056	0.0586	82.6
RSA BIL	Norway	Agder	2	2023	June	101	27.3	0.056	0.0586	82.6
RSA BIL	Norway	Agder	2	2023	July	51	27.3	0.056	0.0586	82.6
RSA BIL	Norway	Agder	2	2023	August	75	27.3	0.056	0.0586	82.6
RSA BIL	Norway	Agder	2	2023	September	65	27.3	0.056	0.0586	82.6
RSA BIL	Norway	Agder	2	2023	October	218	27.3	0.056	0.0586	82.6
RSA BIL	Norway	Agder	2	2023	November	308	27.3	0.056	0.0586	82.6
RSA BIL	Norway	Agder	2	2023	December	331	27.3	0.056	0.0586	82.6
RSA BIL	Norway	Agder	2	2024	January	147	27.3	0.056	0.0586	82.6
RSA BIL	Norway	Agder	2	2024	February	155	27.3	0.056	0.0586	82.6
RSA BIL	Norway	Agder	2	2024	March	182	27.3	0.056	0.0586	82.6
RSA BIL	Norway	Agder	2	2024	April	284	27.3	0.056	0.0586	82.6
RSA BIL	Norway	Agder	2	2024	May	152	27.3	0.056	0.0586	82.6
RSA BIL	Norway	Østfold/Viken	2	2023	May	102	76.3	0.022	0.0586	82.6
RSA BIL	Norway	Østfold/Viken	2	2023	June	101	76.3	0.022	0.0586	82.6
RSA BIL	Norway	Østfold/Viken	2	2023	July	51	76.3	0.022	0.0586	82.6
RSA BIL	Norway	Østfold/Viken	2	2023	August	75	76.3	0.022	0.0586	82.6
RSA BIL	Norway	Østfold/Viken	2	2023	September	65	76.3	0.022	0.0586	82.6
RSA BIL	Norway	Østfold/Viken	2	2023	October	218	76.3	0.022	0.0586	82.6
RSA BIL	Norway	Østfold/Viken	2	2023	November	308	76.3	0.022	0.0586	82.6
RSA BIL	Norway	Østfold/Viken	2	2023	December	331	76.3	0.022	0.0586	82.6
RSA BIL	Norway	Østfold/Viken	2	2024	January	147	76.3	0.022	0.0586	82.6
RSA BIL	Norway	Østfold/Viken	2	2024	February	155	76.3	0.022	0.0586	82.6
RSA BIL	Norway	Østfold/Viken	2	2024	March	182	76.3	0.022	0.0586	82.6
RSA BIL	Norway	Østfold/Viken	2	2024	April	284	76.3	0.022	0.0586	82.6
RSA BIL	Norway	Østfold/Viken	2	2024	May	152	76.3	0.022	0.0586	82.6
RSA BIL	Norway	Akershus/Viken	1	2023	May	102	135.7	0.022	0.0586	82.6
RSA BIL	Norway	Akershus/Viken	1	2023	June	101	135.7	0.022	0.0586	82.6
RSA BIL	Norway	Akershus/Viken	1	2023	July	51	135.7	0.022	0.0586	82.6
RSA BIL	Norway	Akershus/Viken	1	2023	August	75	135.7	0.022	0.0586	82.6
RSA BIL	Norway	Akershus/Viken	1	2023	September	65	135.7	0.022	0.0586	82.6
RSA BIL	Norway	Akershus/Viken	1	2023	October	218	135.7	0.022	0.0586	82.6
RSA BIL	Norway	Akershus/Viken	1	2023	November	308	135.7	0.022	0.0586	82.6
RSA BIL	Norway	Akershus/Viken	1	2023	December	331	135.7	0.022	0.0586	82.6
RSA BIL	Norway	Akershus/Viken	1	2024	January	147	135.7	0.022	0.0586	82.6
RSA BIL	Norway	Akershus/Viken	1	2024	February	155	135.7	0.022	0.0586	82.6
RSA BIL	Norway	Akershus/Viken	1	2024	March	182	135.7	0.022	0.0586	82.6
RSA BIL	Norway	Akershus/Viken	1	2024	April	284	135.7	0.022	0.0586	82.6
RSA BIL	Norway	Akershus/Viken	1	2024	May	152	135.7	0.022	0.0586	82.6
RSA BIL	Norway	Oslo	1	2023	May	102	1,590.9	0.043	0.0586	82.6
RSA BIL	Norway	Oslo	1	2023	June	101	1,590.9	0.043	0.0586	82.6
RSA BIL	Norway	Oslo	1	2023	July	51	1,590.9	0.043	0.0586	82.6
RSA BIL	Norway	Oslo	1	2023	August	75	1,590.9	0.043	0.0586	82.6
RSA BIL	Norway	Oslo	1	2023	September	65	1,590.9	0.043	0.0586	82.6
RSA BIL	Norway	Oslo	1	2023	October	218	1,590.9	0.043	0.0586	82.6
RSA BIL	Norway	Oslo	1	2023	November	308	1,590.9	0.043	0.0586	82.6
RSA BIL	Norway	Oslo	1	2023	December	331	1,590.9	0.043	0.0586	82.6
RSA BIL	Norway	Oslo	1	2024	January	147	1,590.9	0.043	0.0586	82.6
RSA BIL	Norway	Oslo	1	2024	February	155	1,590.9	0.043	0.0586	82.6
RSA BIL	Norway	Oslo	1	2024	March	182	1,590.9	0.043	0.0586	82.6
RSA BIL	Norway	Oslo	1	2024	April	284	1,590.9	0.043	0.0586	82.6
RSA BIL	Norway	Oslo	1	2024	May	152	1,590.9	0.043	0.0586	82.6
Bilsenteret Finnsnes	Norway	Troms	1	2023	May	102	6.6	0.058	0.0586	82.6
Bilsenteret Finnsnes	Norway	Troms	1	2023	June	101	6.6	0.058	0.0586	82.6
Bilsenteret Finnsnes	Norway	Troms	1	2023	July	51	6.6	0.058	0.0586	82.6
Bilsenteret Finnsnes	Norway	Troms	1	2023	August	75	6.6	0.058	0.0586	82.6
Bilsenteret Finnsnes	Norway	Troms	1	2023	September	65	6.6	0.058	0.0586	82.6
Bilsenteret Finnsnes	Norway	Troms	1	2023	October	218	6.6	0.058	0.0586	82.6
Bilsenteret Finnsnes	Norway	Troms	1	2023	November	308	6.6	0.058	0.0586	82.6
Bilsenteret Finnsnes	Norway	Troms	1	2023	December	331	6.6	0.058	0.0586	82.6
Bilsenteret Finnsnes	Norway	Troms	1	2024	January	147	6.6	0.058	0.0586	82.6
Bilsenteret Finnsnes	Norway	Troms	1	2024	February	155	6.6	0.058	0.0586	82.6
Bilsenteret Finnsnes	Norway	Troms	1	2024	March	182	6.6	0.058	0.0586	82.6
Bilsenteret Finnsnes	Norway	Troms	1	2024	April	284	6.6	0.058	0.0586	82.6
Bilsenteret Finnsnes	Norway	Troms	1	2024	May	152	6.6	0.058	0.0586	82.6

Dealership_Name	Country	Region	Number_of_Outlets	Year	Month	Monthly_Sales_Volume_per_Country	Regional_Population_Density	Local_Economic_Growth	Cultural_Difference_Score	Regulatory_Environment_Score
Bilhuset Harstad	Norway	Troms	1	2023	May	102	6.6	0.058	0.0586	82.6
Bilhuset Harstad	Norway	Troms	1	2023	June	101	6.6	0.058	0.0586	82.6
Bilhuset Harstad	Norway	Troms	1	2023	July	51	6.6	0.058	0.0586	82.6
Bilhuset Harstad	Norway	Troms	1	2023	August	75	6.6	0.058	0.0586	82.6
Bilhuset Harstad	Norway	Troms	1	2023	September	65	6.6	0.058	0.0586	82.6
Bilhuset Harstad	Norway	Troms	1	2023	October	218	6.6	0.058	0.0586	82.6
Bilhuset Harstad	Norway	Troms	1	2023	November	308	6.6	0.058	0.0586	82.6
Bilhuset Harstad	Norway	Troms	1	2023	December	331	6.6	0.058	0.0586	82.6
Bilhuset Harstad	Norway	Troms	1	2024	January	147	6.6	0.058	0.0586	82.6
Bilhuset Harstad	Norway	Troms	1	2024	February	155	6.6	0.058	0.0586	82.6
Bilhuset Harstad	Norway	Troms	1	2024	March	182	6.6	0.058	0.0586	82.6
Bilhuset Harstad	Norway	Troms	1	2024	April	284	6.6	0.058	0.0586	82.6
Bilhuset Harstad	Norway	Troms	1	2024	May	152	6.6	0.058	0.0586	82.6
Sommerseth	Norway	Nordland/Nordlánda	1	2023	May	102	6.6	0.049	0.0586	82.6
Sommerseth	Norway	Nordland/Nordlánda	1	2023	June	101	6.6	0.049	0.0586	82.6
Sommerseth	Norway	Nordland/Nordlánda	1	2023	July	51	6.6	0.049	0.0586	82.6
Sommerseth	Norway	Nordland/Nordlánda	1	2023	August	75	6.6	0.049	0.0586	82.6
Sommerseth	Norway	Nordland/Nordlánda	1	2023	September	65	6.6	0.049	0.0586	82.6
Sommerseth	Norway	Nordland/Nordlánda	1	2023	October	218	6.6	0.049	0.0586	82.6
Sommerseth	Norway	Nordland/Nordlánda	1	2023	November	308	6.6	0.049	0.0586	82.6
Sommerseth	Norway	Nordland/Nordlánda	1	2023	December	331	6.6	0.049	0.0586	82.6
Sommerseth	Norway	Nordland/Nordlánda	1	2024	January	147	6.6	0.049	0.0586	82.6
Sommerseth	Norway	Nordland/Nordlánda	1	2024	February	155	6.6	0.049	0.0586	82.6
Sommerseth	Norway	Nordland/Nordlánda	1	2024	March	182	6.6	0.049	0.0586	82.6
Sommerseth	Norway	Nordland/Nordlánda	1	2024	April	284	6.6	0.049	0.0586	82.6
Sommerseth	Norway	Nordland/Nordlánda	1	2024	May	152	6.6	0.049	0.0586	82.6
Flygt Bil	Norway	Nordland/Nordlánda	1	2023	May	102	6.6	0.049	0.0586	82.6
Flygt Bil	Norway	Nordland/Nordlánda	1	2023	June	101	6.6	0.049	0.0586	82.6
Flygt Bil	Norway	Nordland/Nordlánda	1	2023	July	51	6.6	0.049	0.0586	82.6
Flygt Bil	Norway	Nordland/Nordlánda	1	2023	August	75	6.6	0.049	0.0586	82.6
Flygt Bil	Norway	Nordland/Nordlánda	1	2023	September	65	6.6	0.049	0.0586	82.6
Flygt Bil	Norway	Nordland/Nordlánda	1	2023	October	218	6.6	0.049	0.0586	82.6
Flygt Bil	Norway	Nordland/Nordlánda	1	2023	November	308	6.6	0.049	0.0586	82.6
Flygt Bil	Norway	Nordland/Nordlánda	1	2023	December	331	6.6	0.049	0.0586	82.6
Flygt Bil	Norway	Nordland/Nordlánda	1	2024	January	147	6.6	0.049	0.0586	82.6
Flygt Bil	Norway	Nordland/Nordlánda	1	2024	February	155	6.6	0.049	0.0586	82.6
Flygt Bil	Norway	Nordland/Nordlánda	1	2024	March	182	6.6	0.049	0.0586	82.6
Flygt Bil	Norway	Nordland/Nordlánda	1	2024	April	284	6.6	0.049	0.0586	82.6
Flygt Bil	Norway	Nordland/Nordlánda	1	2024	May	152	6.6	0.049	0.0586	82.6
Nordvik CAR	Norway	Nordland/Nordlánda	1	2023	May	102	6.6	0.049	0.0586	82.6
Nordvik CAR	Norway	Nordland/Nordlánda	1	2023	June	101	6.6	0.049	0.0586	82.6
Nordvik CAR	Norway	Nordland/Nordlánda	1	2023	July	51	6.6	0.049	0.0586	82.6
Nordvik CAR	Norway	Nordland/Nordlánda	1	2023	August	75	6.6	0.049	0.0586	82.6
Nordvik CAR	Norway	Nordland/Nordlánda	1	2023	September	65	6.6	0.049	0.0586	82.6
Nordvik CAR	Norway	Nordland/Nordlánda	1	2023	October	218	6.6	0.049	0.0586	82.6
Nordvik CAR	Norway	Nordland/Nordlánda	1	2023	November	308	6.6	0.049	0.0586	82.6
Nordvik CAR	Norway	Nordland/Nordlánda	1	2023	December	331	6.6	0.049	0.0586	82.6
Nordvik CAR	Norway	Nordland/Nordlánda	1	2024	January	147	6.6	0.049	0.0586	82.6
Nordvik CAR	Norway	Nordland/Nordlánda	1	2024	February	155	6.6	0.049	0.0586	82.6
Nordvik CAR	Norway	Nordland/Nordlánda	1	2024	March	182	6.6	0.049	0.0586	82.6
Nordvik CAR	Norway	Nordland/Nordlánda	1	2024	April	284	6.6	0.049	0.0586	82.6
Nordvik CAR	Norway	Nordland/Nordlánda	1	2024	May	152	6.6	0.049	0.0586	82.6
Høylandet	Norway	Trøndelag	3	2023	May	102	12.0	0.045	0.0586	82.6
Høylandet Auto	Norway	Trøndelag	3	2023	June	101	12.0	0.045	0.0586	82.6
Høylandet Auto	Norway	Trøndelag	3	2023	July	51	12.0	0.045	0.0586	82.6
Høylandet Auto	Norway	Trøndelag	3	2023	August	75	12.0	0.045	0.0586	82.6
Høylandet Auto	Norway	Trøndelag	3	2023	September	65	12.0	0.045	0.0586	82.6
Høylandet Auto	Norway	Trøndelag	3	2023	October	218	12.0	0.045	0.0586	82.6
Høylandet Auto	Norway	Trøndelag	3	2023	November	308	12.0	0.045	0.0586	82.6
Høylandet Auto	Norway	Trøndelag	3	2023	December	331	12.0	0.045	0.0586	82.6
Høylandet Auto	Norway	Trøndelag	3	2024	January	147	12.0	0.045	0.0586	82.6
Høylandet Auto	Norway	Trøndelag	3	2024	February	155	12.0	0.045	0.0586	82.6
Høylandet Auto	Norway	Trøndelag	3	2024	March	182	12.0	0.045	0.0586	82.6
Høylandet Auto	Norway	Trøndelag	3	2024	April	284	12.0	0.045	0.0586	82.6
Høylandet Auto	Norway	Trøndelag	3	2024	May	152	12.0	0.045	0.0586	82.6
Kristoffersen	Norway	Trøndelag	1	2023	May	102	12.0	0.045	0.0586	82.6
Kristoffersen Bil	Norway	Trøndelag	1	2023	June	101	12.0	0.045	0.0586	82.6
Kristoffersen Bil	Norway	Trøndelag	1	2023	July	51	12.0	0.045	0.0586	82.6
Kristoffersen Bil	Norway	Trøndelag	1	2023	August	75	12.0	0.045	0.0586	82.6
Kristoffersen Bil	Norway	Trøndelag	1	2023	September	65	12.0	0.045	0.0586	82.6
Kristoffersen Bil	Norway	Trøndelag	1	2023	October	218	12.0	0.045	0.0586	82.6
Kristoffersen Bil	Norway	Trøndelag	1	2023	November	308	12.0	0.045	0.0586	82.6
Kristoffersen Bil	Norway	Trøndelag	1	2023	December	331	12.0	0.045	0.0586	82.6
Kristoffersen Bil	Norway	Trøndelag	1	2024	January	147	12.0	0.045	0.0586	82.6
Kristoffersen Bil	Norway	Trøndelag	1	2024	February	155	12.0	0.045	0.0586	82.6
Kristoffersen Bil	Norway	Trøndelag	1	2024	March	182	12.0	0.045	0.0586	82.6
Kristoffersen Bil	Norway	Trøndelag	1	2024	April	284	12.0	0.045	0.0586	82.6
Kristoffersen Bil	Norway	Trøndelag	1	2024	May	152	12.0	0.045	0.0586	82.6

Dealership_Name	Country	Region	Number_of_Outlets	Year	Month	Monthly_Sales_Volume_per_Country	Regional_Population_Density	Local_Economic_Growth	Cultural_Difference_Score	Regulatory_Environment_Score
Bil & Gummiservice	Norway	Møre og Romsdal	1	2023	May	102	18.2	0.071	0.0586	82.6
Bil & Gummiservice	Norway	Møre og Romsdal	1	2023	June	101	18.2	0.071	0.0586	82.6
Bil & Gummiservice	Norway	Møre og Romsdal	1	2023	July	51	18.2	0.071	0.0586	82.6
Bil & Gummiservice	Norway	Møre og Romsdal	1	2023	August	75	18.2	0.071	0.0586	82.6
Bil & Gummiservice	Norway	Møre og Romsdal	1	2023	September	65	18.2	0.071	0.0586	82.6
Bil & Gummiservice	Norway	Møre og Romsdal	1	2023	October	218	18.2	0.071	0.0586	82.6
Bil & Gummiservice	Norway	Møre og Romsdal	1	2023	November	308	18.2	0.071	0.0586	82.6
Bil & Gummiservice	Norway	Møre og Romsdal	1	2023	December	331	18.2	0.071	0.0586	82.6
Bil & Gummiservice	Norway	Møre og Romsdal	1	2024	January	147	18.2	0.071	0.0586	82.6
Bil & Gummiservice	Norway	Møre og Romsdal	1	2024	February	155	18.2	0.071	0.0586	82.6
Bil & Gummiservice	Norway	Møre og Romsdal	1	2024	March	182	18.2	0.071	0.0586	82.6
Bil & Gummiservice	Norway	Møre og Romsdal	1	2024	April	284	18.2	0.071	0.0586	82.6
Bil & Gummiservice	Norway	Møre og Romsdal	1	2024	May	152	18.2	0.071	0.0586	82.6
Frydenbø Bilsenter	Norway	Vestland	3	2023	May	102	19.1	0.042	0.0586	82.6
Frydenbø Bilsenter	Norway	Vestland	3	2023	June	101	19.1	0.042	0.0586	82.6
Frydenbø Bilsenter	Norway	Vestland	3	2023	July	51	19.1	0.042	0.0586	82.6
Frydenbø Bilsenter	Norway	Vestland	3	2023	August	75	19.1	0.042	0.0586	82.6
Frydenbø Bilsenter	Norway	Vestland	3	2023	September	65	19.1	0.042	0.0586	82.6
Frydenbø Bilsenter	Norway	Vestland	3	2023	October	218	19.1	0.042	0.0586	82.6
Frydenbø Bilsenter	Norway	Vestland	3	2023	November	308	19.1	0.042	0.0586	82.6
Frydenbø Bilsenter	Norway	Vestland	3	2023	December	331	19.1	0.042	0.0586	82.6
Frydenbø Bilsenter	Norway	Vestland	3	2024	January	147	19.1	0.042	0.0586	82.6
Frydenbø Bilsenter	Norway	Vestland	3	2024	February	155	19.1	0.042	0.0586	82.6
Frydenbø Bilsenter	Norway	Vestland	3	2024	March	182	19.1	0.042	0.0586	82.6
Frydenbø Bilsenter	Norway	Vestland	3	2024	April	284	19.1	0.042	0.0586	82.6
Frydenbø Bilsenter	Norway	Vestland	3	2024	May	152	19.1	0.042	0.0586	82.6
Frydenbø	Norway	Agder	1	2023	May	102	27.3	0.056	0.0586	82.6
Frydenbø Bilsenter	Norway	Agder	1	2023	June	101	27.3	0.056	0.0586	82.6
Frydenbø Bilsenter	Norway	Agder	1	2023	July	51	27.3	0.056	0.0586	82.6
Frydenbø Bilsenter	Norway	Agder	1	2023	August	75	27.3	0.056	0.0586	82.6
Frydenbø Bilsenter	Norway	Agder	1	2023	September	65	27.3	0.056	0.0586	82.6
Frydenbø Bilsenter	Norway	Agder	1	2023	October	218	27.3	0.056	0.0586	82.6
Frydenbø Bilsenter	Norway	Agder	1	2023	November	308	27.3	0.056	0.0586	82.6
Frydenbø Bilsenter	Norway	Agder	1	2023	December	331	27.3	0.056	0.0586	82.6
Frydenbø Bilsenter	Norway	Agder	1	2024	January	147	27.3	0.056	0.0586	82.6
Frydenbø Bilsenter	Norway	Agder	1	2024	February	155	27.3	0.056	0.0586	82.6
Frydenbø Bilsenter	Norway	Agder	1	2024	March	182	27.3	0.056	0.0586	82.6
Frydenbø Bilsenter	Norway	Agder	1	2024	April	284	27.3	0.056	0.0586	82.6
Frydenbø Bilsenter	Norway	Agder	1	2024	May	152	27.3	0.056	0.0586	82.6
Oddvar Bjelde	Norway	Vestland	1	2023	May	102	19.1	0.042	0.0586	82.6
Oddvar Bjelde & Co	Norway	Vestland	1	2023	June	101	19.1	0.042	0.0586	82.6
Oddvar Bjelde & Co	Norway	Vestland	1	2023	July	51	19.1	0.042	0.0586	82.6
Oddvar Bjelde & Co	Norway	Vestland	1	2023	August	75	19.1	0.042	0.0586	82.6
Oddvar Bjelde & Co	Norway	Vestland	1	2023	September	65	19.1	0.042	0.0586	82.6
Oddvar Bjelde & Co	Norway	Vestland	1	2023	October	218	19.1	0.042	0.0586	82.6
Oddvar Bjelde & Co	Norway	Vestland	1	2023	November	308	19.1	0.042	0.0586	82.6
Oddvar Bjelde & Co	Norway	Vestland	1	2023	December	331	19.1	0.042	0.0586	82.6
Oddvar Bjelde & Co	Norway	Vestland	1	2024	January	147	19.1	0.042	0.0586	82.6
Oddvar Bjelde & Co	Norway	Vestland	1	2024	February	155	19.1	0.042	0.0586	82.6
Oddvar Bjelde & Co	Norway	Vestland	1	2024	March	182	19.1	0.042	0.0586	82.6
Oddvar Bjelde & Co	Norway	Vestland	1	2024	April	284	19.1	0.042	0.0586	82.6
Oddvar Bjelde & Co	Norway	Vestland	1	2024	May	152	19.1	0.042	0.0586	82.6

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Dealership_Name	Country	Region	Number_of_Outlets	Year	Month	Monthly_Sales_Volume_per_Country	Regional_Population_Density	Local_Economic_Growth	Cultural_Difference_Score	Regulatory_Environment_Score
Autosalg	Norway	Vestland	1	2023	May	102	19.1	0.042	0.0586	82.6
Autosalg	Norway	Vestland	1	2023	June	101	19.1	0.042	0.0586	82.6
Autosalg	Norway	Vestland	1	2023	July	51	19.1	0.042	0.0586	82.6
Autosalg	Norway	Vestland	1	2023	August	75	19.1	0.042	0.0586	82.6
Autosalg	Norway	Vestland	1	2023	September	65	19.1	0.042	0.0586	82.6
Autosalg	Norway	Vestland	1	2023	October	218	19.1	0.042	0.0586	82.6
Autosalg	Norway	Vestland	1	2023	November	308	19.1	0.042	0.0586	82.6
Autosalg	Norway	Vestland	1	2023	December	331	19.1	0.042	0.0586	82.6
Autosalg	Norway	Vestland	1	2024	January	147	19.1	0.042	0.0586	82.6
Autosalg	Norway	Vestland	1	2024	February	155	19.1	0.042	0.0586	82.6
Autosalg	Norway	Vestland	1	2024	March	182	19.1	0.042	0.0586	82.6
Autosalg	Norway	Vestland	1	2024	April	284	19.1	0.042	0.0586	82.6
Autosalg	Norway	Vestland	1	2024	May	152	19.1	0.042	0.0586	82.6
Øystese Mek.Verkstad	Norway	Vestland	1	2023	May	102	19.1	0.042	0.0586	82.6
Øystese Mek.Verkstad	Norway	Vestland	1	2023	June	101	19.1	0.042	0.0586	82.6
Øystese Mek.Verkstad	Norway	Vestland	1	2023	July	51	19.1	0.042	0.0586	82.6
Øystese Mek.Verkstad	Norway	Vestland	1	2023	August	75	19.1	0.042	0.0586	82.6
Øystese Mek.Verkstad	Norway	Vestland	1	2023	September	65	19.1	0.042	0.0586	82.6
Øystese Mek.Verkstad	Norway	Vestland	1	2023	October	218	19.1	0.042	0.0586	82.6
Øystese Mek.Verkstad	Norway	Vestland	1	2023	November	308	19.1	0.042	0.0586	82.6
Øystese Mek.Verkstad	Norway	Vestland	1	2023	December	331	19.1	0.042	0.0586	82.6
Øystese Mek.Verkstad	Norway	Vestland	1	2024	January	147	19.1	0.042	0.0586	82.6
Øystese Mek.Verkstad	Norway	Vestland	1	2024	February	155	19.1	0.042	0.0586	82.6
Øystese Mek.Verkstad	Norway	Vestland	1	2024	March	182	19.1	0.042	0.0586	82.6
Øystese Mek.Verkstad	Norway	Vestland	1	2024	April	284	19.1	0.042	0.0586	82.6
Øystese Mek.Verkstad	Norway	Vestland	1	2024	May	152	19.1	0.042	0.0586	82.6
Bilsenteret	Norway	Rogaland	1	2023	May	102	54.1	0.048	0.0586	82.6
Bilsenteret Haugesund	Norway	Rogaland	1	2023	June	101	54.1	0.048	0.0586	82.6
Bilsenteret Haugesund	Norway	Rogaland	1	2023	July	51	54.1	0.048	0.0586	82.6
Bilsenteret Haugesund	Norway	Rogaland	1	2023	August	75	54.1	0.048	0.0586	82.6
Bilsenteret Haugesund	Norway	Rogaland	1	2023	September	65	54.1	0.048	0.0586	82.6
Bilsenteret Haugesund	Norway	Rogaland	1	2023	October	218	54.1	0.048	0.0586	82.6
Bilsenteret Haugesund	Norway	Rogaland	1	2023	November	308	54.1	0.048	0.0586	82.6
Bilsenteret Haugesund	Norway	Rogaland	1	2023	December	331	54.1	0.048	0.0586	82.6
Bilsenteret Haugesund	Norway	Rogaland	1	2024	January	147	54.1	0.048	0.0586	82.6
Bilsenteret Haugesund	Norway	Rogaland	1	2024	February	155	54.1	0.048	0.0586	82.6
Bilsenteret Haugesund	Norway	Rogaland	1	2024	March	182	54.1	0.048	0.0586	82.6
Bilsenteret Haugesund	Norway	Rogaland	1	2024	April	284	54.1	0.048	0.0586	82.6
Bilsenteret Haugesund	Norway	Rogaland	1	2024	May	152	54.1	0.048	0.0586	82.6
Holmane Bil	Norway	Rogaland	1	2023	May	102	54.1	0.048	0.0586	82.6
Holmane Bil	Norway	Rogaland	1	2023	June	101	54.1	0.048	0.0586	82.6
Holmane Bil	Norway	Rogaland	1	2023	July	51	54.1	0.048	0.0586	82.6
Holmane Bil	Norway	Rogaland	1	2023	August	75	54.1	0.048	0.0586	82.6
Holmane Bil	Norway	Rogaland	1	2023	September	65	54.1	0.048	0.0586	82.6
Holmane Bil	Norway	Rogaland	1	2023	October	218	54.1	0.048	0.0586	82.6
Holmane Bil	Norway	Rogaland	1	2023	November	308	54.1	0.048	0.0586	82.6
Holmane Bil	Norway	Rogaland	1	2023	December	331	54.1	0.048	0.0586	82.6
Holmane Bil	Norway	Rogaland	1	2024	January	147	54.1	0.048	0.0586	82.6
Holmane Bil	Norway	Rogaland	1	2024	February	155	54.1	0.048	0.0586	82.6
Holmane Bil	Norway	Rogaland	1	2024	March	182	54.1	0.048	0.0586	82.6
Holmane Bil	Norway	Rogaland	1	2024	April	284	54.1	0.048	0.0586	82.6
Holmane Bil	Norway	Rogaland	1	2024	May	152	54.1	0.048	0.0586	82.6
Seljord Bil	Norway	Telemark	1	2023	May	102	12.2	0.063	0.0586	82.6
Seljord Bil	Norway	Telemark	1	2023	June	101	12.2	0.063	0.0586	82.6
Seljord Bil	Norway	Telemark	1	2023	July	51	12.2	0.063	0.0586	82.6
Seljord Bil	Norway	Telemark	1	2023	August	75	12.2	0.063	0.0586	82.6
Seljord Bil	Norway	Telemark	1	2023	September	65	12.2	0.063	0.0586	82.6
Seljord Bil	Norway	Telemark	1	2023	October	218	12.2	0.063	0.0586	82.6
Seljord Bil	Norway	Telemark	1	2023	November	308	12.2	0.063	0.0586	82.6
Seljord Bil	Norway	Telemark	1	2023	December	331	12.2	0.063	0.0586	82.6
Seljord Bil	Norway	Telemark	1	2024	January	147	12.2	0.063	0.0586	82.6
Seljord Bil	Norway	Telemark	1	2024	February	155	12.2	0.063	0.0586	82.6
Seljord Bil	Norway	Telemark	1	2024	March	182	12.2	0.063	0.0586	82.6
Seljord Bil	Norway	Telemark	1	2024	April	284	12.2	0.063	0.0586	82.6
Seljord Bil	Norway	Telemark	1	2024	May	152	12.2	0.063	0.0586	82.6
Bilservice	Norway	Buskerud/Viken	1	2023	May	102	20.2	0.022	0.0586	82.6
Bilservice	Norway	Buskerud/Viken	1	2023	June	101	20.2	0.022	0.0586	82.6
Bilservice	Norway	Buskerud/Viken	1	2023	July	51	20.2	0.022	0.0586	82.6
Bilservice	Norway	Buskerud/Viken	1	2023	August	75	20.2	0.022	0.0586	82.6
Bilservice	Norway	Buskerud/Viken	1	2023	September	65	20.2	0.022	0.0586	82.6
Bilservice	Norway	Buskerud/Viken	1	2023	October	218	20.2	0.022	0.0586	82.6
Bilservice	Norway	Buskerud/Viken	1	2023	November	308	20.2	0.022	0.0586	82.6
Bilservice	Norway	Buskerud/Viken	1	2023	December	331	20.2	0.022	0.0586	82.6
Bilservice	Norway	Buskerud/Viken	1	2024	January	147	20.2	0.022	0.0586	82.6
Bilservice	Norway	Buskerud/Viken	1	2024	February	155	20.2	0.022	0.0586	82.6
Bilservice	Norway	Buskerud/Viken	1	2024	March	182	20.2	0.022	0.0586	82.6
Bilservice	Norway	Buskerud/Viken	1	2024	April	284	20.2	0.022	0.0586	82.6
Bilservice	Norway	Buskerud/Viken	1	2024	May	152	20.2	0.022	0.0586	82.6

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Dealership_Name	Country	Region	Number_of_Outlets	Year	Month	Monthly_Sales_Volume_per_Country	Regional_Population_Density	Local_Economic_Growth	Cultural_Difference_Score	Regulatory_Environment_Score
Bilservice	Norway	Vestfold	2	2023	May	102	117.5	0.063	0.0586	82.6
Bilservice	Norway	Vestfold	2	2023	June	101	117.5	0.063	0.0586	82.6
Bilservice	Norway	Vestfold	2	2023	July	51	117.5	0.063	0.0586	82.6
Bilservice	Norway	Vestfold	2	2023	August	75	117.5	0.063	0.0586	82.6
Bilservice	Norway	Vestfold	2	2023	September	65	117.5	0.063	0.0586	82.6
Bilservice	Norway	Vestfold	2	2023	October	218	117.5	0.063	0.0586	82.6
Bilservice	Norway	Vestfold	2	2023	November	308	117.5	0.063	0.0586	82.6
Bilservice	Norway	Vestfold	2	2023	December	331	117.5	0.063	0.0586	82.6
Bilservice	Norway	Vestfold	2	2024	January	147	117.5	0.063	0.0586	82.6
Bilservice	Norway	Vestfold	2	2024	February	155	117.5	0.063	0.0586	82.6
Bilservice	Norway	Vestfold	2	2024	March	182	117.5	0.063	0.0586	82.6
Bilservice	Norway	Vestfold	2	2024	April	284	117.5	0.063	0.0586	82.6
Bilservice	Norway	Vestfold	2	2024	May	152	117.5	0.063	0.0586	82.6
Tønsberg Auto	Norway	Vestfold	1	2023	May	102	117.5	0.063	0.0586	82.6
Tønsberg Auto	Norway	Vestfold	1	2023	June	101	117.5	0.063	0.0586	82.6
Tønsberg Auto	Norway	Vestfold	1	2023	July	51	117.5	0.063	0.0586	82.6
Tønsberg Auto	Norway	Vestfold	1	2023	August	75	117.5	0.063	0.0586	82.6
Tønsberg Auto	Norway	Vestfold	1	2023	September	65	117.5	0.063	0.0586	82.6
Tønsberg Auto	Norway	Vestfold	1	2023	October	218	117.5	0.063	0.0586	82.6
Tønsberg Auto	Norway	Vestfold	1	2023	November	308	117.5	0.063	0.0586	82.6
Tønsberg Auto	Norway	Vestfold	1	2023	December	331	117.5	0.063	0.0586	82.6
Tønsberg Auto	Norway	Vestfold	1	2024	January	147	117.5	0.063	0.0586	82.6
Tønsberg Auto	Norway	Vestfold	1	2024	February	155	117.5	0.063	0.0586	82.6
Tønsberg Auto	Norway	Vestfold	1	2024	March	182	117.5	0.063	0.0586	82.6
Tønsberg Auto	Norway	Vestfold	1	2024	April	284	117.5	0.063	0.0586	82.6
Tønsberg Auto	Norway	Vestfold	1	2024	May	152	117.5	0.063	0.0586	82.6
Brennes Auto	Norway	Østfold/Viken	1	2023	May	102	76.3	0.022	0.0586	82.6
Brennes Auto	Norway	Østfold/Viken	1	2023	June	101	76.3	0.022	0.0586	82.6
Brennes Auto	Norway	Østfold/Viken	1	2023	July	51	76.3	0.022	0.0586	82.6
Brennes Auto	Norway	Østfold/Viken	1	2023	August	75	76.3	0.022	0.0586	82.6
Brennes Auto	Norway	Østfold/Viken	1	2023	September	65	76.3	0.022	0.0586	82.6
Brennes Auto	Norway	Østfold/Viken	1	2023	October	218	76.3	0.022	0.0586	82.6
Brennes Auto	Norway	Østfold/Viken	1	2023	November	308	76.3	0.022	0.0586	82.6
Brennes Auto	Norway	Østfold/Viken	1	2023	December	331	76.3	0.022	0.0586	82.6
Brennes Auto	Norway	Østfold/Viken	1	2024	January	147	76.3	0.022	0.0586	82.6
Brennes Auto	Norway	Østfold/Viken	1	2024	February	155	76.3	0.022	0.0586	82.6
Brennes Auto	Norway	Østfold/Viken	1	2024	March	182	76.3	0.022	0.0586	82.6
Brennes Auto	Norway	Østfold/Viken	1	2024	April	284	76.3	0.022	0.0586	82.6
Brennes Auto	Norway	Østfold/Viken	1	2024	May	152	76.3	0.022	0.0586	82.6
Jensen &	Norway	Østfold/Viken	1	2023	May	102	76.3	0.022	0.0586	82.6
Jensen & Scheele Auto	Norway	Østfold/Viken	1	2023	June	101	76.3	0.022	0.0586	82.6
Jensen & Scheele Auto	Norway	Østfold/Viken	1	2023	July	51	76.3	0.022	0.0586	82.6
Jensen & Scheele Auto	Norway	Østfold/Viken	1	2023	August	75	76.3	0.022	0.0586	82.6
Jensen & Scheele Auto	Norway	Østfold/Viken	1	2023	September	65	76.3	0.022	0.0586	82.6
Jensen & Scheele Auto	Norway	Østfold/Viken	1	2023	October	218	76.3	0.022	0.0586	82.6
Jensen & Scheele Auto	Norway	Østfold/Viken	1	2023	November	308	76.3	0.022	0.0586	82.6
Jensen & Scheele Auto	Norway	Østfold/Viken	1	2023	December	331	76.3	0.022	0.0586	82.6
Jensen & Scheele Auto	Norway	Østfold/Viken	1	2024	January	147	76.3	0.022	0.0586	82.6
Jensen & Scheele Auto	Norway	Østfold/Viken	1	2024	February	155	76.3	0.022	0.0586	82.6
Jensen & Scheele Auto	Norway	Østfold/Viken	1	2024	March	182	76.3	0.022	0.0586	82.6
Jensen & Scheele Auto	Norway	Østfold/Viken	1	2024	April	284	76.3	0.022	0.0586	82.6
Jensen & Scheele Auto	Norway	Østfold/Viken	1	2024	May	152	76.3	0.022	0.0586	82.6
Birger N Haug	Norway	Oslo	1	2023	May	102	1,590.9	0.043	0.0586	82.6
Birger N Haug	Norway	Oslo	1	2023	June	101	1,590.9	0.043	0.0586	82.6
Birger N Haug	Norway	Oslo	1	2023	July	51	1,590.9	0.043	0.0586	82.6
Birger N Haug	Norway	Oslo	1	2023	August	75	1,590.9	0.043	0.0586	82.6
Birger N Haug	Norway	Oslo	1	2023	September	65	1,590.9	0.043	0.0586	82.6
Birger N Haug	Norway	Oslo	1	2023	October	218	1,590.9	0.043	0.0586	82.6
Birger N Haug	Norway	Oslo	1	2023	November	308	1,590.9	0.043	0.0586	82.6
Birger N Haug	Norway	Oslo	1	2023	December	331	1,590.9	0.043	0.0586	82.6
Birger N Haug	Norway	Oslo	1	2024	January	147	1,590.9	0.043	0.0586	82.6
Birger N Haug	Norway	Oslo	1	2024	February	155	1,590.9	0.043	0.0586	82.6
Birger N Haug	Norway	Oslo	1	2024	March	182	1,590.9	0.043	0.0586	82.6
Birger N Haug	Norway	Oslo	1	2024	April	284	1,590.9	0.043	0.0586	82.6
Birger N Haug	Norway	Oslo	1	2024	May	152	1,590.9	0.043	0.0586	82.6

Dealership_Name	Country	Region	Number_of_Outlets	Year	Month	Monthly_Sales_Volume_per_Country	Regional_Population_Density	Local_Economic_Growth	Cultural_Difference_Score	Regulatory_Environment_Score
Østerås Bilsenter	Norway	Akershus/Viken	1	2023	May	102	135.7	0.022	0.0586	82.6
Østerås Bilsenter	Norway	Akershus/Viken	1	2023	June	101	135.7	0.022	0.0586	82.6
Østerås Bilsenter	Norway	Akershus/Viken	1	2023	July	51	135.7	0.022	0.0586	82.6
Østerås Bilsenter	Norway	Akershus/Viken	1	2023	August	75	135.7	0.022	0.0586	82.6
Østerås Bilsenter	Norway	Akershus/Viken	1	2023	September	65	135.7	0.022	0.0586	82.6
Østerås Bilsenter	Norway	Akershus/Viken	1	2023	October	218	135.7	0.022	0.0586	82.6
Østerås Bilsenter	Norway	Akershus/Viken	1	2023	November	308	135.7	0.022	0.0586	82.6
Østerås Bilsenter	Norway	Akershus/Viken	1	2023	December	331	135.7	0.022	0.0586	82.6
Østerås Bilsenter	Norway	Akershus/Viken	1	2024	January	147	135.7	0.022	0.0586	82.6
Østerås Bilsenter	Norway	Akershus/Viken	1	2024	February	155	135.7	0.022	0.0586	82.6
Østerås Bilsenter	Norway	Akershus/Viken	1	2024	March	182	135.7	0.022	0.0586	82.6
Østerås Bilsenter	Norway	Akershus/Viken	1	2024	April	284	135.7	0.022	0.0586	82.6
Østerås Bilsenter	Norway	Akershus/Viken	1	2024	May	152	135.7	0.022	0.0586	82.6
Sverre Haugli Bilforretning	Norway	Buskerud/Viken	1	2023	May	102	20.2	0.022	0.0586	82.6
Sverre Haugli Bilforretning	Norway	Buskerud/Viken	1	2023	June	101	20.2	0.022	0.0586	82.6
Sverre Haugli Bilforretning	Norway	Buskerud/Viken	1	2023	July	51	20.2	0.022	0.0586	82.6
Sverre Haugli Bilforretning	Norway	Buskerud/Viken	1	2023	August	75	20.2	0.022	0.0586	82.6
Sverre Haugli Bilforretning	Norway	Buskerud/Viken	1	2023	September	65	20.2	0.022	0.0586	82.6
Sverre Haugli Bilforretning	Norway	Buskerud/Viken	1	2023	October	218	20.2	0.022	0.0586	82.6
Sverre Haugli Bilforretning	Norway	Buskerud/Viken	1	2023	November	308	20.2	0.022	0.0586	82.6
Sverre Haugli Bilforretning	Norway	Buskerud/Viken	1	2023	December	331	20.2	0.022	0.0586	82.6
Sverre Haugli Bilforretning	Norway	Buskerud/Viken	1	2024	January	147	20.2	0.022	0.0586	82.6
Sverre Haugli Bilforretning	Norway	Buskerud/Viken	1	2024	February	155	20.2	0.022	0.0586	82.6
Sverre Haugli Bilforretning	Norway	Buskerud/Viken	1	2024	March	182	20.2	0.022	0.0586	82.6
Sverre Haugli Bilforretning	Norway	Buskerud/Viken	1	2024	April	284	20.2	0.022	0.0586	82.6
Sverre Haugli Bilforretning	Norway	Buskerud/Viken	1	2024	May	152	20.2	0.022	0.0586	82.6
Mobile	Norway	Innlandet	4	2023	May	102	7.4	0.036	0.0586	82.6
Mobile	Norway	Innlandet	4	2023	June	101	7.4	0.036	0.0586	82.6
Mobile	Norway	Innlandet	4	2023	July	51	7.4	0.036	0.0586	82.6
Mobile	Norway	Innlandet	4	2023	August	75	7.4	0.036	0.0586	82.6
Mobile	Norway	Innlandet	4	2023	September	65	7.4	0.036	0.0586	82.6
Mobile	Norway	Innlandet	4	2023	October	218	7.4	0.036	0.0586	82.6
Mobile	Norway	Innlandet	4	2023	November	308	7.4	0.036	0.0586	82.6
Mobile	Norway	Innlandet	4	2023	December	331	7.4	0.036	0.0586	82.6
Mobile	Norway	Innlandet	4	2024	January	147	7.4	0.036	0.0586	82.6
Mobile	Norway	Innlandet	4	2024	February	155	7.4	0.036	0.0586	82.6
Mobile	Norway	Innlandet	4	2024	March	182	7.4	0.036	0.0586	82.6
Mobile	Norway	Innlandet	4	2024	April	284	7.4	0.036	0.0586	82.6
Mobile	Norway	Innlandet	4	2024	May	152	7.4	0.036	0.0586	82.6
Senger Gruppe	Germany	Schleswig-Holstein	1	2023	May	49	190.7	0.009	0.1682	79.7
Senger Gruppe	Germany	Schleswig-Holstein	1	2023	June	53	190.7	0.009	0.1682	79.7
Senger Gruppe	Germany	Schleswig-Holstein	1	2023	July	367	190.7	0.009	0.1682	79.7
Senger Gruppe	Germany	Schleswig-Holstein	1	2023	August	1985	190.7	0.009	0.1682	79.7
Senger Gruppe	Germany	Schleswig-Holstein	1	2023	September	182	190.7	0.009	0.1682	79.7
Senger Gruppe	Germany	Schleswig-Holstein	1	2023	October	199	190.7	0.009	0.1682	79.7
Senger Gruppe	Germany	Schleswig-Holstein	1	2023	November	305	190.7	0.009	0.1682	79.7
Senger Gruppe	Germany	Schleswig-Holstein	1	2023	December	627	190.7	0.009	0.1682	79.7
Senger Gruppe	Germany	Schleswig-Holstein	1	2024	January	112	190.7	0.009	0.1682	79.7
Senger Gruppe	Germany	Schleswig-Holstein	1	2024	February	68	190.7	0.009	0.1682	79.7
Senger Gruppe	Germany	Schleswig-Holstein	1	2024	March	128	190.7	0.009	0.1682	79.7
Senger Gruppe	Germany	Schleswig-Holstein	1	2024	April	144	190.7	0.009	0.1682	79.7
Senger Gruppe	Germany	Schleswig-Holstein	1	2024	May	183	190.7	0.009	0.1682	79.7
Senger Gruppe	Germany	Nordrhein-Westfalen (North Rhine-Westphalia)	3	2023	May	49	532.8	0.005	0.1682	79.7
Senger Gruppe	Germany	Nordrhein-Westfalen (North Rhine-Westphalia)	3	2023	June	53	532.8	0.005	0.1682	79.7
Senger Gruppe	Germany	Nordrhein-Westfalen (North Rhine-Westphalia)	3	2023	July	367	532.8	0.005	0.1682	79.7
Senger Gruppe	Germany	Nordrhein-Westfalen (North Rhine-Westphalia)	3	2023	August	1985	532.8	0.005	0.1682	79.7
Senger Gruppe	Germany	Nordrhein-Westfalen (North Rhine-Westphalia)	3	2023	September	182	532.8	0.005	0.1682	79.7
Senger Gruppe	Germany	Nordrhein-Westfalen (North Rhine-Westphalia)	3	2023	October	199	532.8	0.005	0.1682	79.7
Senger Gruppe	Germany	Nordrhein-Westfalen (North Rhine-Westphalia)	3	2023	November	305	532.8	0.005	0.1682	79.7
Senger Gruppe	Germany	Nordrhein-Westfalen (North Rhine-Westphalia)	3	2023	December	627	532.8	0.005	0.1682	79.7
Senger Gruppe	Germany	Nordrhein-Westfalen (North Rhine-Westphalia)	3	2024	January	112	532.8	0.005	0.1682	79.7
Senger Gruppe	Germany	Nordrhein-Westfalen (North Rhine-Westphalia)	3	2024	February	68	532.8	0.005	0.1682	79.7
Senger Gruppe	Germany	Nordrhein-Westfalen (North Rhine-Westphalia)	3	2024	March	128	532.8	0.005	0.1682	79.7
Senger Gruppe	Germany	Nordrhein-Westfalen (North Rhine-Westphalia)	3	2024	April	144	532.8	0.005	0.1682	79.7
Senger Gruppe	Germany	Nordrhein-Westfalen (North Rhine-Westphalia)	3	2024	May	183	532.8	0.005	0.1682	79.7

Dealership_Name	Country	Region	Number_of_Outlets	Year	Month	Monthly_Sales_Volume_per_Country	Regional_Population_Density	Local_Economic_Growth	Cultural_Difference_Score	Regulatory_Environment_Score
STERNAUTO	Germany	Mecklenburg-Vorpommern	1	2023	May	49	71.8	0.011	0.1682	79.7
STERNAUTO	Germany	Mecklenburg-Vorpommern	1	2023	June	53	71.8	0.011	0.1682	79.7
STERNAUTO	Germany	Mecklenburg-Vorpommern	1	2023	July	367	71.8	0.011	0.1682	79.7
STERNAUTO	Germany	Mecklenburg-Vorpommern	1	2023	August	1985	71.8	0.011	0.1682	79.7
STERNAUTO	Germany	Mecklenburg-Vorpommern	1	2023	September	182	71.8	0.011	0.1682	79.7
STERNAUTO	Germany	Mecklenburg-Vorpommern	1	2023	October	199	71.8	0.011	0.1682	79.7
STERNAUTO	Germany	Mecklenburg-Vorpommern	1	2023	November	305	71.8	0.011	0.1682	79.7
STERNAUTO	Germany	Mecklenburg-Vorpommern	1	2023	December	627	71.8	0.011	0.1682	79.7
STERNAUTO	Germany	Mecklenburg-Vorpommern	1	2024	January	112	71.8	0.011	0.1682	79.7
STERNAUTO	Germany	Mecklenburg-Vorpommern	1	2024	February	68	71.8	0.011	0.1682	79.7
STERNAUTO	Germany	Mecklenburg-Vorpommern	1	2024	March	128	71.8	0.011	0.1682	79.7
STERNAUTO	Germany	Mecklenburg-Vorpommern	1	2024	April	144	71.8	0.011	0.1682	79.7
STERNAUTO	Germany	Mecklenburg-Vorpommern	1	2024	May	183	71.8	0.011	0.1682	79.7
STERNAUTO	Germany	Berlin	1	2023	May	49	4,392.9	0.011	0.1682	79.7
STERNAUTO	Germany	Berlin	1	2023	June	53	4,392.9	0.011	0.1682	79.7
STERNAUTO	Germany	Berlin	1	2023	July	367	4,392.9	0.011	0.1682	79.7
STERNAUTO	Germany	Berlin	1	2023	August	1985	4,392.9	0.011	0.1682	79.7
STERNAUTO	Germany	Berlin	1	2023	September	182	4,392.9	0.011	0.1682	79.7
STERNAUTO	Germany	Berlin	1	2023	October	199	4,392.9	0.011	0.1682	79.7
STERNAUTO	Germany	Berlin	1	2023	November	305	4,392.9	0.011	0.1682	79.7
STERNAUTO	Germany	Berlin	1	2023	December	627	4,392.9	0.011	0.1682	79.7
STERNAUTO	Germany	Berlin	1	2024	January	112	4,392.9	0.011	0.1682	79.7
STERNAUTO	Germany	Berlin	1	2024	February	68	4,392.9	0.011	0.1682	79.7
STERNAUTO	Germany	Berlin	1	2024	March	128	4,392.9	0.011	0.1682	79.7
STERNAUTO	Germany	Berlin	1	2024	April	144	4,392.9	0.011	0.1682	79.7
STERNAUTO	Germany	Berlin	1	2024	May	183	4,392.9	0.011	0.1682	79.7
STERNAUTO	Germany	Brandenburg	1	2023	May	49	88.1	0.008	0.1682	79.7
STERNAUTO	Germany	Brandenburg	1	2023	June	53	88.1	0.008	0.1682	79.7
STERNAUTO	Germany	Brandenburg	1	2023	July	367	88.1	0.008	0.1682	79.7
STERNAUTO	Germany	Brandenburg	1	2023	August	1985	88.1	0.008	0.1682	79.7
STERNAUTO	Germany	Brandenburg	1	2023	September	182	88.1	0.008	0.1682	79.7
STERNAUTO	Germany	Brandenburg	1	2023	October	199	88.1	0.008	0.1682	79.7
STERNAUTO	Germany	Brandenburg	1	2023	November	305	88.1	0.008	0.1682	79.7
STERNAUTO	Germany	Brandenburg	1	2023	December	627	88.1	0.008	0.1682	79.7
STERNAUTO	Germany	Brandenburg	1	2024	January	112	88.1	0.008	0.1682	79.7
STERNAUTO	Germany	Brandenburg	1	2024	February	68	88.1	0.008	0.1682	79.7
STERNAUTO	Germany	Brandenburg	1	2024	March	128	88.1	0.008	0.1682	79.7
STERNAUTO	Germany	Brandenburg	1	2024	April	144	88.1	0.008	0.1682	79.7
STERNAUTO	Germany	Brandenburg	1	2024	May	183	88.1	0.008	0.1682	79.7
STERNAUTO	Germany	Sachsen-Anhalt (Saxony-Anhalt)	1	2023	May	49	107.6	0.008	0.1682	79.7
STERNAUTO	Germany	Sachsen-Anhalt (Saxony-Anhalt)	1	2023	June	53	107.6	0.008	0.1682	79.7
STERNAUTO	Germany	Sachsen-Anhalt (Saxony-Anhalt)	1	2023	July	367	107.6	0.008	0.1682	79.7
STERNAUTO	Germany	Sachsen-Anhalt (Saxony-Anhalt)	1	2023	August	1985	107.6	0.008	0.1682	79.7
STERNAUTO	Germany	Sachsen-Anhalt (Saxony-Anhalt)	1	2023	September	182	107.6	0.008	0.1682	79.7
STERNAUTO	Germany	Sachsen-Anhalt (Saxony-Anhalt)	1	2023	October	199	107.6	0.008	0.1682	79.7
STERNAUTO	Germany	Sachsen-Anhalt (Saxony-Anhalt)	1	2023	November	305	107.6	0.008	0.1682	79.7
STERNAUTO	Germany	Sachsen-Anhalt (Saxony-Anhalt)	1	2023	December	627	107.6	0.008	0.1682	79.7
STERNAUTO	Germany	Sachsen-Anhalt (Saxony-Anhalt)	1	2024	January	112	107.6	0.008	0.1682	79.7
STERNAUTO	Germany	Sachsen-Anhalt (Saxony-Anhalt)	1	2024	February	68	107.6	0.008	0.1682	79.7
STERNAUTO	Germany	Sachsen-Anhalt (Saxony-Anhalt)	1	2024	March	128	107.6	0.008	0.1682	79.7
STERNAUTO	Germany	Sachsen-Anhalt (Saxony-Anhalt)	1	2024	April	144	107.6	0.008	0.1682	79.7
STERNAUTO	Germany	Sachsen-Anhalt (Saxony-Anhalt)	1	2024	May	183	107.6	0.008	0.1682	79.7
STERNAUTO	Germany	Thüringen (Thuringia)	1	2023	May	49	131.2	0.012	0.1682	79.7
STERNAUTO	Germany	Thüringen (Thuringia)	1	2023	June	53	131.2	0.012	0.1682	79.7
STERNAUTO	Germany	Thüringen (Thuringia)	1	2023	July	367	131.2	0.012	0.1682	79.7
STERNAUTO	Germany	Thüringen (Thuringia)	1	2023	August	1985	131.2	0.012	0.1682	79.7
STERNAUTO	Germany	Thüringen (Thuringia)	1	2023	September	182	131.2	0.012	0.1682	79.7
STERNAUTO	Germany	Thüringen (Thuringia)	1	2023	October	199	131.2	0.012	0.1682	79.7
STERNAUTO	Germany	Thüringen (Thuringia)	1	2023	November	305	131.2	0.012	0.1682	79.7
STERNAUTO	Germany	Thüringen (Thuringia)	1	2023	December	627	131.2	0.012	0.1682	79.7
STERNAUTO	Germany	Thüringen (Thuringia)	1	2024	January	112	131.2	0.012	0.1682	79.7
STERNAUTO	Germany	Thüringen (Thuringia)	1	2024	February	68	131.2	0.012	0.1682	79.7
STERNAUTO	Germany	Thüringen (Thuringia)	1	2024	March	128	131.2	0.012	0.1682	79.7
STERNAUTO	Germany	Thüringen (Thuringia)	1	2024	April	144	131.2	0.012	0.1682	79.7
STERNAUTO	Germany	Thüringen (Thuringia)	1	2024	May	183	131.2	0.012	0.1682	79.7

Dealership_Name	Country	Region	Number_of_Outlets	Year	Month	Monthly_Sales_Volume_per_Country	Regional_Population_Density	Local_Economic_Growth	Cultural_Difference_Score	Regulatory_Environment_Score
STERNAUTO	Germany	Sachsen (Saxony)	2	2023	May	49	223.6	0.011	0.1682	79.7
STERNAUTO	Germany	Sachsen (Saxony)	2	2023	June	53	223.6	0.011	0.1682	79.7
STERNAUTO	Germany	Sachsen (Saxony)	2	2023	July	367	223.6	0.011	0.1682	79.7
STERNAUTO	Germany	Sachsen (Saxony)	2	2023	August	1985	223.6	0.011	0.1682	79.7
STERNAUTO	Germany	Sachsen (Saxony)	2	2023	September	182	223.6	0.011	0.1682	79.7
STERNAUTO	Germany	Sachsen (Saxony)	2	2023	October	199	223.6	0.011	0.1682	79.7
STERNAUTO	Germany	Sachsen (Saxony)	2	2023	November	305	223.6	0.011	0.1682	79.7
STERNAUTO	Germany	Sachsen (Saxony)	2	2023	December	627	223.6	0.011	0.1682	79.7
STERNAUTO	Germany	Sachsen (Saxony)	2	2024	January	112	223.6	0.011	0.1682	79.7
STERNAUTO	Germany	Sachsen (Saxony)	2	2024	February	68	223.6	0.011	0.1682	79.7
STERNAUTO	Germany	Sachsen (Saxony)	2	2024	March	128	223.6	0.011	0.1682	79.7
STERNAUTO	Germany	Sachsen (Saxony)	2	2024	April	144	223.6	0.011	0.1682	79.7
STERNAUTO	Germany	Sachsen (Saxony)	2	2024	May	183	223.6	0.011	0.1682	79.7
SPT Avior SE & Co. KG	Germany	Hamburg	1	2023	May	49	2,638.1	0.000	0.1682	79.7
SPT Avior SE & Co. KG	Germany	Hamburg	1	2023	June	53	2,638.1	0.000	0.1682	79.7
SPT Avior SE & Co. KG	Germany	Hamburg	1	2023	July	367	2,638.1	0.000	0.1682	79.7
SPT Avior SE & Co. KG	Germany	Hamburg	1	2023	August	1985	2,638.1	0.000	0.1682	79.7
SPT Avior SE & Co. KG	Germany	Hamburg	1	2023	September	182	2,638.1	0.000	0.1682	79.7
SPT Avior SE & Co. KG	Germany	Hamburg	1	2023	October	199	2,638.1	0.000	0.1682	79.7
SPT Avior SE & Co. KG	Germany	Hamburg	1	2023	November	305	2,638.1	0.000	0.1682	79.7
SPT Avior SE & Co. KG	Germany	Hamburg	1	2023	December	627	2,638.1	0.000	0.1682	79.7
SPT Avior SE & Co. KG	Germany	Hamburg	1	2024	January	112	2,638.1	0.000	0.1682	79.7
SPT Avior SE & Co. KG	Germany	Hamburg	1	2024	February	68	2,638.1	0.000	0.1682	79.7
SPT Avior SE & Co. KG	Germany	Hamburg	1	2024	March	128	2,638.1	0.000	0.1682	79.7
SPT Avior SE & Co. KG	Germany	Hamburg	1	2024	April	144	2,638.1	0.000	0.1682	79.7
SPT Avior SE & Co. KG	Germany	Hamburg	1	2024	May	183	2,638.1	0.000	0.1682	79.7
SPT Avior SE & Co. KG	Germany	Niedersachsen (Lower Saxony)	1	2023	May	49	170.7	0.009	0.1682	79.7
SPT Avior SE & Co. KG	Germany	Niedersachsen (Lower Saxony)	1	2023	June	53	170.7	0.009	0.1682	79.7
SPT Avior SE & Co. KG	Germany	Niedersachsen (Lower Saxony)	1	2023	July	367	170.7	0.009	0.1682	79.7
SPT Avior SE & Co. KG	Germany	Niedersachsen (Lower Saxony)	1	2023	August	1985	170.7	0.009	0.1682	79.7
SPT Avior SE & Co. KG	Germany	Niedersachsen (Lower Saxony)	1	2023	September	182	170.7	0.009	0.1682	79.7
SPT Avior SE & Co. KG	Germany	Niedersachsen (Lower Saxony)	1	2023	October	199	170.7	0.009	0.1682	79.7
SPT Avior SE & Co. KG	Germany	Niedersachsen (Lower Saxony)	1	2023	November	305	170.7	0.009	0.1682	79.7
SPT Avior SE & Co. KG	Germany	Niedersachsen (Lower Saxony)	1	2023	December	627	170.7	0.009	0.1682	79.7
SPT Avior SE & Co. KG	Germany	Niedersachsen (Lower Saxony)	1	2024	January	112	170.7	0.009	0.1682	79.7
SPT Avior SE & Co. KG	Germany	Niedersachsen (Lower Saxony)	1	2024	February	68	170.7	0.009	0.1682	79.7
SPT Avior SE & Co. KG	Germany	Niedersachsen (Lower Saxony)	1	2024	March	128	170.7	0.009	0.1682	79.7
SPT Avior SE & Co. KG	Germany	Niedersachsen (Lower Saxony)	1	2024	April	144	170.7	0.009	0.1682	79.7
SPT Avior SE & Co. KG	Germany	Niedersachsen (Lower Saxony)	1	2024	May	183	170.7	0.009	0.1682	79.7
Glinicke	Germany	Nordrhein-Westfalen (North Rhine-Westphalia)	1	2023	May	49	532.8	0.005	0.1682	79.7
Glinicke	Germany	Nordrhein-Westfalen (North Rhine-Westphalia)	1	2023	June	53	532.8	0.005	0.1682	79.7
Glinicke	Germany	Nordrhein-Westfalen (North Rhine-Westphalia)	1	2023	July	367	532.8	0.005	0.1682	79.7
Glinicke	Germany	Nordrhein-Westfalen (North Rhine-Westphalia)	1	2023	August	1985	532.8	0.005	0.1682	79.7
Glinicke	Germany	Nordrhein-Westfalen (North Rhine-Westphalia)	1	2023	September	182	532.8	0.005	0.1682	79.7
Glinicke	Germany	Nordrhein-Westfalen (North Rhine-Westphalia)	1	2023	October	199	532.8	0.005	0.1682	79.7
Glinicke	Germany	Nordrhein-Westfalen (North Rhine-Westphalia)	1	2023	November	305	532.8	0.005	0.1682	79.7
Glinicke	Germany	Nordrhein-Westfalen (North Rhine-Westphalia)	1	2023	December	627	532.8	0.005	0.1682	79.7
Glinicke	Germany	Nordrhein-Westfalen (North Rhine-Westphalia)	1	2024	January	112	532.8	0.005	0.1682	79.7
Glinicke	Germany	Nordrhein-Westfalen (North Rhine-Westphalia)	1	2024	February	68	532.8	0.005	0.1682	79.7
Glinicke	Germany	Nordrhein-Westfalen (North Rhine-Westphalia)	1	2024	March	128	532.8	0.005	0.1682	79.7
Glinicke	Germany	Nordrhein-Westfalen (North Rhine-Westphalia)	1	2024	April	144	532.8	0.005	0.1682	79.7
Glinicke	Germany	Nordrhein-Westfalen (North Rhine-Westphalia)	1	2024	May	183	532.8	0.005	0.1682	79.7
Glinicke	Germany	Niedersachsen (Lower Saxony)	1	2023	May	49	170.7	0.009	0.1682	79.7
Glinicke	Germany	Niedersachsen (Lower Saxony)	1	2023	June	53	170.7	0.009	0.1682	79.7
Glinicke	Germany	Niedersachsen (Lower Saxony)	1	2023	July	367	170.7	0.009	0.1682	79.7
Glinicke	Germany	Niedersachsen (Lower Saxony)	1	2023	August	1985	170.7	0.009	0.1682	79.7
Glinicke	Germany	Niedersachsen (Lower Saxony)	1	2023	September	182	170.7	0.009	0.1682	79.7
Glinicke	Germany	Niedersachsen (Lower Saxony)	1	2023	October	199	170.7	0.009	0.1682	79.7
Glinicke	Germany	Niedersachsen (Lower Saxony)	1	2023	November	305	170.7	0.009	0.1682	79.7
Glinicke	Germany	Niedersachsen (Lower Saxony)	1	2023	December	627	170.7	0.009	0.1682	79.7
Glinicke	Germany	Niedersachsen (Lower Saxony)	1	2024	January	112	170.7	0.009	0.1682	79.7
Glinicke	Germany	Niedersachsen (Lower Saxony)	1	2024	February	68	170.7	0.009	0.1682	79.7
Glinicke	Germany	Niedersachsen (Lower Saxony)	1	2024	March	128	170.7	0.009	0.1682	79.7
Glinicke	Germany	Niedersachsen (Lower Saxony)	1	2024	April	144	170.7	0.009	0.1682	79.7
Glinicke	Germany	Niedersachsen (Lower Saxony)	1	2024	May	183	170.7	0.009	0.1682	79.7

Dealership_Name	Country	Region	Number_of_Outlets	Year	Month	Monthly_Sales_Volume_per_Country	Regional_Population_Density	Local_Economic_Growth	Cultural_Difference_Score	Regulatory_Environment_Score
Glinicke	Germany	Hessen (Hesse)	1	2023	May	49	301.5	0.001	0.1682	79.7
Glinicke	Germany	Hessen (Hesse)	1	2023	June	53	301.5	0.001	0.1682	79.7
Glinicke	Germany	Hessen (Hesse)	1	2023	July	367	301.5	0.001	0.1682	79.7
Glinicke	Germany	Hessen (Hesse)	1	2023	August	1985	301.5	0.001	0.1682	79.7
Glinicke	Germany	Hessen (Hesse)	1	2023	September	182	301.5	0.001	0.1682	79.7
Glinicke	Germany	Hessen (Hesse)	1	2023	October	199	301.5	0.001	0.1682	79.7
Glinicke	Germany	Hessen (Hesse)	1	2023	November	305	301.5	0.001	0.1682	79.7
Glinicke	Germany	Hessen (Hesse)	1	2023	December	627	301.5	0.001	0.1682	79.7
Glinicke	Germany	Hessen (Hesse)	1	2024	January	112	301.5	0.001	0.1682	79.7
Glinicke	Germany	Hessen (Hesse)	1	2024	February	68	301.5	0.001	0.1682	79.7
Glinicke	Germany	Hessen (Hesse)	1	2024	March	128	301.5	0.001	0.1682	79.7
Glinicke	Germany	Hessen (Hesse)	1	2024	April	144	301.5	0.001	0.1682	79.7
Glinicke	Germany	Hessen (Hesse)	1	2024	May	183	301.5	0.001	0.1682	79.7
Torpedo Gruppe	Germany	Hessen (Hesse)	1	2023	May	49	301.5	0.001	0.1682	79.7
Torpedo Gruppe	Germany	Hessen (Hesse)	1	2023	June	53	301.5	0.001	0.1682	79.7
Torpedo Gruppe	Germany	Hessen (Hesse)	1	2023	July	367	301.5	0.001	0.1682	79.7
Torpedo Gruppe	Germany	Hessen (Hesse)	1	2023	August	1985	301.5	0.001	0.1682	79.7
Torpedo Gruppe	Germany	Hessen (Hesse)	1	2023	September	182	301.5	0.001	0.1682	79.7
Torpedo Gruppe	Germany	Hessen (Hesse)	1	2023	October	199	301.5	0.001	0.1682	79.7
Torpedo Gruppe	Germany	Hessen (Hesse)	1	2023	November	305	301.5	0.001	0.1682	79.7
Torpedo Gruppe	Germany	Hessen (Hesse)	1	2023	December	627	301.5	0.001	0.1682	79.7
Torpedo Gruppe	Germany	Hessen (Hesse)	1	2024	January	112	301.5	0.001	0.1682	79.7
Torpedo Gruppe	Germany	Hessen (Hesse)	1	2024	February	68	301.5	0.001	0.1682	79.7
Torpedo Gruppe	Germany	Hessen (Hesse)	1	2024	March	128	301.5	0.001	0.1682	79.7
Torpedo Gruppe	Germany	Hessen (Hesse)	1	2024	April	144	301.5	0.001	0.1682	79.7
Torpedo Gruppe	Germany	Hessen (Hesse)	1	2024	May	183	301.5	0.001	0.1682	79.7
Torpedo Gruppe	Germany	Baden-Württemberg	1	2023	May	49	316.8	0.006	0.1682	79.7
Torpedo Gruppe	Germany	Baden-Württemberg	1	2023	June	53	316.8	0.006	0.1682	79.7
Torpedo Gruppe	Germany	Baden-Württemberg	1	2023	July	367	316.8	0.006	0.1682	79.7
Torpedo Gruppe	Germany	Baden-Württemberg	1	2023	August	1985	316.8	0.006	0.1682	79.7
Torpedo Gruppe	Germany	Baden-Württemberg	1	2023	September	182	316.8	0.006	0.1682	79.7
Torpedo Gruppe	Germany	Baden-Württemberg	1	2023	October	199	316.8	0.006	0.1682	79.7
Torpedo Gruppe	Germany	Baden-Württemberg	1	2023	November	305	316.8	0.006	0.1682	79.7
Torpedo Gruppe	Germany	Baden-Württemberg	1	2023	December	627	316.8	0.006	0.1682	79.7
Torpedo Gruppe	Germany	Baden-Württemberg	1	2024	January	112	316.8	0.006	0.1682	79.7
Torpedo Gruppe	Germany	Baden-Württemberg	1	2024	February	68	316.8	0.006	0.1682	79.7
Torpedo Gruppe	Germany	Baden-Württemberg	1	2024	March	128	316.8	0.006	0.1682	79.7
Torpedo Gruppe	Germany	Baden-Württemberg	1	2024	April	144	316.8	0.006	0.1682	79.7
Torpedo Gruppe	Germany	Baden-Württemberg	1	2024	May	183	316.8	0.006	0.1682	79.7
Hedin Automotive DE	Germany	Baden-Württemberg	1	2023	May	49	316.8	0.006	0.1682	79.7
Hedin Automotive DE	Germany	Baden-Württemberg	1	2023	June	53	316.8	0.006	0.1682	79.7
Hedin Automotive DE	Germany	Baden-Württemberg	1	2023	July	367	316.8	0.006	0.1682	79.7
Hedin Automotive DE	Germany	Baden-Württemberg	1	2023	August	1985	316.8	0.006	0.1682	79.7
Hedin Automotive DE	Germany	Baden-Württemberg	1	2023	September	182	316.8	0.006	0.1682	79.7
Hedin Automotive DE	Germany	Baden-Württemberg	1	2023	October	199	316.8	0.006	0.1682	79.7
Hedin Automotive DE	Germany	Baden-Württemberg	1	2023	November	305	316.8	0.006	0.1682	79.7
Hedin Automotive DE	Germany	Baden-Württemberg	1	2023	December	627	316.8	0.006	0.1682	79.7
Hedin Automotive DE	Germany	Baden-Württemberg	1	2024	January	112	316.8	0.006	0.1682	79.7
Hedin Automotive DE	Germany	Baden-Württemberg	1	2024	February	68	316.8	0.006	0.1682	79.7
Hedin Automotive DE	Germany	Baden-Württemberg	1	2024	March	128	316.8	0.006	0.1682	79.7
Hedin Automotive DE	Germany	Baden-Württemberg	1	2024	April	144	316.8	0.006	0.1682	79.7
Hedin Automotive DE	Germany	Baden-Württemberg	1	2024	May	183	316.8	0.006	0.1682	79.7

Dealership_Name	Country	Region	Number_of_Outlets	Year	Month	Monthly_Sales_Volume_per_Country	Regional_Population_Density	Local_Economic_Growth	Cultural_Difference_Score	Regulatory_Environment_Score
Hedin Automotive DE	Germany	Rheinland-Pfalz	1	2023	May	49	209.6	0.005	0.1682	79.7
Hedin Automotive DE	Germany	Rheinland-Pfalz	1	2023	June	53	209.6	0.005	0.1682	79.7
Hedin Automotive DE	Germany	Rheinland-Pfalz	1	2023	July	367	209.6	0.005	0.1682	79.7
Hedin Automotive DE	Germany	Rheinland-Pfalz	1	2023	August	1985	209.6	0.005	0.1682	79.7
Hedin Automotive DE	Germany	Rheinland-Pfalz	1	2023	September	182	209.6	0.005	0.1682	79.7
Hedin Automotive DE	Germany	Rheinland-Pfalz	1	2023	October	199	209.6	0.005	0.1682	79.7
Hedin Automotive DE	Germany	Rheinland-Pfalz	1	2023	November	305	209.6	0.005	0.1682	79.7
Hedin Automotive DE	Germany	Rheinland-Pfalz	1	2023	December	627	209.6	0.005	0.1682	79.7
Hedin Automotive DE	Germany	Rheinland-Pfalz	1	2024	January	112	209.6	0.005	0.1682	79.7
Hedin Automotive DE	Germany	Rheinland-Pfalz	1	2024	February	68	209.6	0.005	0.1682	79.7
Hedin Automotive DE	Germany	Rheinland-Pfalz	1	2024	March	128	209.6	0.005	0.1682	79.7
Hedin Automotive DE	Germany	Rheinland-Pfalz	1	2024	April	144	209.6	0.005	0.1682	79.7
Hedin Automotive DE	Germany	Rheinland-Pfalz	1	2024	May	183	209.6	0.005	0.1682	79.7
Riess Gruppe	Germany	Baden-Württemberg	2	2023	May	49	316.8	0.006	0.1682	79.7
Riess Gruppe	Germany	Baden-Württemberg	2	2023	June	53	316.8	0.006	0.1682	79.7
Riess Gruppe	Germany	Baden-Württemberg	2	2023	July	367	316.8	0.006	0.1682	79.7
Riess Gruppe	Germany	Baden-Württemberg	2	2023	August	1985	316.8	0.006	0.1682	79.7
Riess Gruppe	Germany	Baden-Württemberg	2	2023	September	182	316.8	0.006	0.1682	79.7
Riess Gruppe	Germany	Baden-Württemberg	2	2023	October	199	316.8	0.006	0.1682	79.7
Riess Gruppe	Germany	Baden-Württemberg	2	2023	November	305	316.8	0.006	0.1682	79.7
Riess Gruppe	Germany	Baden-Württemberg	2	2023	December	627	316.8	0.006	0.1682	79.7
Riess Gruppe	Germany	Baden-Württemberg	2	2024	January	112	316.8	0.006	0.1682	79.7
Riess Gruppe	Germany	Baden-Württemberg	2	2024	February	68	316.8	0.006	0.1682	79.7
Riess Gruppe	Germany	Baden-Württemberg	2	2024	March	128	316.8	0.006	0.1682	79.7
Riess Gruppe	Germany	Baden-Württemberg	2	2024	April	144	316.8	0.006	0.1682	79.7
Riess Gruppe	Germany	Baden-Württemberg	2	2024	May	183	316.8	0.006	0.1682	79.7
Reisacher	Germany	Baden-Württemberg	1	2023	May	49	316.8	0.006	0.1682	79.7
Reisacher	Germany	Baden-Württemberg	1	2023	June	53	316.8	0.006	0.1682	79.7
Reisacher	Germany	Baden-Württemberg	1	2023	July	367	316.8	0.006	0.1682	79.7
Reisacher	Germany	Baden-Württemberg	1	2023	August	1985	316.8	0.006	0.1682	79.7
Reisacher	Germany	Baden-Württemberg	1	2023	September	182	316.8	0.006	0.1682	79.7
Reisacher	Germany	Baden-Württemberg	1	2023	October	199	316.8	0.006	0.1682	79.7
Reisacher	Germany	Baden-Württemberg	1	2023	November	305	316.8	0.006	0.1682	79.7
Reisacher	Germany	Baden-Württemberg	1	2023	December	627	316.8	0.006	0.1682	79.7
Reisacher	Germany	Baden-Württemberg	1	2024	January	112	316.8	0.006	0.1682	79.7
Reisacher	Germany	Baden-Württemberg	1	2024	February	68	316.8	0.006	0.1682	79.7
Reisacher	Germany	Baden-Württemberg	1	2024	March	128	316.8	0.006	0.1682	79.7
Reisacher	Germany	Baden-Württemberg	1	2024	April	144	316.8	0.006	0.1682	79.7
Reisacher	Germany	Baden-Württemberg	1	2024	May	183	316.8	0.006	0.1682	79.7
Reisacher	Germany	Bayern (Bavaria)	3	2023	May	49	189.9	0.008	0.1682	79.7
Reisacher	Germany	Bayern (Bavaria)	3	2023	June	53	189.9	0.008	0.1682	79.7
Reisacher	Germany	Bayern (Bavaria)	3	2023	July	367	189.9	0.008	0.1682	79.7
Reisacher	Germany	Bayern (Bavaria)	3	2023	August	1985	189.9	0.008	0.1682	79.7
Reisacher	Germany	Bayern (Bavaria)	3	2023	September	182	189.9	0.008	0.1682	79.7
Reisacher	Germany	Bayern (Bavaria)	3	2023	October	199	189.9	0.008	0.1682	79.7
Reisacher	Germany	Bayern (Bavaria)	3	2023	November	305	189.9	0.008	0.1682	79.7
Reisacher	Germany	Bayern (Bavaria)	3	2023	December	627	189.9	0.008	0.1682	79.7
Reisacher	Germany	Bayern (Bavaria)	3	2024	January	112	189.9	0.008	0.1682	79.7
Reisacher	Germany	Bayern (Bavaria)	3	2024	February	68	189.9	0.008	0.1682	79.7
Reisacher	Germany	Bayern (Bavaria)	3	2024	March	128	189.9	0.008	0.1682	79.7
Reisacher	Germany	Bayern (Bavaria)	3	2024	April	144	189.9	0.008	0.1682	79.7
Reisacher	Germany	Bayern (Bavaria)	3	2024	May	183	189.9	0.008	0.1682	79.7
Ilha Verde	Portugal	Açores (Azores)	1	2023	May	41	103.3	0.068	0.0468	76.5
Ilha Verde	Portugal	Açores (Azores)	1	2023	June	26	103.3	0.068	0.0468	76.5
Ilha Verde	Portugal	Açores (Azores)	1	2023	July	33	103.3	0.068	0.0468	76.5
Ilha Verde	Portugal	Açores (Azores)	1	2023	August	18	103.3	0.068	0.0468	76.5
Ilha Verde	Portugal	Açores (Azores)	1	2023	September	37	103.3	0.068	0.0468	76.5
Ilha Verde	Portugal	Açores (Azores)	1	2023	October	61	103.3	0.068	0.0468	76.5
Ilha Verde	Portugal	Açores (Azores)	1	2023	November	55	103.3	0.068	0.0468	76.5
Ilha Verde	Portugal	Açores (Azores)	1	2023	December	179	103.3	0.068	0.0468	76.5
Ilha Verde	Portugal	Açores (Azores)	1	2024	January	128	103.3	0.068	0.0468	76.5
Ilha Verde	Portugal	Açores (Azores)	1	2024	February	123	103.3	0.068	0.0468	76.5
Ilha Verde	Portugal	Açores (Azores)	1	2024	March	160	103.3	0.068	0.0468	76.5
Ilha Verde	Portugal	Açores (Azores)	1	2024	April	171	103.3	0.068	0.0468	76.5
Ilha Verde	Portugal	Açores (Azores)	1	2024	May	133	103.3	0.068	0.0468	76.5
MSCAR	Portugal	Algarve	1	2023	May	41	95.0	0.170	0.0468	76.5
MSCAR	Portugal	Algarve	1	2023	June	26	95.0	0.170	0.0468	76.5
MSCAR	Portugal	Algarve	1	2023	July	33	95.0	0.170	0.0468	76.5
MSCAR	Portugal	Algarve	1	2023	August	18	95.0	0.170	0.0468	76.5
MSCAR	Portugal	Algarve	1	2023	September	37	95.0	0.170	0.0468	76.5
MSCAR	Portugal	Algarve	1	2023	October	61	95.0	0.170	0.0468	76.5
MSCAR	Portugal	Algarve	1	2023	November	55	95.0	0.170	0.0468	76.5
MSCAR	Portugal	Algarve	1	2023	December	179	95.0	0.170	0.0468	76.5
MSCAR	Portugal	Algarve	1	2024	January	128	95.0	0.170	0.0468	76.5
MSCAR	Portugal	Algarve	1	2024	February	123	95.0	0.170	0.0468	76.5
MSCAR	Portugal	Algarve	1	2024	March	160	95.0	0.170	0.0468	76.5
MSCAR	Portugal	Algarve	1	2024	April	171	95.0	0.170	0.0468	76.5
MSCAR	Portugal	Algarve	1	2024	May	133	95.0	0.170	0.0468	76.5

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Dealership_Name	Country	Region	Number_of_Outlets	Year	Month	Monthly_Sales_Volume_per_Country	Regional_Population_Density	Local_Economic_Growth	Cultural_Difference_Score	Regulatory_Environment_Score
Caetano Tec	Portugal	Lisboa (Lisbon)	3	2023	May	41	1,026.6	0.082	0.0468	76.5
Caetano Tec	Portugal	Lisboa (Lisbon)	3	2023	June	26	1,026.6	0.082	0.0468	76.5
Caetano Tec	Portugal	Lisboa (Lisbon)	3	2023	July	33	1,026.6	0.082	0.0468	76.5
Caetano Tec	Portugal	Lisboa (Lisbon)	3	2023	August	18	1,026.6	0.082	0.0468	76.5
Caetano Tec	Portugal	Lisboa (Lisbon)	3	2023	September	37	1,026.6	0.082	0.0468	76.5
Caetano Tec	Portugal	Lisboa (Lisbon)	3	2023	October	61	1,026.6	0.082	0.0468	76.5
Caetano Tec	Portugal	Lisboa (Lisbon)	3	2023	November	55	1,026.6	0.082	0.0468	76.5
Caetano Tec	Portugal	Lisboa (Lisbon)	3	2023	December	179	1,026.6	0.082	0.0468	76.5
Caetano Tec	Portugal	Lisboa (Lisbon)	3	2024	January	128	1,026.6	0.082	0.0468	76.5
Caetano Tec	Portugal	Lisboa (Lisbon)	3	2024	February	123	1,026.6	0.082	0.0468	76.5
Caetano Tec	Portugal	Lisboa (Lisbon)	3	2024	March	160	1,026.6	0.082	0.0468	76.5
Caetano Tec	Portugal	Lisboa (Lisbon)	3	2024	April	171	1,026.6	0.082	0.0468	76.5
Caetano Tec	Portugal	Lisboa (Lisbon)	3	2024	May	133	1,026.6	0.082	0.0468	76.5
Caetano Tec	Portugal	Norte (North)	2	2023	May	41	171.0	0.056	0.0468	76.5
Caetano Tec	Portugal	Norte (North)	2	2023	June	26	171.0	0.056	0.0468	76.5
Caetano Tec	Portugal	Norte (North)	2	2023	July	33	171.0	0.056	0.0468	76.5
Caetano Tec	Portugal	Norte (North)	2	2023	August	18	171.0	0.056	0.0468	76.5
Caetano Tec	Portugal	Norte (North)	2	2023	September	37	171.0	0.056	0.0468	76.5
Caetano Tec	Portugal	Norte (North)	2	2023	October	61	171.0	0.056	0.0468	76.5
Caetano Tec	Portugal	Norte (North)	2	2023	November	55	171.0	0.056	0.0468	76.5
Caetano Tec	Portugal	Norte (North)	2	2023	December	179	171.0	0.056	0.0468	76.5
Caetano Tec	Portugal	Norte (North)	2	2024	January	128	171.0	0.056	0.0468	76.5
Caetano Tec	Portugal	Norte (North)	2	2024	February	123	171.0	0.056	0.0468	76.5
Caetano Tec	Portugal	Norte (North)	2	2024	March	160	171.0	0.056	0.0468	76.5
Caetano Tec	Portugal	Norte (North)	2	2024	April	171	171.0	0.056	0.0468	76.5
Caetano Tec	Portugal	Norte (North)	2	2024	May	133	171.0	0.056	0.0468	76.5
Grupo Lizauto	Portugal	Centro (Central)	1	2023	May	41	80.2	0.038	0.0468	76.5
Grupo Lizauto	Portugal	Centro (Central)	1	2023	June	26	80.2	0.038	0.0468	76.5
Grupo Lizauto	Portugal	Centro (Central)	1	2023	July	33	80.2	0.038	0.0468	76.5
Grupo Lizauto	Portugal	Centro (Central)	1	2023	August	18	80.2	0.038	0.0468	76.5
Grupo Lizauto	Portugal	Centro (Central)	1	2023	September	37	80.2	0.038	0.0468	76.5
Grupo Lizauto	Portugal	Centro (Central)	1	2023	October	61	80.2	0.038	0.0468	76.5
Grupo Lizauto	Portugal	Centro (Central)	1	2023	November	55	80.2	0.038	0.0468	76.5
Grupo Lizauto	Portugal	Centro (Central)	1	2023	December	179	80.2	0.038	0.0468	76.5
Grupo Lizauto	Portugal	Centro (Central)	1	2024	January	128	80.2	0.038	0.0468	76.5
Grupo Lizauto	Portugal	Centro (Central)	1	2024	February	123	80.2	0.038	0.0468	76.5
Grupo Lizauto	Portugal	Centro (Central)	1	2024	March	160	80.2	0.038	0.0468	76.5
Grupo Lizauto	Portugal	Centro (Central)	1	2024	April	171	80.2	0.038	0.0468	76.5
Grupo Lizauto	Portugal	Centro (Central)	1	2024	May	133	80.2	0.038	0.0468	76.5
Corvauto	Portugal	Centro (Central)	1	2023	May	41	80.2	0.038	0.0468	76.5
Corvauto	Portugal	Centro (Central)	1	2023	June	26	80.2	0.038	0.0468	76.5
Corvauto	Portugal	Centro (Central)	1	2023	July	33	80.2	0.038	0.0468	76.5
Corvauto	Portugal	Centro (Central)	1	2023	August	18	80.2	0.038	0.0468	76.5
Corvauto	Portugal	Centro (Central)	1	2023	September	37	80.2	0.038	0.0468	76.5
Corvauto	Portugal	Centro (Central)	1	2023	October	61	80.2	0.038	0.0468	76.5
Corvauto	Portugal	Centro (Central)	1	2023	November	55	80.2	0.038	0.0468	76.5
Corvauto	Portugal	Centro (Central)	1	2023	December	179	80.2	0.038	0.0468	76.5
Corvauto	Portugal	Centro (Central)	1	2024	January	128	80.2	0.038	0.0468	76.5
Corvauto	Portugal	Centro (Central)	1	2024	February	123	80.2	0.038	0.0468	76.5
Corvauto	Portugal	Centro (Central)	1	2024	March	160	80.2	0.038	0.0468	76.5
Corvauto	Portugal	Centro (Central)	1	2024	April	171	80.2	0.038	0.0468	76.5
Corvauto	Portugal	Centro (Central)	1	2024	May	133	80.2	0.038	0.0468	76.5
Grupo M. & Costas	Portugal	Norte (North)	1	2023	May	41	171.0	0.056	0.0468	76.5
Grupo M. & Costas	Portugal	Norte (North)	1	2023	June	26	171.0	0.056	0.0468	76.5
Grupo M. & Costas	Portugal	Norte (North)	1	2023	July	33	171.0	0.056	0.0468	76.5
Grupo M. & Costas	Portugal	Norte (North)	1	2023	August	18	171.0	0.056	0.0468	76.5
Grupo M. & Costas	Portugal	Norte (North)	1	2023	September	37	171.0	0.056	0.0468	76.5
Grupo M. & Costas	Portugal	Norte (North)	1	2023	October	61	171.0	0.056	0.0468	76.5
Grupo M. & Costas	Portugal	Norte (North)	1	2023	November	55	171.0	0.056	0.0468	76.5
Grupo M. & Costas	Portugal	Norte (North)	1	2023	December	179	171.0	0.056	0.0468	76.5
Grupo M. & Costas	Portugal	Norte (North)	1	2024	January	128	171.0	0.056	0.0468	76.5
Grupo M. & Costas	Portugal	Norte (North)	1	2024	February	123	171.0	0.056	0.0468	76.5
Grupo M. & Costas	Portugal	Norte (North)	1	2024	March	160	171.0	0.056	0.0468	76.5
Grupo M. & Costas	Portugal	Norte (North)	1	2024	April	171	171.0	0.056	0.0468	76.5
Grupo M. & Costas	Portugal	Norte (North)	1	2024	May	133	171.0	0.056	0.0468	76.5
Grupo Icamotor	Spain	Canarias (Canary Islands)	2	2023	May	28	300.9	0.097	0.4165	77.9
Grupo Icamotor	Spain	Canarias (Canary Islands)	2	2023	June	63	300.9	0.097	0.4165	77.9
Grupo Icamotor	Spain	Canarias (Canary Islands)	2	2023	July	17	300.9	0.097	0.4165	77.9
Grupo Icamotor	Spain	Canarias (Canary Islands)	2	2023	August	20	300.9	0.097	0.4165	77.9
Grupo Icamotor	Spain	Canarias (Canary Islands)	2	2023	September	48	300.9	0.097	0.4165	77.9
Grupo Icamotor	Spain	Canarias (Canary Islands)	2	2023	October	117	300.9	0.097	0.4165	77.9
Grupo Icamotor	Spain	Canarias (Canary Islands)	2	2023	November	151	300.9	0.097	0.4165	77.9
Grupo Icamotor	Spain	Canarias (Canary Islands)	2	2023	December	158	300.9	0.097	0.4165	77.9
Grupo Icamotor	Spain	Canarias (Canary Islands)	2	2024	January	143	300.9	0.097	0.4165	77.9
Grupo Icamotor	Spain	Canarias (Canary Islands)	2	2024	February	186	300.9	0.097	0.4165	77.9
Grupo Icamotor	Spain	Canarias (Canary Islands)	2	2024	March	105	300.9	0.097	0.4165	77.9
Grupo Icamotor	Spain	Canarias (Canary Islands)	2	2024	April	284	300.9	0.097	0.4165	77.9
Grupo Icamotor	Spain	Canarias (Canary Islands)	2	2024	May	203	300.9	0.097	0.4165	77.9

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Dealership_Name	Country	Region	Number_of_Outlets	Year	Month	Monthly_Sales_Volume_per_Country	Regional_Population_Density	Local_Economic_Growth	Cultural_Difference_Score	Regulatory_Environment_Score
Caetano Tec	Spain	Andalucía (Andalusia)	3	2023	May	28	98.5	0.052	0.4165	77.9
Caetano Tec	Spain	Andalucía (Andalusia)	3	2023	June	63	98.5	0.052	0.4165	77.9
Caetano Tec	Spain	Andalucía (Andalusia)	3	2023	July	17	98.5	0.052	0.4165	77.9
Caetano Tec	Spain	Andalucía (Andalusia)	3	2023	August	20	98.5	0.052	0.4165	77.9
Caetano Tec	Spain	Andalucía (Andalusia)	3	2023	September	48	98.5	0.052	0.4165	77.9
Caetano Tec	Spain	Andalucía (Andalusia)	3	2023	October	117	98.5	0.052	0.4165	77.9
Caetano Tec	Spain	Andalucía (Andalusia)	3	2023	November	151	98.5	0.052	0.4165	77.9
Caetano Tec	Spain	Andalucía (Andalusia)	3	2023	December	158	98.5	0.052	0.4165	77.9
Caetano Tec	Spain	Andalucía (Andalusia)	3	2024	January	143	98.5	0.052	0.4165	77.9
Caetano Tec	Spain	Andalucía (Andalusia)	3	2024	February	186	98.5	0.052	0.4165	77.9
Caetano Tec	Spain	Andalucía (Andalusia)	3	2024	March	105	98.5	0.052	0.4165	77.9
Caetano Tec	Spain	Andalucía (Andalusia)	3	2024	April	284	98.5	0.052	0.4165	77.9
Caetano Tec	Spain	Andalucía (Andalusia)	3	2024	May	203	98.5	0.052	0.4165	77.9
QUADIS Dream	Spain	Comunidad Valenciana (Valencian Community)	1	2023	May	28	222.4	0.059	0.4165	77.9
QUADIS Dream	Spain	Comunidad Valenciana (Valencian Community)	1	2023	June	63	222.4	0.059	0.4165	77.9
QUADIS Dream	Spain	Comunidad Valenciana (Valencian Community)	1	2023	July	17	222.4	0.059	0.4165	77.9
QUADIS Dream	Spain	Comunidad Valenciana (Valencian Community)	1	2023	August	20	222.4	0.059	0.4165	77.9
QUADIS Dream	Spain	Comunidad Valenciana (Valencian Community)	1	2023	September	48	222.4	0.059	0.4165	77.9
QUADIS Dream	Spain	Comunidad Valenciana (Valencian Community)	1	2023	October	117	222.4	0.059	0.4165	77.9
QUADIS Dream	Spain	Comunidad Valenciana (Valencian Community)	1	2023	November	151	222.4	0.059	0.4165	77.9
QUADIS Dream	Spain	Comunidad Valenciana (Valencian Community)	1	2023	December	158	222.4	0.059	0.4165	77.9
QUADIS Dream	Spain	Comunidad Valenciana (Valencian Community)	1	2024	January	143	222.4	0.059	0.4165	77.9
QUADIS Dream	Spain	Comunidad Valenciana (Valencian Community)	1	2024	February	186	222.4	0.059	0.4165	77.9
QUADIS Dream	Spain	Comunidad Valenciana (Valencian Community)	1	2024	March	105	222.4	0.059	0.4165	77.9
QUADIS Dream	Spain	Comunidad Valenciana (Valencian Community)	1	2024	April	284	222.4	0.059	0.4165	77.9
QUADIS Dream	Spain	Comunidad Valenciana (Valencian Community)	1	2024	May	203	222.4	0.059	0.4165	77.9
QUADIS Dream	Spain	Islas Baleares (Balearic Islands)	1	2023	May	28	244.8	0.125	0.4165	77.9
QUADIS Dream	Spain	Islas Baleares (Balearic Islands)	1	2023	June	63	244.8	0.125	0.4165	77.9
QUADIS Dream	Spain	Islas Baleares (Balearic Islands)	1	2023	July	17	244.8	0.125	0.4165	77.9
QUADIS Dream	Spain	Islas Baleares (Balearic Islands)	1	2023	August	20	244.8	0.125	0.4165	77.9
QUADIS Dream	Spain	Islas Baleares (Balearic Islands)	1	2023	September	48	244.8	0.125	0.4165	77.9
QUADIS Dream	Spain	Islas Baleares (Balearic Islands)	1	2023	October	117	244.8	0.125	0.4165	77.9
QUADIS Dream	Spain	Islas Baleares (Balearic Islands)	1	2023	November	151	244.8	0.125	0.4165	77.9
QUADIS Dream	Spain	Islas Baleares (Balearic Islands)	1	2023	December	158	244.8	0.125	0.4165	77.9
QUADIS Dream	Spain	Islas Baleares (Balearic Islands)	1	2024	January	143	244.8	0.125	0.4165	77.9
QUADIS Dream	Spain	Islas Baleares (Balearic Islands)	1	2024	February	186	244.8	0.125	0.4165	77.9
QUADIS Dream	Spain	Islas Baleares (Balearic Islands)	1	2024	March	105	244.8	0.125	0.4165	77.9
QUADIS Dream	Spain	Islas Baleares (Balearic Islands)	1	2024	April	284	244.8	0.125	0.4165	77.9
QUADIS Dream	Spain	Islas Baleares (Balearic Islands)	1	2024	May	203	244.8	0.125	0.4165	77.9

Dealership_Name	Country	Region	Number_of_Outlets	Year	Month	Monthly_Sales_Volume_per_Country	Regional_Population_Density	Local_Economic_Growth	Cultural_Difference_Score	Regulatory_Environment_Score
QUADIS Dream	Spain	Cataluña (Catalonia)	3	2023	May	28	243.7	0.060	0.4165	77.9
QUADIS Dream	Spain	Cataluña (Catalonia)	3	2023	June	63	243.7	0.060	0.4165	77.9
QUADIS Dream	Spain	Cataluña (Catalonia)	3	2023	July	17	243.7	0.060	0.4165	77.9
QUADIS Dream	Spain	Cataluña (Catalonia)	3	2023	August	20	243.7	0.060	0.4165	77.9
QUADIS Dream	Spain	Cataluña (Catalonia)	3	2023	September	48	243.7	0.060	0.4165	77.9
QUADIS Dream	Spain	Cataluña (Catalonia)	3	2023	October	117	243.7	0.060	0.4165	77.9
QUADIS Dream	Spain	Cataluña (Catalonia)	3	2023	November	151	243.7	0.060	0.4165	77.9
QUADIS Dream	Spain	Cataluña (Catalonia)	3	2023	December	158	243.7	0.060	0.4165	77.9
QUADIS Dream	Spain	Cataluña (Catalonia)	3	2024	January	143	243.7	0.060	0.4165	77.9
QUADIS Dream	Spain	Cataluña (Catalonia)	3	2024	February	186	243.7	0.060	0.4165	77.9
QUADIS Dream	Spain	Cataluña (Catalonia)	3	2024	March	105	243.7	0.060	0.4165	77.9
QUADIS Dream	Spain	Cataluña (Catalonia)	3	2024	April	284	243.7	0.060	0.4165	77.9
QUADIS Dream	Spain	Cataluña (Catalonia)	3	2024	May	203	243.7	0.060	0.4165	77.9
Blendio	Spain	País Vasco (Basque Country)	1	2023	May	28	305.5	0.060	0.4165	77.9
Blendio	Spain	País Vasco (Basque Country)	1	2023	June	63	305.5	0.060	0.4165	77.9
Blendio	Spain	País Vasco (Basque Country)	1	2023	July	17	305.5	0.060	0.4165	77.9
Blendio	Spain	País Vasco (Basque Country)	1	2023	August	20	305.5	0.060	0.4165	77.9
Blendio	Spain	País Vasco (Basque Country)	1	2023	September	48	305.5	0.060	0.4165	77.9
Blendio	Spain	País Vasco (Basque Country)	1	2023	October	117	305.5	0.060	0.4165	77.9
Blendio	Spain	País Vasco (Basque Country)	1	2023	November	151	305.5	0.060	0.4165	77.9
Blendio	Spain	País Vasco (Basque Country)	1	2023	December	158	305.5	0.060	0.4165	77.9
Blendio	Spain	País Vasco (Basque Country)	1	2024	January	143	305.5	0.060	0.4165	77.9
Blendio	Spain	País Vasco (Basque Country)	1	2024	February	186	305.5	0.060	0.4165	77.9
Blendio	Spain	País Vasco (Basque Country)	1	2024	March	105	305.5	0.060	0.4165	77.9
Blendio	Spain	País Vasco (Basque Country)	1	2024	April	284	305.5	0.060	0.4165	77.9
Blendio	Spain	País Vasco (Basque Country)	1	2024	May	203	305.5	0.060	0.4165	77.9
Astara Retail	Spain	Comunidad de Madrid (Community of Madrid)	4	2023	May	28	855.6	0.072	0.4165	77.9
Astara Retail	Spain	Comunidad de Madrid (Community of Madrid)	4	2023	June	63	855.6	0.072	0.4165	77.9
Astara Retail	Spain	Comunidad de Madrid (Community of Madrid)	4	2023	July	17	855.6	0.072	0.4165	77.9
Astara Retail	Spain	Comunidad de Madrid (Community of Madrid)	4	2023	August	20	855.6	0.072	0.4165	77.9
Astara Retail	Spain	Comunidad de Madrid (Community of Madrid)	4	2023	September	48	855.6	0.072	0.4165	77.9
Astara Retail	Spain	Comunidad de Madrid (Community of Madrid)	4	2023	October	117	855.6	0.072	0.4165	77.9
Astara Retail	Spain	Comunidad de Madrid (Community of Madrid)	4	2023	November	151	855.6	0.072	0.4165	77.9
Astara Retail	Spain	Comunidad de Madrid (Community of Madrid)	4	2023	December	158	855.6	0.072	0.4165	77.9
Astara Retail	Spain	Comunidad de Madrid (Community of Madrid)	4	2024	January	143	855.6	0.072	0.4165	77.9
Astara Retail	Spain	Comunidad de Madrid (Community of Madrid)	4	2024	February	186	855.6	0.072	0.4165	77.9
Astara Retail	Spain	Comunidad de Madrid (Community of Madrid)	4	2024	March	105	855.6	0.072	0.4165	77.9
Astara Retail	Spain	Comunidad de Madrid (Community of Madrid)	4	2024	April	284	855.6	0.072	0.4165	77.9
Astara Retail	Spain	Comunidad de Madrid (Community of Madrid)	4	2024	May	203	855.6	0.072	0.4165	77.9
Plichta	Poland	Pomorskie (Pomeranian)	1	2023	May	0	130.4	0.059	0.1183	76.4
Plichta	Poland	Pomorskie (Pomeranian)	1	2023	June	0	130.4	0.059	0.1183	76.4
Plichta	Poland	Pomorskie (Pomeranian)	1	2023	July	1	130.4	0.059	0.1183	76.4
Plichta	Poland	Pomorskie (Pomeranian)	1	2023	August	0	130.4	0.059	0.1183	76.4
Plichta	Poland	Pomorskie (Pomeranian)	1	2023	September	0	130.4	0.059	0.1183	76.4
Plichta	Poland	Pomorskie (Pomeranian)	1	2023	October	0	130.4	0.059	0.1183	76.4
Plichta	Poland	Pomorskie (Pomeranian)	1	2023	November	0	130.4	0.059	0.1183	76.4
Plichta	Poland	Pomorskie (Pomeranian)	1	2023	December	0	130.4	0.059	0.1183	76.4
Plichta	Poland	Pomorskie (Pomeranian)	1	2024	January	0	130.4	0.059	0.1183	76.4
Plichta	Poland	Pomorskie (Pomeranian)	1	2024	February	0	130.4	0.059	0.1183	76.4
Plichta	Poland	Pomorskie (Pomeranian)	1	2024	March	0	130.4	0.059	0.1183	76.4
Plichta	Poland	Pomorskie (Pomeranian)	1	2024	April	1	130.4	0.059	0.1183	76.4
Plichta	Poland	Pomorskie (Pomeranian)	1	2024	May	9	130.4	0.059	0.1183	76.4

Dealership_Name	Country	Region	Number_of_Outlets	Year	Month	Monthly_Sales_Volume_per_Country	Regional_Population_Density	Local_Economic_Growth	Cultural_Difference_Score	Regulatory_Environment_Score
Plichta	Poland	Kujawsko-pomorskie (Kuyavian–Pomerania n)	1	2023	May	0	112.9	0.049	0.1183	76.4
Plichta	Poland	Kujawsko-pomorskie (Kuyavian–Pomerania n)	1	2023	June	0	112.9	0.049	0.1183	76.4
Plichta	Poland	Kujawsko-pomorskie (Kuyavian–Pomerania n)	1	2023	July	1	112.9	0.049	0.1183	76.4
Plichta	Poland	Kujawsko-pomorskie (Kuyavian–Pomerania n)	1	2023	August	0	112.9	0.049	0.1183	76.4
Plichta	Poland	Kujawsko-pomorskie (Kuyavian–Pomerania n)	1	2023	September	0	112.9	0.049	0.1183	76.4
Plichta	Poland	Kujawsko-pomorskie (Kuyavian–Pomerania n)	1	2023	October	0	112.9	0.049	0.1183	76.4
Plichta	Poland	Kujawsko-pomorskie (Kuyavian–Pomerania n)	1	2023	November	0	112.9	0.049	0.1183	76.4
Plichta	Poland	Kujawsko-pomorskie (Kuyavian–Pomerania n)	1	2023	December	0	112.9	0.049	0.1183	76.4
Plichta	Poland	Kujawsko-pomorskie (Kuyavian–Pomerania n)	1	2024	January	0	112.9	0.049	0.1183	76.4
Plichta	Poland	Kujawsko-pomorskie (Kuyavian–Pomerania n)	1	2024	February	0	112.9	0.049	0.1183	76.4
Plichta	Poland	Kujawsko-pomorskie (Kuyavian–Pomerania n)	1	2024	March	0	112.9	0.049	0.1183	76.4
Plichta	Poland	Kujawsko-pomorskie (Kuyavian–Pomerania n)	1	2024	April	1	112.9	0.049	0.1183	76.4
Plichta	Poland	Kujawsko-pomorskie (Kuyavian–Pomerania n)	1	2024	May	9	112.9	0.049	0.1183	76.4
Grupa Cichy-Zasada	Poland	Wielkopolskie (Greater Poland)	1	2023	May	0	117.3	0.052	0.1183	76.4
Grupa Cichy-Zasada	Poland	Wielkopolskie (Greater Poland)	1	2023	June	0	117.3	0.052	0.1183	76.4
Grupa Cichy-Zasada	Poland	Wielkopolskie (Greater Poland)	1	2023	July	1	117.3	0.052	0.1183	76.4
Grupa Cichy-Zasada	Poland	Wielkopolskie (Greater Poland)	1	2023	August	0	117.3	0.052	0.1183	76.4
Grupa Cichy-Zasada	Poland	Wielkopolskie (Greater Poland)	1	2023	September	0	117.3	0.052	0.1183	76.4
Grupa Cichy-Zasada	Poland	Wielkopolskie (Greater Poland)	1	2023	October	0	117.3	0.052	0.1183	76.4
Grupa Cichy-Zasada	Poland	Wielkopolskie (Greater Poland)	1	2023	November	0	117.3	0.052	0.1183	76.4
Grupa Cichy-Zasada	Poland	Wielkopolskie (Greater Poland)	1	2023	December	0	117.3	0.052	0.1183	76.4
Grupa Cichy-Zasada	Poland	Wielkopolskie (Greater Poland)	1	2024	January	0	117.3	0.052	0.1183	76.4
Grupa Cichy-Zasada	Poland	Wielkopolskie (Greater Poland)	1	2024	February	0	117.3	0.052	0.1183	76.4
Grupa Cichy-Zasada	Poland	Wielkopolskie (Greater Poland)	1	2024	March	0	117.3	0.052	0.1183	76.4
Grupa Cichy-Zasada	Poland	Wielkopolskie (Greater Poland)	1	2024	April	1	117.3	0.052	0.1183	76.4
Grupa Cichy-Zasada	Poland	Wielkopolskie (Greater Poland)	1	2024	May	9	117.3	0.052	0.1183	76.4
Grupa Krotoski	Poland	Warszawski Stołeczny (Warsaw Capital)	2	2023	May	0	513.7	0.072	0.1183	76.4
Grupa Krotoski	Poland	Warszawski Stołeczny (Warsaw Capital)	2	2023	June	0	513.7	0.072	0.1183	76.4
Grupa Krotoski	Poland	Warszawski Stołeczny (Warsaw Capital)	2	2023	July	1	513.7	0.072	0.1183	76.4
Grupa Krotoski	Poland	Warszawski Stołeczny (Warsaw Capital)	2	2023	August	0	513.7	0.072	0.1183	76.4
Grupa Krotoski	Poland	Warszawski Stołeczny (Warsaw Capital)	2	2023	September	0	513.7	0.072	0.1183	76.4
Grupa Krotoski	Poland	Warszawski Stołeczny (Warsaw Capital)	2	2023	October	0	513.7	0.072	0.1183	76.4
Grupa Krotoski	Poland	Warszawski Stołeczny (Warsaw Capital)	2	2023	November	0	513.7	0.072	0.1183	76.4
Grupa Krotoski	Poland	Warszawski Stołeczny (Warsaw Capital)	2	2023	December	0	513.7	0.072	0.1183	76.4
Grupa Krotoski	Poland	Warszawski Stołeczny (Warsaw Capital)	2	2024	January	0	513.7	0.072	0.1183	76.4
Grupa Krotoski	Poland	Warszawski Stołeczny (Warsaw Capital)	2	2024	February	0	513.7	0.072	0.1183	76.4
Grupa Krotoski	Poland	Warszawski Stołeczny (Warsaw Capital)	2	2024	March	0	513.7	0.072	0.1183	76.4
Grupa Krotoski	Poland	Warszawski Stołeczny (Warsaw Capital)	2	2024	April	1	513.7	0.072	0.1183	76.4
Grupa Krotoski	Poland	Warszawski Stołeczny (Warsaw Capital)	2	2024	May	9	513.7	0.072	0.1183	76.4

Dealership_Name	Country	Region	Number_of_Outlets	Year	Month	Monthly_Sales_Volume_per_Country	Regional_Population_Density	Local_Economic_Growth	Cultural_Difference_Score	Regulatory_Environment_Score
Auto Bernhard	Austria	Tirol (Tyrol)	1	2023	May	79	61.4	0.094	0.1068	78.7
Auto Bernhard	Austria	Tirol (Tyrol)	1	2023	June	90	61.4	0.094	0.1068	78.7
Auto Bernhard	Austria	Tirol (Tyrol)	1	2023	July	52	61.4	0.094	0.1068	78.7
Auto Bernhard	Austria	Tirol (Tyrol)	1	2023	August	95	61.4	0.094	0.1068	78.7
Auto Bernhard	Austria	Tirol (Tyrol)	1	2023	September	139	61.4	0.094	0.1068	78.7
Auto Bernhard	Austria	Tirol (Tyrol)	1	2023	October	124	61.4	0.094	0.1068	78.7
Auto Bernhard	Austria	Tirol (Tyrol)	1	2023	November	190	61.4	0.094	0.1068	78.7
Auto Bernhard	Austria	Tirol (Tyrol)	1	2023	December	112	61.4	0.094	0.1068	78.7
Auto Bernhard	Austria	Tirol (Tyrol)	1	2024	January	157	61.4	0.094	0.1068	78.7
Auto Bernhard	Austria	Tirol (Tyrol)	1	2024	February	184	61.4	0.094	0.1068	78.7
Auto Bernhard	Austria	Tirol (Tyrol)	1	2024	March	341	61.4	0.094	0.1068	78.7
Auto Bernhard	Austria	Tirol (Tyrol)	1	2024	April	252	61.4	0.094	0.1068	78.7
Auto Bernhard	Austria	Tirol (Tyrol)	1	2024	May	284	61.4	0.094	0.1068	78.7
Auto Harb	Austria	Steiermark (Styria)	1	2023	May	79	77.5	0.035	0.1068	78.7
Auto Harb	Austria	Steiermark (Styria)	1	2023	June	90	77.5	0.035	0.1068	78.7
Auto Harb	Austria	Steiermark (Styria)	1	2023	July	52	77.5	0.035	0.1068	78.7
Auto Harb	Austria	Steiermark (Styria)	1	2023	August	95	77.5	0.035	0.1068	78.7
Auto Harb	Austria	Steiermark (Styria)	1	2023	September	139	77.5	0.035	0.1068	78.7
Auto Harb	Austria	Steiermark (Styria)	1	2023	October	124	77.5	0.035	0.1068	78.7
Auto Harb	Austria	Steiermark (Styria)	1	2023	November	190	77.5	0.035	0.1068	78.7
Auto Harb	Austria	Steiermark (Styria)	1	2023	December	112	77.5	0.035	0.1068	78.7
Auto Harb	Austria	Steiermark (Styria)	1	2024	January	157	77.5	0.035	0.1068	78.7
Auto Harb	Austria	Steiermark (Styria)	1	2024	February	184	77.5	0.035	0.1068	78.7
Auto Harb	Austria	Steiermark (Styria)	1	2024	March	341	77.5	0.035	0.1068	78.7
Auto Harb	Austria	Steiermark (Styria)	1	2024	April	252	77.5	0.035	0.1068	78.7
Auto Harb	Austria	Steiermark (Styria)	1	2024	May	284	77.5	0.035	0.1068	78.7
Aichlseder	Austria	Kärnten (Carinthia)	1	2023	May	79	60.5	0.067	0.1068	78.7
Aichlseder	Austria	Kärnten (Carinthia)	1	2023	June	90	60.5	0.067	0.1068	78.7
Aichlseder	Austria	Kärnten (Carinthia)	1	2023	July	52	60.5	0.067	0.1068	78.7
Aichlseder	Austria	Kärnten (Carinthia)	1	2023	August	95	60.5	0.067	0.1068	78.7
Aichlseder	Austria	Kärnten (Carinthia)	1	2023	September	139	60.5	0.067	0.1068	78.7
Aichlseder	Austria	Kärnten (Carinthia)	1	2023	October	124	60.5	0.067	0.1068	78.7
Aichlseder	Austria	Kärnten (Carinthia)	1	2023	November	190	60.5	0.067	0.1068	78.7
Aichlseder	Austria	Kärnten (Carinthia)	1	2023	December	112	60.5	0.067	0.1068	78.7
Aichlseder	Austria	Kärnten (Carinthia)	1	2024	January	157	60.5	0.067	0.1068	78.7
Aichlseder	Austria	Kärnten (Carinthia)	1	2024	February	184	60.5	0.067	0.1068	78.7
Aichlseder	Austria	Kärnten (Carinthia)	1	2024	March	341	60.5	0.067	0.1068	78.7
Aichlseder	Austria	Kärnten (Carinthia)	1	2024	April	252	60.5	0.067	0.1068	78.7
Aichlseder	Austria	Kärnten (Carinthia)	1	2024	May	284	60.5	0.067	0.1068	78.7
Autohaus Fürst	Austria	Burgenland	1	2023	May	79	79.2	0.045	0.1068	78.7
Autohaus Fürst	Austria	Burgenland	1	2023	June	90	79.2	0.045	0.1068	78.7
Autohaus Fürst	Austria	Burgenland	1	2023	July	52	79.2	0.045	0.1068	78.7
Autohaus Fürst	Austria	Burgenland	1	2023	August	95	79.2	0.045	0.1068	78.7
Autohaus Fürst	Austria	Burgenland	1	2023	September	139	79.2	0.045	0.1068	78.7
Autohaus Fürst	Austria	Burgenland	1	2023	October	124	79.2	0.045	0.1068	78.7
Autohaus Fürst	Austria	Burgenland	1	2023	November	190	79.2	0.045	0.1068	78.7
Autohaus Fürst	Austria	Burgenland	1	2023	December	112	79.2	0.045	0.1068	78.7
Autohaus Fürst	Austria	Burgenland	1	2024	January	157	79.2	0.045	0.1068	78.7
Autohaus Fürst	Austria	Burgenland	1	2024	February	184	79.2	0.045	0.1068	78.7
Autohaus Fürst	Austria	Burgenland	1	2024	March	341	79.2	0.045	0.1068	78.7
Autohaus Fürst	Austria	Burgenland	1	2024	April	252	79.2	0.045	0.1068	78.7
Autohaus Fürst	Austria	Burgenland	1	2024	May	284	79.2	0.045	0.1068	78.7
Goidinger	Austria	Tirol (Tyrol)	1	2023	May	79	61.4	0.094	0.1068	78.7
Goidinger	Austria	Tirol (Tyrol)	1	2023	June	90	61.4	0.094	0.1068	78.7
Goidinger	Austria	Tirol (Tyrol)	1	2023	July	52	61.4	0.094	0.1068	78.7
Goidinger	Austria	Tirol (Tyrol)	1	2023	August	95	61.4	0.094	0.1068	78.7
Goidinger	Austria	Tirol (Tyrol)	1	2023	September	139	61.4	0.094	0.1068	78.7
Goidinger	Austria	Tirol (Tyrol)	1	2023	October	124	61.4	0.094	0.1068	78.7
Goidinger	Austria	Tirol (Tyrol)	1	2023	November	190	61.4	0.094	0.1068	78.7
Goidinger	Austria	Tirol (Tyrol)	1	2023	December	112	61.4	0.094	0.1068	78.7
Goidinger	Austria	Tirol (Tyrol)	1	2024	January	157	61.4	0.094	0.1068	78.7
Goidinger	Austria	Tirol (Tyrol)	1	2024	February	184	61.4	0.094	0.1068	78.7
Goidinger	Austria	Tirol (Tyrol)	1	2024	March	341	61.4	0.094	0.1068	78.7
Goidinger	Austria	Tirol (Tyrol)	1	2024	April	252	61.4	0.094	0.1068	78.7
Goidinger	Austria	Tirol (Tyrol)	1	2024	May	284	61.4	0.094	0.1068	78.7
Kienzl	Austria	Steiermark (Styria)	1	2023	May	79	77.5	0.035	0.1068	78.7
Kienzl	Austria	Steiermark (Styria)	1	2023	June	90	77.5	0.035	0.1068	78.7
Kienzl	Austria	Steiermark (Styria)	1	2023	July	52	77.5	0.035	0.1068	78.7
Kienzl	Austria	Steiermark (Styria)	1	2023	August	95	77.5	0.035	0.1068	78.7
Kienzl	Austria	Steiermark (Styria)	1	2023	September	139	77.5	0.035	0.1068	78.7
Kienzl	Austria	Steiermark (Styria)	1	2023	October	124	77.5	0.035	0.1068	78.7
Kienzl	Austria	Steiermark (Styria)	1	2023	November	190	77.5	0.035	0.1068	78.7
Kienzl	Austria	Steiermark (Styria)	1	2023	December	112	77.5	0.035	0.1068	78.7
Kienzl	Austria	Steiermark (Styria)	1	2024	January	157	77.5	0.035	0.1068	78.7
Kienzl	Austria	Steiermark (Styria)	1	2024	February	184	77.5	0.035	0.1068	78.7
Kienzl	Austria	Steiermark (Styria)	1	2024	March	341	77.5	0.035	0.1068	78.7
Kienzl	Austria	Steiermark (Styria)	1	2024	April	252	77.5	0.035	0.1068	78.7
Kienzl	Austria	Steiermark (Styria)	1	2024	May	284	77.5	0.035	0.1068	78.7

Dealership_Name	Country	Region	Number_of_Outlets	Year	Month	Monthly_Sales_Volume_per_Country	Regional_Population_Density	Local_Economic_Growth	Cultural_Difference_Score	Regulatory_Environment_Score
Autohaus Koller	Austria	Niederösterreich (Lower Austria)	1	2023	May	79	90.4	0.038	0.1068	78.7
Autohaus Koller	Austria	Niederösterreich (Lower Austria)	1	2023	June	90	90.4	0.038	0.1068	78.7
Autohaus Koller	Austria	Niederösterreich (Lower Austria)	1	2023	July	52	90.4	0.038	0.1068	78.7
Autohaus Koller	Austria	Niederösterreich (Lower Austria)	1	2023	August	95	90.4	0.038	0.1068	78.7
Autohaus Koller	Austria	Niederösterreich (Lower Austria)	1	2023	September	139	90.4	0.038	0.1068	78.7
Autohaus Koller	Austria	Niederösterreich (Lower Austria)	1	2023	October	124	90.4	0.038	0.1068	78.7
Autohaus Koller	Austria	Niederösterreich (Lower Austria)	1	2023	November	190	90.4	0.038	0.1068	78.7
Autohaus Koller	Austria	Niederösterreich (Lower Austria)	1	2023	December	112	90.4	0.038	0.1068	78.7
Autohaus Koller	Austria	Niederösterreich (Lower Austria)	1	2024	January	157	90.4	0.038	0.1068	78.7
Autohaus Koller	Austria	Niederösterreich (Lower Austria)	1	2024	February	184	90.4	0.038	0.1068	78.7
Autohaus Koller	Austria	Niederösterreich (Lower Austria)	1	2024	March	341	90.4	0.038	0.1068	78.7
Autohaus Koller	Austria	Niederösterreich (Lower Austria)	1	2024	April	252	90.4	0.038	0.1068	78.7
Autohaus Koller	Austria	Niederösterreich (Lower Austria)	1	2024	May	284	90.4	0.038	0.1068	78.7
Leibetseder	Austria	Oberösterreich (Upper Austria)	1	2023	May	79	129.2	0.036	0.1068	78.7
Leibetseder	Austria	Oberösterreich (Upper Austria)	1	2023	June	90	129.2	0.036	0.1068	78.7
Leibetseder	Austria	Oberösterreich (Upper Austria)	1	2023	July	52	129.2	0.036	0.1068	78.7
Leibetseder	Austria	Oberösterreich (Upper Austria)	1	2023	August	95	129.2	0.036	0.1068	78.7
Leibetseder	Austria	Oberösterreich (Upper Austria)	1	2023	September	139	129.2	0.036	0.1068	78.7
Leibetseder	Austria	Oberösterreich (Upper Austria)	1	2023	October	124	129.2	0.036	0.1068	78.7
Leibetseder	Austria	Oberösterreich (Upper Austria)	1	2023	November	190	129.2	0.036	0.1068	78.7
Leibetseder	Austria	Oberösterreich (Upper Austria)	1	2023	December	112	129.2	0.036	0.1068	78.7
Leibetseder	Austria	Oberösterreich (Upper Austria)	1	2024	January	157	129.2	0.036	0.1068	78.7
Leibetseder	Austria	Oberösterreich (Upper Austria)	1	2024	February	184	129.2	0.036	0.1068	78.7
Leibetseder	Austria	Oberösterreich (Upper Austria)	1	2024	March	341	129.2	0.036	0.1068	78.7
Leibetseder	Austria	Oberösterreich (Upper Austria)	1	2024	April	252	129.2	0.036	0.1068	78.7
Leibetseder	Austria	Oberösterreich (Upper Austria)	1	2024	May	284	129.2	0.036	0.1068	78.7
Pichler	Austria	Oberösterreich (Upper Austria)	2	2023	May	79	129.2	0.036	0.1068	78.7
Pichler	Austria	Oberösterreich (Upper Austria)	2	2023	June	90	129.2	0.036	0.1068	78.7
Pichler	Austria	Oberösterreich (Upper Austria)	2	2023	July	52	129.2	0.036	0.1068	78.7
Pichler	Austria	Oberösterreich (Upper Austria)	2	2023	August	95	129.2	0.036	0.1068	78.7
Pichler	Austria	Oberösterreich (Upper Austria)	2	2023	September	139	129.2	0.036	0.1068	78.7
Pichler	Austria	Oberösterreich (Upper Austria)	2	2023	October	124	129.2	0.036	0.1068	78.7
Pichler	Austria	Oberösterreich (Upper Austria)	2	2023	November	190	129.2	0.036	0.1068	78.7
Pichler	Austria	Oberösterreich (Upper Austria)	2	2023	December	112	129.2	0.036	0.1068	78.7
Pichler	Austria	Oberösterreich (Upper Austria)	2	2024	January	157	129.2	0.036	0.1068	78.7
Pichler	Austria	Oberösterreich (Upper Austria)	2	2024	February	184	129.2	0.036	0.1068	78.7
Pichler	Austria	Oberösterreich (Upper Austria)	2	2024	March	341	129.2	0.036	0.1068	78.7
Pichler	Austria	Oberösterreich (Upper Austria)	2	2024	April	252	129.2	0.036	0.1068	78.7
Pichler	Austria	Oberösterreich (Upper Austria)	2	2024	May	284	129.2	0.036	0.1068	78.7
Autohaus Schick	Austria	Tirol (Tyrol)	1	2023	May	79	61.4	0.094	0.1068	78.7
Autohaus Schick	Austria	Tirol (Tyrol)	1	2023	June	90	61.4	0.094	0.1068	78.7
Autohaus Schick	Austria	Tirol (Tyrol)	1	2023	July	52	61.4	0.094	0.1068	78.7
Autohaus Schick	Austria	Tirol (Tyrol)	1	2023	August	95	61.4	0.094	0.1068	78.7
Autohaus Schick	Austria	Tirol (Tyrol)	1	2023	September	139	61.4	0.094	0.1068	78.7
Autohaus Schick	Austria	Tirol (Tyrol)	1	2023	October	124	61.4	0.094	0.1068	78.7
Autohaus Schick	Austria	Tirol (Tyrol)	1	2023	November	190	61.4	0.094	0.1068	78.7
Autohaus Schick	Austria	Tirol (Tyrol)	1	2023	December	112	61.4	0.094	0.1068	78.7
Autohaus Schick	Austria	Tirol (Tyrol)	1	2024	January	157	61.4	0.094	0.1068	78.7
Autohaus Schick	Austria	Tirol (Tyrol)	1	2024	February	184	61.4	0.094	0.1068	78.7
Autohaus Schick	Austria	Tirol (Tyrol)	1	2024	March	341	61.4	0.094	0.1068	78.7
Autohaus Schick	Austria	Tirol (Tyrol)	1	2024	April	252	61.4	0.094	0.1068	78.7
Autohaus Schick	Austria	Tirol (Tyrol)	1	2024	May	284	61.4	0.094	0.1068	78.7

Dealership_Name	Country	Region	Number_of_Outlets	Year	Month	Monthly_Sales_Volume_per_Country	Regional_Population_Density	Local_Economic_Growth	Cultural_Difference_Score	Regulatory_Environment_Score
Schmidberger	Austria	Oberösterreich (Upper Austria)	2	2023	May	79	129.2	0.036	0.1068	78.7
Schmidberger	Austria	Oberösterreich (Upper Austria)	2	2023	June	90	129.2	0.036	0.1068	78.7
Schmidberger	Austria	Oberösterreich (Upper Austria)	2	2023	July	52	129.2	0.036	0.1068	78.7
Schmidberger	Austria	Oberösterreich (Upper Austria)	2	2023	August	95	129.2	0.036	0.1068	78.7
Schmidberger	Austria	Oberösterreich (Upper Austria)	2	2023	September	139	129.2	0.036	0.1068	78.7
Schmidberger	Austria	Oberösterreich (Upper Austria)	2	2023	October	124	129.2	0.036	0.1068	78.7
Schmidberger	Austria	Oberösterreich (Upper Austria)	2	2023	November	190	129.2	0.036	0.1068	78.7
Schmidberger	Austria	Oberösterreich (Upper Austria)	2	2023	December	112	129.2	0.036	0.1068	78.7
Schmidberger	Austria	Oberösterreich (Upper Austria)	2	2024	January	157	129.2	0.036	0.1068	78.7
Schmidberger	Austria	Oberösterreich (Upper Austria)	2	2024	February	184	129.2	0.036	0.1068	78.7
Schmidberger	Austria	Oberösterreich (Upper Austria)	2	2024	March	341	129.2	0.036	0.1068	78.7
Schmidberger	Austria	Oberösterreich (Upper Austria)	2	2024	April	252	129.2	0.036	0.1068	78.7
Schmidberger	Austria	Oberösterreich (Upper Austria)	2	2024	May	284	129.2	0.036	0.1068	78.7
Autopartner Karl	Austria	Niederösterreich (Lower Austria)	1	2023	May	79	90.4	0.038	0.1068	78.7
Autopartner Karl	Austria	Niederösterreich (Lower Austria)	1	2023	June	90	90.4	0.038	0.1068	78.7
Autopartner Karl	Austria	Niederösterreich (Lower Austria)	1	2023	July	52	90.4	0.038	0.1068	78.7
Autopartner Karl	Austria	Niederösterreich (Lower Austria)	1	2023	August	95	90.4	0.038	0.1068	78.7
Autopartner Karl	Austria	Niederösterreich (Lower Austria)	1	2023	September	139	90.4	0.038	0.1068	78.7
Autopartner Karl	Austria	Niederösterreich (Lower Austria)	1	2023	October	124	90.4	0.038	0.1068	78.7
Autopartner Karl	Austria	Niederösterreich (Lower Austria)	1	2023	November	190	90.4	0.038	0.1068	78.7
Autopartner Karl	Austria	Niederösterreich (Lower Austria)	1	2023	December	112	90.4	0.038	0.1068	78.7
Autopartner Karl	Austria	Niederösterreich (Lower Austria)	1	2024	January	157	90.4	0.038	0.1068	78.7
Autopartner Karl	Austria	Niederösterreich (Lower Austria)	1	2024	February	184	90.4	0.038	0.1068	78.7
Autopartner Karl	Austria	Niederösterreich (Lower Austria)	1	2024	March	341	90.4	0.038	0.1068	78.7
Autopartner Karl	Austria	Niederösterreich (Lower Austria)	1	2024	April	252	90.4	0.038	0.1068	78.7
Autopartner Karl	Austria	Niederösterreich (Lower Austria)	1	2024	May	284	90.4	0.038	0.1068	78.7
Denzel Gruppe	Austria	Niederösterreich (Lower Austria)	1	2023	May	79	90.4	0.038	0.1068	78.7
Denzel Gruppe	Austria	Niederösterreich (Lower Austria)	1	2023	June	90	90.4	0.038	0.1068	78.7
Denzel Gruppe	Austria	Niederösterreich (Lower Austria)	1	2023	July	52	90.4	0.038	0.1068	78.7
Denzel Gruppe	Austria	Niederösterreich (Lower Austria)	1	2023	August	95	90.4	0.038	0.1068	78.7
Denzel Gruppe	Austria	Niederösterreich (Lower Austria)	1	2023	September	139	90.4	0.038	0.1068	78.7
Denzel Gruppe	Austria	Niederösterreich (Lower Austria)	1	2023	October	124	90.4	0.038	0.1068	78.7
Denzel Gruppe	Austria	Niederösterreich (Lower Austria)	1	2023	November	190	90.4	0.038	0.1068	78.7
Denzel Gruppe	Austria	Niederösterreich (Lower Austria)	1	2023	December	112	90.4	0.038	0.1068	78.7
Denzel Gruppe	Austria	Niederösterreich (Lower Austria)	1	2024	January	157	90.4	0.038	0.1068	78.7
Denzel Gruppe	Austria	Niederösterreich (Lower Austria)	1	2024	February	184	90.4	0.038	0.1068	78.7
Denzel Gruppe	Austria	Niederösterreich (Lower Austria)	1	2024	March	341	90.4	0.038	0.1068	78.7
Denzel Gruppe	Austria	Niederösterreich (Lower Austria)	1	2024	April	252	90.4	0.038	0.1068	78.7
Denzel Gruppe	Austria	Niederösterreich (Lower Austria)	1	2024	May	284	90.4	0.038	0.1068	78.7
Denzel Gruppe	Austria	Steiermark (Styria)	1	2023	May	79	77.5	0.035	0.1068	78.7
Denzel Gruppe	Austria	Steiermark (Styria)	1	2023	June	90	77.5	0.035	0.1068	78.7
Denzel Gruppe	Austria	Steiermark (Styria)	1	2023	July	52	77.5	0.035	0.1068	78.7
Denzel Gruppe	Austria	Steiermark (Styria)	1	2023	August	95	77.5	0.035	0.1068	78.7
Denzel Gruppe	Austria	Steiermark (Styria)	1	2023	September	139	77.5	0.035	0.1068	78.7
Denzel Gruppe	Austria	Steiermark (Styria)	1	2023	October	124	77.5	0.035	0.1068	78.7
Denzel Gruppe	Austria	Steiermark (Styria)	1	2023	November	190	77.5	0.035	0.1068	78.7
Denzel Gruppe	Austria	Steiermark (Styria)	1	2023	December	112	77.5	0.035	0.1068	78.7
Denzel Gruppe	Austria	Steiermark (Styria)	1	2024	January	157	77.5	0.035	0.1068	78.7
Denzel Gruppe	Austria	Steiermark (Styria)	1	2024	February	184	77.5	0.035	0.1068	78.7
Denzel Gruppe	Austria	Steiermark (Styria)	1	2024	March	341	77.5	0.035	0.1068	78.7
Denzel Gruppe	Austria	Steiermark (Styria)	1	2024	April	252	77.5	0.035	0.1068	78.7
Denzel Gruppe	Austria	Steiermark (Styria)	1	2024	May	284	77.5	0.035	0.1068	78.7

Dealership_Name	Country	Region	Number_of_Outlets	Year	Month	Monthly_Sales_Volume_per_Country	Regional_Population_Density	Local_Economic_Growth	Cultural_Difference_Score	Regulatory_Environment_Score
Denzel Gruppe	Austria	Wien (Vienna)	1	2023	May	79	4,941.5	0.038	0.1068	78.7
Denzel Gruppe	Austria	Wien (Vienna)	1	2023	June	90	4,941.5	0.038	0.1068	78.7
Denzel Gruppe	Austria	Wien (Vienna)	1	2023	July	52	4,941.5	0.038	0.1068	78.7
Denzel Gruppe	Austria	Wien (Vienna)	1	2023	August	95	4,941.5	0.038	0.1068	78.7
Denzel Gruppe	Austria	Wien (Vienna)	1	2023	September	139	4,941.5	0.038	0.1068	78.7
Denzel Gruppe	Austria	Wien (Vienna)	1	2023	October	124	4,941.5	0.038	0.1068	78.7
Denzel Gruppe	Austria	Wien (Vienna)	1	2023	November	190	4,941.5	0.038	0.1068	78.7
Denzel Gruppe	Austria	Wien (Vienna)	1	2023	December	112	4,941.5	0.038	0.1068	78.7
Denzel Gruppe	Austria	Wien (Vienna)	1	2024	January	157	4,941.5	0.038	0.1068	78.7
Denzel Gruppe	Austria	Wien (Vienna)	1	2024	February	184	4,941.5	0.038	0.1068	78.7
Denzel Gruppe	Austria	Wien (Vienna)	1	2024	March	341	4,941.5	0.038	0.1068	78.7
Denzel Gruppe	Austria	Wien (Vienna)	1	2024	April	252	4,941.5	0.038	0.1068	78.7
Denzel Gruppe	Austria	Wien (Vienna)	1	2024	May	284	4,941.5	0.038	0.1068	78.7
Czeczelits	Austria	Niederösterreich (Lower Austria)	1	2023	May	79	90.4	0.038	0.1068	78.7
Czeczelits	Austria	Niederösterreich (Lower Austria)	1	2023	June	90	90.4	0.038	0.1068	78.7
Czeczelits	Austria	Niederösterreich (Lower Austria)	1	2023	July	52	90.4	0.038	0.1068	78.7
Czeczelits	Austria	Niederösterreich (Lower Austria)	1	2023	August	95	90.4	0.038	0.1068	78.7
Czeczelits	Austria	Niederösterreich (Lower Austria)	1	2023	September	139	90.4	0.038	0.1068	78.7
Czeczelits	Austria	Niederösterreich (Lower Austria)	1	2023	October	124	90.4	0.038	0.1068	78.7
Czeczelits	Austria	Niederösterreich (Lower Austria)	1	2023	November	190	90.4	0.038	0.1068	78.7
Czeczelits	Austria	Niederösterreich (Lower Austria)	1	2023	December	112	90.4	0.038	0.1068	78.7
Czeczelits	Austria	Niederösterreich (Lower Austria)	1	2024	January	157	90.4	0.038	0.1068	78.7
Czeczelits	Austria	Niederösterreich (Lower Austria)	1	2024	February	184	90.4	0.038	0.1068	78.7
Czeczelits	Austria	Niederösterreich (Lower Austria)	1	2024	March	341	90.4	0.038	0.1068	78.7
Czeczelits	Austria	Niederösterreich (Lower Austria)	1	2024	April	252	90.4	0.038	0.1068	78.7
Czeczelits	Austria	Niederösterreich (Lower Austria)	1	2024	May	284	90.4	0.038	0.1068	78.7
Danner Fida	Austria	Oberösterreich (Upper Austria)	1	2023	May	79	129.2	0.036	0.1068	78.7
Danner Fida	Austria	Oberösterreich (Upper Austria)	1	2023	June	90	129.2	0.036	0.1068	78.7
Danner Fida	Austria	Oberösterreich (Upper Austria)	1	2023	July	52	129.2	0.036	0.1068	78.7
Danner Fida	Austria	Oberösterreich (Upper Austria)	1	2023	August	95	129.2	0.036	0.1068	78.7
Danner Fida	Austria	Oberösterreich (Upper Austria)	1	2023	September	139	129.2	0.036	0.1068	78.7
Danner Fida	Austria	Oberösterreich (Upper Austria)	1	2023	October	124	129.2	0.036	0.1068	78.7
Danner Fida	Austria	Oberösterreich (Upper Austria)	1	2023	November	190	129.2	0.036	0.1068	78.7
Danner Fida	Austria	Oberösterreich (Upper Austria)	1	2023	December	112	129.2	0.036	0.1068	78.7
Danner Fida	Austria	Oberösterreich (Upper Austria)	1	2024	January	157	129.2	0.036	0.1068	78.7
Danner Fida	Austria	Oberösterreich (Upper Austria)	1	2024	February	184	129.2	0.036	0.1068	78.7
Danner Fida	Austria	Oberösterreich (Upper Austria)	1	2024	March	341	129.2	0.036	0.1068	78.7
Danner Fida	Austria	Oberösterreich (Upper Austria)	1	2024	April	252	129.2	0.036	0.1068	78.7
Danner Fida	Austria	Oberösterreich (Upper Austria)	1	2024	May	284	129.2	0.036	0.1068	78.7
Autohaus Brunner	Austria	Tirol (Tyrol)	1	2023	May	79	61.4	0.094	0.1068	78.7
Autohaus Brunner	Austria	Tirol (Tyrol)	1	2023	June	90	61.4	0.094	0.1068	78.7
Autohaus Brunner	Austria	Tirol (Tyrol)	1	2023	July	52	61.4	0.094	0.1068	78.7
Autohaus Brunner	Austria	Tirol (Tyrol)	1	2023	August	95	61.4	0.094	0.1068	78.7
Autohaus Brunner	Austria	Tirol (Tyrol)	1	2023	September	139	61.4	0.094	0.1068	78.7
Autohaus Brunner	Austria	Tirol (Tyrol)	1	2023	October	124	61.4	0.094	0.1068	78.7
Autohaus Brunner	Austria	Tirol (Tyrol)	1	2023	November	190	61.4	0.094	0.1068	78.7
Autohaus Brunner	Austria	Tirol (Tyrol)	1	2023	December	112	61.4	0.094	0.1068	78.7
Autohaus Brunner	Austria	Tirol (Tyrol)	1	2024	January	157	61.4	0.094	0.1068	78.7
Autohaus Brunner	Austria	Tirol (Tyrol)	1	2024	February	184	61.4	0.094	0.1068	78.7
Autohaus Brunner	Austria	Tirol (Tyrol)	1	2024	March	341	61.4	0.094	0.1068	78.7
Autohaus Brunner	Austria	Tirol (Tyrol)	1	2024	April	252	61.4	0.094	0.1068	78.7
Autohaus Brunner	Austria	Tirol (Tyrol)	1	2024	May	284	61.4	0.094	0.1068	78.7

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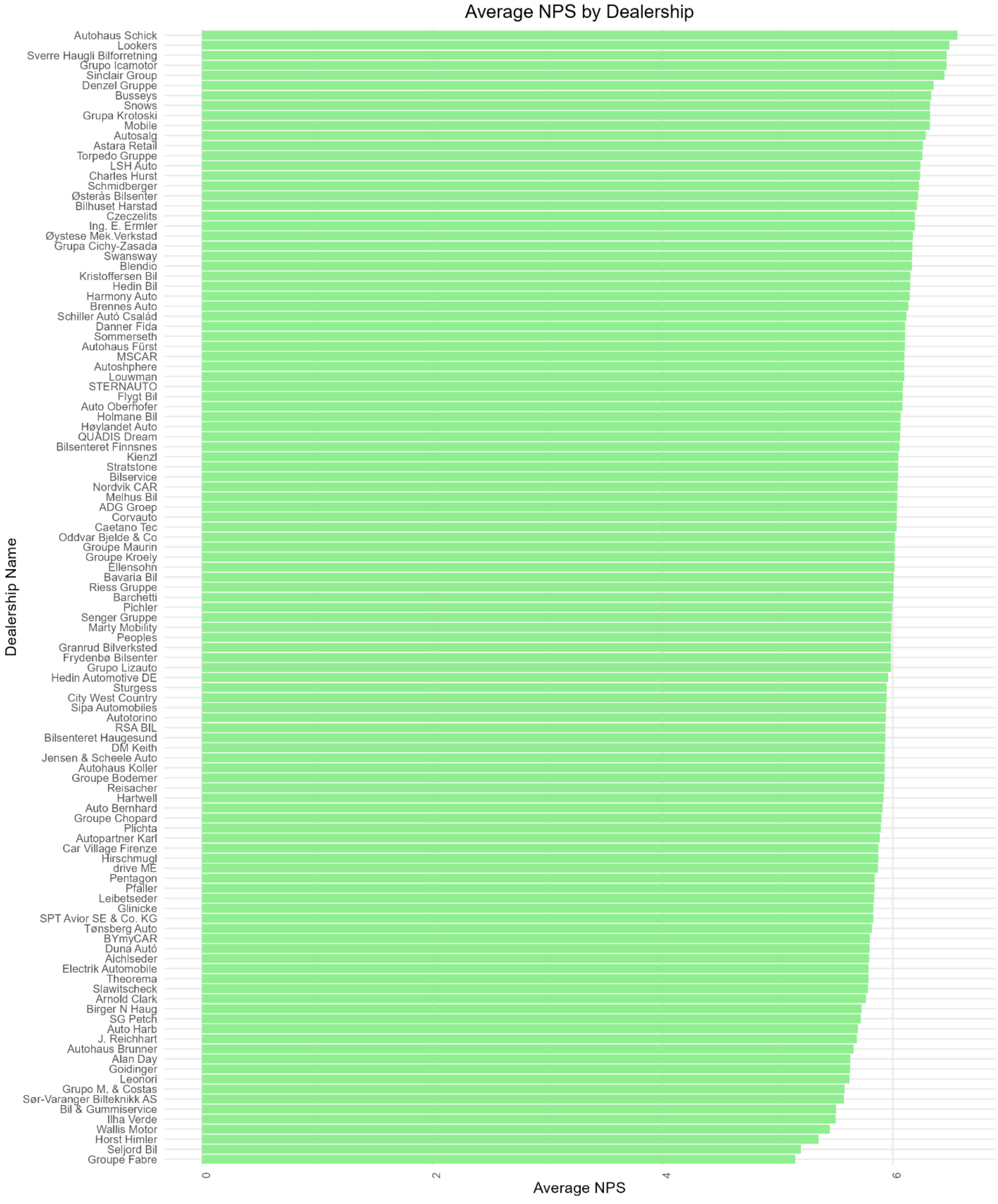
Dealership_Name	Country	Region	Number_of_Outlets	Year	Month	Monthly_Sales_Volume_per_Country	Regional_Population_Density	Local_Economic_Growth	Cultural_Difference_Score	Regulatory_Environment_Score
Hirschmugl	Austria	Steiermark (Styria)	1	2023	May	79	77.5	0.035	0.1068	78.7
Hirschmugl	Austria	Steiermark (Styria)	1	2023	June	90	77.5	0.035	0.1068	78.7
Hirschmugl	Austria	Steiermark (Styria)	1	2023	July	52	77.5	0.035	0.1068	78.7
Hirschmugl	Austria	Steiermark (Styria)	1	2023	August	95	77.5	0.035	0.1068	78.7
Hirschmugl	Austria	Steiermark (Styria)	1	2023	September	139	77.5	0.035	0.1068	78.7
Hirschmugl	Austria	Steiermark (Styria)	1	2023	October	124	77.5	0.035	0.1068	78.7
Hirschmugl	Austria	Steiermark (Styria)	1	2023	November	190	77.5	0.035	0.1068	78.7
Hirschmugl	Austria	Steiermark (Styria)	1	2023	December	112	77.5	0.035	0.1068	78.7
Hirschmugl	Austria	Steiermark (Styria)	1	2024	January	157	77.5	0.035	0.1068	78.7
Hirschmugl	Austria	Steiermark (Styria)	1	2024	February	184	77.5	0.035	0.1068	78.7
Hirschmugl	Austria	Steiermark (Styria)	1	2024	March	341	77.5	0.035	0.1068	78.7
Hirschmugl	Austria	Steiermark (Styria)	1	2024	April	252	77.5	0.035	0.1068	78.7
Hirschmugl	Austria	Steiermark (Styria)	1	2024	May	284	77.5	0.035	0.1068	78.7
Horst Himler	Austria	Steiermark (Styria)	1	2023	May	79	77.5	0.035	0.1068	78.7
Horst Himler	Austria	Steiermark (Styria)	1	2023	June	90	77.5	0.035	0.1068	78.7
Horst Himler	Austria	Steiermark (Styria)	1	2023	July	52	77.5	0.035	0.1068	78.7
Horst Himler	Austria	Steiermark (Styria)	1	2023	August	95	77.5	0.035	0.1068	78.7
Horst Himler	Austria	Steiermark (Styria)	1	2023	September	139	77.5	0.035	0.1068	78.7
Horst Himler	Austria	Steiermark (Styria)	1	2023	October	124	77.5	0.035	0.1068	78.7
Horst Himler	Austria	Steiermark (Styria)	1	2023	November	190	77.5	0.035	0.1068	78.7
Horst Himler	Austria	Steiermark (Styria)	1	2023	December	112	77.5	0.035	0.1068	78.7
Horst Himler	Austria	Steiermark (Styria)	1	2024	January	157	77.5	0.035	0.1068	78.7
Horst Himler	Austria	Steiermark (Styria)	1	2024	February	184	77.5	0.035	0.1068	78.7
Horst Himler	Austria	Steiermark (Styria)	1	2024	March	341	77.5	0.035	0.1068	78.7
Horst Himler	Austria	Steiermark (Styria)	1	2024	April	252	77.5	0.035	0.1068	78.7
Horst Himler	Austria	Steiermark (Styria)	1	2024	May	284	77.5	0.035	0.1068	78.7
Ing. E. Ermler	Austria	Burgenland	1	2023	May	79	79.2	0.045	0.1068	78.7
Ing. E. Ermler	Austria	Burgenland	1	2023	June	90	79.2	0.045	0.1068	78.7
Ing. E. Ermler	Austria	Burgenland	1	2023	July	52	79.2	0.045	0.1068	78.7
Ing. E. Ermler	Austria	Burgenland	1	2023	August	95	79.2	0.045	0.1068	78.7
Ing. E. Ermler	Austria	Burgenland	1	2023	September	139	79.2	0.045	0.1068	78.7
Ing. E. Ermler	Austria	Burgenland	1	2023	October	124	79.2	0.045	0.1068	78.7
Ing. E. Ermler	Austria	Burgenland	1	2023	November	190	79.2	0.045	0.1068	78.7
Ing. E. Ermler	Austria	Burgenland	1	2023	December	112	79.2	0.045	0.1068	78.7
Ing. E. Ermler	Austria	Burgenland	1	2024	January	157	79.2	0.045	0.1068	78.7
Ing. E. Ermler	Austria	Burgenland	1	2024	February	184	79.2	0.045	0.1068	78.7
Ing. E. Ermler	Austria	Burgenland	1	2024	March	341	79.2	0.045	0.1068	78.7
Ing. E. Ermler	Austria	Burgenland	1	2024	April	252	79.2	0.045	0.1068	78.7
Ing. E. Ermler	Austria	Burgenland	1	2024	May	284	79.2	0.045	0.1068	78.7
J. Reichhart	Austria	Oberösterreich (Upper Austria)	1	2023	May	79	129.2	0.036	0.1068	78.7
J. Reichhart	Austria	Oberösterreich (Upper Austria)	1	2023	June	90	129.2	0.036	0.1068	78.7
J. Reichhart	Austria	Oberösterreich (Upper Austria)	1	2023	July	52	129.2	0.036	0.1068	78.7
J. Reichhart	Austria	Oberösterreich (Upper Austria)	1	2023	August	95	129.2	0.036	0.1068	78.7
J. Reichhart	Austria	Oberösterreich (Upper Austria)	1	2023	September	139	129.2	0.036	0.1068	78.7
J. Reichhart	Austria	Oberösterreich (Upper Austria)	1	2023	October	124	129.2	0.036	0.1068	78.7
J. Reichhart	Austria	Oberösterreich (Upper Austria)	1	2023	November	190	129.2	0.036	0.1068	78.7
J. Reichhart	Austria	Oberösterreich (Upper Austria)	1	2023	December	112	129.2	0.036	0.1068	78.7
J. Reichhart	Austria	Oberösterreich (Upper Austria)	1	2024	January	157	129.2	0.036	0.1068	78.7
J. Reichhart	Austria	Oberösterreich (Upper Austria)	1	2024	February	184	129.2	0.036	0.1068	78.7
J. Reichhart	Austria	Oberösterreich (Upper Austria)	1	2024	March	341	129.2	0.036	0.1068	78.7
J. Reichhart	Austria	Oberösterreich (Upper Austria)	1	2024	April	252	129.2	0.036	0.1068	78.7
J. Reichhart	Austria	Oberösterreich (Upper Austria)	1	2024	May	284	129.2	0.036	0.1068	78.7
Ellensohn	Austria	Vorarlberg	2	2023	May	79	159.6	0.039	0.1068	78.7
Ellensohn	Austria	Vorarlberg	2	2023	June	90	159.6	0.039	0.1068	78.7
Ellensohn	Austria	Vorarlberg	2	2023	July	52	159.6	0.039	0.1068	78.7
Ellensohn	Austria	Vorarlberg	2	2023	August	95	159.6	0.039	0.1068	78.7
Ellensohn	Austria	Vorarlberg	2	2023	September	139	159.6	0.039	0.1068	78.7
Ellensohn	Austria	Vorarlberg	2	2023	October	124	159.6	0.039	0.1068	78.7
Ellensohn	Austria	Vorarlberg	2	2023	November	190	159.6	0.039	0.1068	78.7
Ellensohn	Austria	Vorarlberg	2	2023	December	112	159.6	0.039	0.1068	78.7
Ellensohn	Austria	Vorarlberg	2	2024	January	157	159.6	0.039	0.1068	78.7
Ellensohn	Austria	Vorarlberg	2	2024	February	184	159.6	0.039	0.1068	78.7
Ellensohn	Austria	Vorarlberg	2	2024	March	341	159.6	0.039	0.1068	78.7
Ellensohn	Austria	Vorarlberg	2	2024	April	252	159.6	0.039	0.1068	78.7
Ellensohn	Austria	Vorarlberg	2	2024	May	284	159.6	0.039	0.1068	78.7
Marty Mobility	Austria	Niederösterreich (Lower Austria)	1	2023	May	79	90.4	0.038	0.1068	78.7
Marty Mobility	Austria	Niederösterreich (Lower Austria)	1	2023	June	90	90.4	0.038	0.1068	78.7
Marty Mobility	Austria	Niederösterreich (Lower Austria)	1	2023	July	52	90.4	0.038	0.1068	78.7
Marty Mobility	Austria	Niederösterreich (Lower Austria)	1	2023	August	95	90.4	0.038	0.1068	78.7
Marty Mobility	Austria	Niederösterreich (Lower Austria)	1	2023	September	139	90.4	0.038	0.1068	78.7
Marty Mobility	Austria	Niederösterreich (Lower Austria)	1	2023	October	124	90.4	0.038	0.1068	78.7
Marty Mobility	Austria	Niederösterreich (Lower Austria)	1	2023	November	190	90.4	0.038	0.1068	78.7
Marty Mobility	Austria	Niederösterreich (Lower Austria)	1	2023	December	112	90.4	0.038	0.1068	78.7
Marty Mobility	Austria	Niederösterreich (Lower Austria)	1	2024	January	157	90.4	0.038	0.1068	78.7
Marty Mobility	Austria	Niederösterreich (Lower Austria)	1	2024	February	184	90.4	0.038	0.1068	78.7
Marty Mobility	Austria	Niederösterreich (Lower Austria)	1	2024	March	341	90.4	0.038	0.1068	78.7
Marty Mobility	Austria	Niederösterreich (Lower Austria)	1	2024	April	252	90.4	0.038	0.1068	78.7
Marty Mobility	Austria	Niederösterreich (Lower Austria)	1	2024	May	284	90.4	0.038	0.1068	78.7

Dealership_Name	Country	Region	Number_of_Outlets	Year	Month	Monthly_Sales_Volume_per_Country	Regional_Population_Density	Local_Economic_Growth	Cultural_Difference_Score	Regulatory_Environment_Score
Auto Oberhofer	Austria	Tirol (Tyrol)	1	2023	May	79	61.4	0.094	0.1068	78.7
Auto Oberhofer	Austria	Tirol (Tyrol)	1	2023	June	90	61.4	0.094	0.1068	78.7
Auto Oberhofer	Austria	Tirol (Tyrol)	1	2023	July	52	61.4	0.094	0.1068	78.7
Auto Oberhofer	Austria	Tirol (Tyrol)	1	2023	August	95	61.4	0.094	0.1068	78.7
Auto Oberhofer	Austria	Tirol (Tyrol)	1	2023	September	139	61.4	0.094	0.1068	78.7
Auto Oberhofer	Austria	Tirol (Tyrol)	1	2023	October	124	61.4	0.094	0.1068	78.7
Auto Oberhofer	Austria	Tirol (Tyrol)	1	2023	November	190	61.4	0.094	0.1068	78.7
Auto Oberhofer	Austria	Tirol (Tyrol)	1	2023	December	112	61.4	0.094	0.1068	78.7
Auto Oberhofer	Austria	Tirol (Tyrol)	1	2024	January	157	61.4	0.094	0.1068	78.7
Auto Oberhofer	Austria	Tirol (Tyrol)	1	2024	February	184	61.4	0.094	0.1068	78.7
Auto Oberhofer	Austria	Tirol (Tyrol)	1	2024	March	341	61.4	0.094	0.1068	78.7
Auto Oberhofer	Austria	Tirol (Tyrol)	1	2024	April	252	61.4	0.094	0.1068	78.7
Auto Oberhofer	Austria	Tirol (Tyrol)	1	2024	May	284	61.4	0.094	0.1068	78.7
Pfaller	Austria	Niederösterreich (Lower Austria)	1	2023	May	79	90.4	0.038	0.1068	78.7
Pfaller	Austria	Niederösterreich (Lower Austria)	1	2023	June	90	90.4	0.038	0.1068	78.7
Pfaller	Austria	Niederösterreich (Lower Austria)	1	2023	July	52	90.4	0.038	0.1068	78.7
Pfaller	Austria	Niederösterreich (Lower Austria)	1	2023	August	95	90.4	0.038	0.1068	78.7
Pfaller	Austria	Niederösterreich (Lower Austria)	1	2023	September	139	90.4	0.038	0.1068	78.7
Pfaller	Austria	Niederösterreich (Lower Austria)	1	2023	October	124	90.4	0.038	0.1068	78.7
Pfaller	Austria	Niederösterreich (Lower Austria)	1	2023	November	190	90.4	0.038	0.1068	78.7
Pfaller	Austria	Niederösterreich (Lower Austria)	1	2023	December	112	90.4	0.038	0.1068	78.7
Pfaller	Austria	Niederösterreich (Lower Austria)	1	2024	January	157	90.4	0.038	0.1068	78.7
Pfaller	Austria	Niederösterreich (Lower Austria)	1	2024	February	184	90.4	0.038	0.1068	78.7
Pfaller	Austria	Niederösterreich (Lower Austria)	1	2024	March	341	90.4	0.038	0.1068	78.7
Pfaller	Austria	Niederösterreich (Lower Austria)	1	2024	April	252	90.4	0.038	0.1068	78.7
Pfaller	Austria	Niederösterreich (Lower Austria)	1	2024	May	284	90.4	0.038	0.1068	78.7
Slawitscheck	Austria	Niederösterreich (Lower Austria)	1	2023	May	79	90.4	0.038	0.1068	78.7
Slawitscheck	Austria	Niederösterreich (Lower Austria)	1	2023	June	90	90.4	0.038	0.1068	78.7
Slawitscheck	Austria	Niederösterreich (Lower Austria)	1	2023	July	52	90.4	0.038	0.1068	78.7
Slawitscheck	Austria	Niederösterreich (Lower Austria)	1	2023	August	95	90.4	0.038	0.1068	78.7
Slawitscheck	Austria	Niederösterreich (Lower Austria)	1	2023	September	139	90.4	0.038	0.1068	78.7
Slawitscheck	Austria	Niederösterreich (Lower Austria)	1	2023	October	124	90.4	0.038	0.1068	78.7
Slawitscheck	Austria	Niederösterreich (Lower Austria)	1	2023	November	190	90.4	0.038	0.1068	78.7
Slawitscheck	Austria	Niederösterreich (Lower Austria)	1	2023	December	112	90.4	0.038	0.1068	78.7
Slawitscheck	Austria	Niederösterreich (Lower Austria)	1	2024	January	157	90.4	0.038	0.1068	78.7
Slawitscheck	Austria	Niederösterreich (Lower Austria)	1	2024	February	184	90.4	0.038	0.1068	78.7
Slawitscheck	Austria	Niederösterreich (Lower Austria)	1	2024	March	341	90.4	0.038	0.1068	78.7
Slawitscheck	Austria	Niederösterreich (Lower Austria)	1	2024	April	252	90.4	0.038	0.1068	78.7
Slawitscheck	Austria	Niederösterreich (Lower Austria)	1	2024	May	284	90.4	0.038	0.1068	78.7
drive ME	Austria	Oberösterreich (Upper Austria)	2	2023	May	79	129.2	0.036	0.1068	78.7
drive ME	Austria	Oberösterreich (Upper Austria)	2	2023	June	90	129.2	0.036	0.1068	78.7
drive ME	Austria	Oberösterreich (Upper Austria)	2	2023	July	52	129.2	0.036	0.1068	78.7
drive ME	Austria	Oberösterreich (Upper Austria)	2	2023	August	95	129.2	0.036	0.1068	78.7
drive ME	Austria	Oberösterreich (Upper Austria)	2	2023	September	139	129.2	0.036	0.1068	78.7
drive ME	Austria	Oberösterreich (Upper Austria)	2	2023	October	124	129.2	0.036	0.1068	78.7
drive ME	Austria	Oberösterreich (Upper Austria)	2	2023	November	190	129.2	0.036	0.1068	78.7
drive ME	Austria	Oberösterreich (Upper Austria)	2	2023	December	112	129.2	0.036	0.1068	78.7
drive ME	Austria	Oberösterreich (Upper Austria)	2	2024	January	157	129.2	0.036	0.1068	78.7
drive ME	Austria	Oberösterreich (Upper Austria)	2	2024	February	184	129.2	0.036	0.1068	78.7
drive ME	Austria	Oberösterreich (Upper Austria)	2	2024	March	341	129.2	0.036	0.1068	78.7
drive ME	Austria	Oberösterreich (Upper Austria)	2	2024	April	252	129.2	0.036	0.1068	78.7
drive ME	Austria	Oberösterreich (Upper Austria)	2	2024	May	284	129.2	0.036	0.1068	78.7

Dealership_Name	Country	Region	Number_of_Outlets	Year	Month	Monthly_Sales_Volume_per_Country	Regional_Population_Density	Local_Economic_Growth	Cultural_Difference_Score	Regulatory_Environment_Score
Bavaria Bil	Sweden	Mellersta Norrland (Middle Norrland)	2	2023	May	145	5.3	0.053	0.0600	82.0
Bavaria Bil	Sweden	Mellersta Norrland (Middle Norrland)	2	2023	June	307	5.3	0.053	0.0600	82.0
Bavaria Bil	Sweden	Mellersta Norrland (Middle Norrland)	2	2023	July	839	5.3	0.053	0.0600	82.0
Bavaria Bil	Sweden	Mellersta Norrland (Middle Norrland)	2	2023	August	324	5.3	0.053	0.0600	82.0
Bavaria Bil	Sweden	Mellersta Norrland (Middle Norrland)	2	2023	September	601	5.3	0.053	0.0600	82.0
Bavaria Bil	Sweden	Mellersta Norrland (Middle Norrland)	2	2023	October	405	5.3	0.053	0.0600	82.0
Bavaria Bil	Sweden	Mellersta Norrland (Middle Norrland)	2	2023	November	325	5.3	0.053	0.0600	82.0
Bavaria Bil	Sweden	Mellersta Norrland (Middle Norrland)	2	2023	December	234	5.3	0.053	0.0600	82.0
Bavaria Bil	Sweden	Mellersta Norrland (Middle Norrland)	2	2024	January	63	5.3	0.053	0.0600	82.0
Bavaria Bil	Sweden	Mellersta Norrland (Middle Norrland)	2	2024	February	58	5.3	0.053	0.0600	82.0
Bavaria Bil	Sweden	Mellersta Norrland (Middle Norrland)	2	2024	March	96	5.3	0.053	0.0600	82.0
Bavaria Bil	Sweden	Mellersta Norrland (Middle Norrland)	2	2024	April	97	5.3	0.053	0.0600	82.0
Bavaria Bil	Sweden	Mellersta Norrland (Middle Norrland)	2	2024	May	105	5.3	0.053	0.0600	82.0
Bavaria Bil	Sweden	Norra Mellansverige (North Middle Sweden)	1	2023	May	145	13.5	0.038	0.0600	82.0
Bavaria Bil	Sweden	Norra Mellansverige (North Middle Sweden)	1	2023	June	307	13.5	0.038	0.0600	82.0
Bavaria Bil	Sweden	Norra Mellansverige (North Middle Sweden)	1	2023	July	839	13.5	0.038	0.0600	82.0
Bavaria Bil	Sweden	Norra Mellansverige (North Middle Sweden)	1	2023	August	324	13.5	0.038	0.0600	82.0
Bavaria Bil	Sweden	Norra Mellansverige (North Middle Sweden)	1	2023	September	601	13.5	0.038	0.0600	82.0
Bavaria Bil	Sweden	Norra Mellansverige (North Middle Sweden)	1	2023	October	405	13.5	0.038	0.0600	82.0
Bavaria Bil	Sweden	Norra Mellansverige (North Middle Sweden)	1	2023	November	325	13.5	0.038	0.0600	82.0
Bavaria Bil	Sweden	Norra Mellansverige (North Middle Sweden)	1	2023	December	234	13.5	0.038	0.0600	82.0
Bavaria Bil	Sweden	Norra Mellansverige (North Middle Sweden)	1	2024	January	63	13.5	0.038	0.0600	82.0
Bavaria Bil	Sweden	Norra Mellansverige (North Middle Sweden)	1	2024	February	58	13.5	0.038	0.0600	82.0
Bavaria Bil	Sweden	Norra Mellansverige (North Middle Sweden)	1	2024	March	96	13.5	0.038	0.0600	82.0
Bavaria Bil	Sweden	Norra Mellansverige (North Middle Sweden)	1	2024	April	97	13.5	0.038	0.0600	82.0
Bavaria Bil	Sweden	Norra Mellansverige (North Middle Sweden)	1	2024	May	105	13.5	0.038	0.0600	82.0
Hedin Bil	Sweden	Östra Mellansverige (East Middle Sweden)	4	2023	May	145	45.7	0.042	0.0600	82.0
Hedin Bil	Sweden	Östra Mellansverige (East Middle Sweden)	4	2023	June	307	45.7	0.042	0.0600	82.0
Hedin Bil	Sweden	Östra Mellansverige (East Middle Sweden)	4	2023	July	839	45.7	0.042	0.0600	82.0
Hedin Bil	Sweden	Östra Mellansverige (East Middle Sweden)	4	2023	August	324	45.7	0.042	0.0600	82.0
Hedin Bil	Sweden	Östra Mellansverige (East Middle Sweden)	4	2023	September	601	45.7	0.042	0.0600	82.0
Hedin Bil	Sweden	Östra Mellansverige (East Middle Sweden)	4	2023	October	405	45.7	0.042	0.0600	82.0
Hedin Bil	Sweden	Östra Mellansverige (East Middle Sweden)	4	2023	November	325	45.7	0.042	0.0600	82.0
Hedin Bil	Sweden	Östra Mellansverige (East Middle Sweden)	4	2023	December	234	45.7	0.042	0.0600	82.0
Hedin Bil	Sweden	Östra Mellansverige (East Middle Sweden)	4	2024	January	63	45.7	0.042	0.0600	82.0
Hedin Bil	Sweden	Östra Mellansverige (East Middle Sweden)	4	2024	February	58	45.7	0.042	0.0600	82.0
Hedin Bil	Sweden	Östra Mellansverige (East Middle Sweden)	4	2024	March	96	45.7	0.042	0.0600	82.0
Hedin Bil	Sweden	Östra Mellansverige (East Middle Sweden)	4	2024	April	97	45.7	0.042	0.0600	82.0
Hedin Bil	Sweden	Östra Mellansverige (East Middle Sweden)	4	2024	May	105	45.7	0.042	0.0600	82.0

Dealership_Name	Country	Region	Number_of_Outlets	Year	Month	Monthly_Sales_Volume_per_Country	Regional_Population_Density	Local_Economic_Growth	Cultural_Difference_Score	Regulatory_Environment_Score
Hedin Bil	Sweden	Stockholm	3	2023	May	145	372.1	0.015	0.0600	82.0
Hedin Bil	Sweden	Stockholm	3	2023	June	307	372.1	0.015	0.0600	82.0
Hedin Bil	Sweden	Stockholm	3	2023	July	839	372.1	0.015	0.0600	82.0
Hedin Bil	Sweden	Stockholm	3	2023	August	324	372.1	0.015	0.0600	82.0
Hedin Bil	Sweden	Stockholm	3	2023	September	601	372.1	0.015	0.0600	82.0
Hedin Bil	Sweden	Stockholm	3	2023	October	405	372.1	0.015	0.0600	82.0
Hedin Bil	Sweden	Stockholm	3	2023	November	325	372.1	0.015	0.0600	82.0
Hedin Bil	Sweden	Stockholm	3	2023	December	234	372.1	0.015	0.0600	82.0
Hedin Bil	Sweden	Stockholm	3	2024	January	63	372.1	0.015	0.0600	82.0
Hedin Bil	Sweden	Stockholm	3	2024	February	58	372.1	0.015	0.0600	82.0
Hedin Bil	Sweden	Stockholm	3	2024	March	96	372.1	0.015	0.0600	82.0
Hedin Bil	Sweden	Stockholm	3	2024	April	97	372.1	0.015	0.0600	82.0
Hedin Bil	Sweden	Stockholm	3	2024	May	105	372.1	0.015	0.0600	82.0
Hedin Bil	Sweden	Västsverige (West Sweden)	8	2023	May	145	71.6	0.049	0.0600	82.0
Hedin Bil	Sweden	Västsverige (West Sweden)	8	2023	June	307	71.6	0.049	0.0600	82.0
Hedin Bil	Sweden	Västsverige (West Sweden)	8	2023	July	839	71.6	0.049	0.0600	82.0
Hedin Bil	Sweden	Västsverige (West Sweden)	8	2023	August	324	71.6	0.049	0.0600	82.0
Hedin Bil	Sweden	Västsverige (West Sweden)	8	2023	September	601	71.6	0.049	0.0600	82.0
Hedin Bil	Sweden	Västsverige (West Sweden)	8	2023	October	405	71.6	0.049	0.0600	82.0
Hedin Bil	Sweden	Västsverige (West Sweden)	8	2023	November	325	71.6	0.049	0.0600	82.0
Hedin Bil	Sweden	Västsverige (West Sweden)	8	2023	December	234	71.6	0.049	0.0600	82.0
Hedin Bil	Sweden	Västsverige (West Sweden)	8	2024	January	63	71.6	0.049	0.0600	82.0
Hedin Bil	Sweden	Västsverige (West Sweden)	8	2024	February	58	71.6	0.049	0.0600	82.0
Hedin Bil	Sweden	Västsverige (West Sweden)	8	2024	March	96	71.6	0.049	0.0600	82.0
Hedin Bil	Sweden	Västsverige (West Sweden)	8	2024	April	97	71.6	0.049	0.0600	82.0
Hedin Bil	Sweden	Västsverige (West Sweden)	8	2024	May	105	71.6	0.049	0.0600	82.0
Hedin Bil	Sweden	Sydsverige (South Sweden)	3	2023	May	145	112.8	0.017	0.0600	82.0
Hedin Bil	Sweden	Sydsverige (South Sweden)	3	2023	June	307	112.8	0.017	0.0600	82.0
Hedin Bil	Sweden	Sydsverige (South Sweden)	3	2023	July	839	112.8	0.017	0.0600	82.0
Hedin Bil	Sweden	Sydsverige (South Sweden)	3	2023	August	324	112.8	0.017	0.0600	82.0
Hedin Bil	Sweden	Sydsverige (South Sweden)	3	2023	September	601	112.8	0.017	0.0600	82.0
Hedin Bil	Sweden	Sydsverige (South Sweden)	3	2023	October	405	112.8	0.017	0.0600	82.0
Hedin Bil	Sweden	Sydsverige (South Sweden)	3	2023	November	325	112.8	0.017	0.0600	82.0
Hedin Bil	Sweden	Sydsverige (South Sweden)	3	2023	December	234	112.8	0.017	0.0600	82.0
Hedin Bil	Sweden	Sydsverige (South Sweden)	3	2024	January	63	112.8	0.017	0.0600	82.0
Hedin Bil	Sweden	Sydsverige (South Sweden)	3	2024	February	58	112.8	0.017	0.0600	82.0
Hedin Bil	Sweden	Sydsverige (South Sweden)	3	2024	March	96	112.8	0.017	0.0600	82.0
Hedin Bil	Sweden	Sydsverige (South Sweden)	3	2024	April	97	112.8	0.017	0.0600	82.0
Hedin Bil	Sweden	Sydsverige (South Sweden)	3	2024	May	105	112.8	0.017	0.0600	82.0
Hedin Bil	Sweden	Småland och öarna (Småland and the islands)	2	2023	May	145	26.6	0.015	0.0600	82.0
Hedin Bil	Sweden	Småland och öarna (Småland and the islands)	2	2023	June	307	26.6	0.015	0.0600	82.0
Hedin Bil	Sweden	Småland och öarna (Småland and the islands)	2	2023	July	839	26.6	0.015	0.0600	82.0
Hedin Bil	Sweden	Småland och öarna (Småland and the islands)	2	2023	August	324	26.6	0.015	0.0600	82.0
Hedin Bil	Sweden	Småland och öarna (Småland and the islands)	2	2023	September	601	26.6	0.015	0.0600	82.0
Hedin Bil	Sweden	Småland och öarna (Småland and the islands)	2	2023	October	405	26.6	0.015	0.0600	82.0
Hedin Bil	Sweden	Småland och öarna (Småland and the islands)	2	2023	November	325	26.6	0.015	0.0600	82.0
Hedin Bil	Sweden	Småland och öarna (Småland and the islands)	2	2023	December	234	26.6	0.015	0.0600	82.0
Hedin Bil	Sweden	Småland och öarna (Småland and the islands)	2	2024	January	63	26.6	0.015	0.0600	82.0
Hedin Bil	Sweden	Småland och öarna (Småland and the islands)	2	2024	February	58	26.6	0.015	0.0600	82.0
Hedin Bil	Sweden	Småland och öarna (Småland and the islands)	2	2024	March	96	26.6	0.015	0.0600	82.0
Hedin Bil	Sweden	Småland och öarna (Småland and the islands)	2	2024	April	97	26.6	0.015	0.0600	82.0
Hedin Bil	Sweden	Småland och öarna (Småland and the islands)	2	2024	May	105	26.6	0.015	0.0600	82.0

Appendix III. Average NPS by Dealership



Appendix IV. Significant Features of Every Predicting Models

Appendix IV.I. Significant Features of Linear Regression

Metric	Significant Features for Linear Regression
Sales Volume	Monthly_Sales_Volume_per_Country
	Dealership_Name
	Region
	Number_of_Salespeople
	Polynomial_Term
	Cultural_Difference_Score
	Regulatory_Environment_Score
	Number_of_Outlets
	Country
	Date
	Month
	Year
	Interaction_Term
	Local_Economic_Growth
	DEA_Efficiency
	Regional_Population_Density
NPS	Dealership_Name
	Region
	DEA_Efficiency
DEA Efficiency	Region
	Regulatory_Environment_Score
	Cultural_Difference_Score
	Regional_Population_Density
	Monthly_Sales_Volume_per_Dealer
	Local_Economic_Growth
	Number_of_Outlets
	NPS_Score
	Number_of_Salespeople
	Service_Completion_Time
	Date

Appendix IV.II. Significant Features of Random Forest

Metric	Significant Features for Random Forest
Sales Volume	Country
	Number_of_Outlets
	Month
	Monthly_Sales_Volume_per_Country
	Regional_Population_Density
	Cultural_Difference_Score
	Regulatory_Environment_Score
	Number_of_Salespeople
	Service_Completion_Time
	Date
	Interaction_Term
	DEA_Efficiency
	Polynomial_Term
NPS	Dealership_Name
	Country
	Region
	Month
	Local_Economic_Growth
	Monthly_Sales_Volume_per_Dealer
	Cultural_Difference_Score
	Regulatory_Environment_Score
	Service_Completion_Time
	Date
	DEA_Efficiency
DEA Efficiency	Dealership_Name
	Regional_Population_Density
	Regulatory_Environment_Score
	Service_Completion_Time
	Interaction_Term
	Number_of_Outlets
	Local_Economic_Growth
	Monthly_Sales_Volume_per_Dealer
	NPS_Score
	Date

Appendix IV.III. Significant Features of SVM

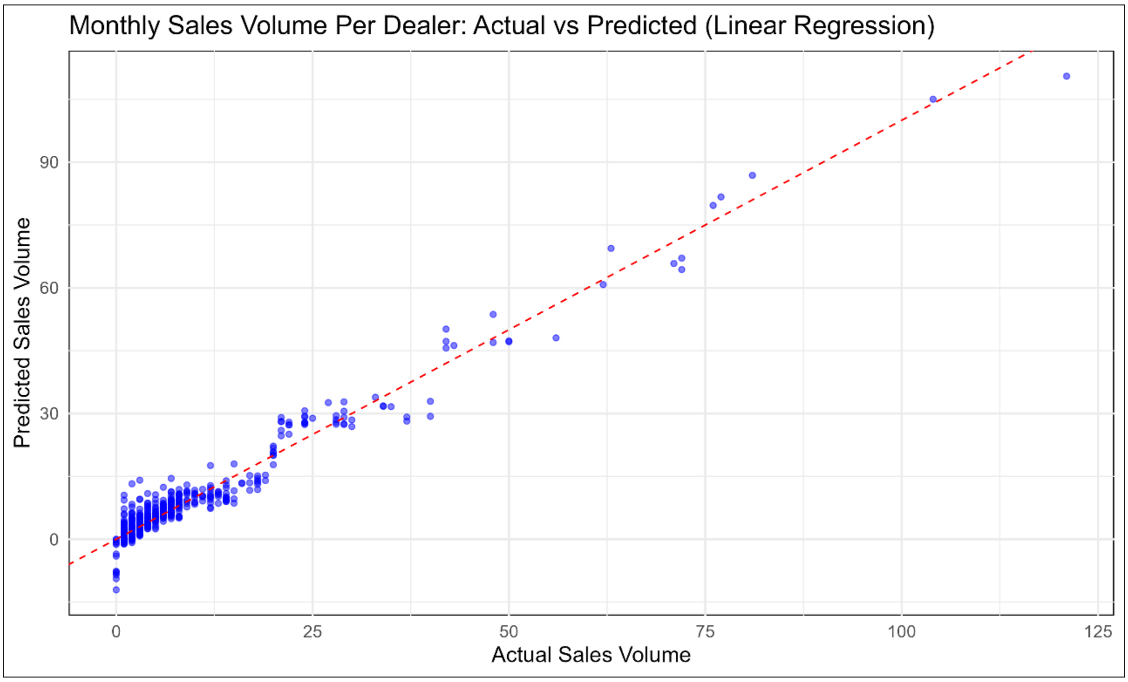
Metric	Selected Features for SVM
Sales Volume	Monthly_Sales_Volume_per_Country
	Number_of_Salespeople
	Polynomial_Term
	DEA_Efficiency
	Interaction_Term
	Regulatory_Environment_Score
	Number_of_Outlets
	Regional_Population_Density
NPS	DEA_Efficiency
	Regional_Population_Density
	Monthly_Sales_Volume_per_Country
	Monthly_Sales_Volume_per_Dealer
	Local_Economic_Growth
	Cultural_Difference_Score

Appendix IV.IV. Significant Features of GBM

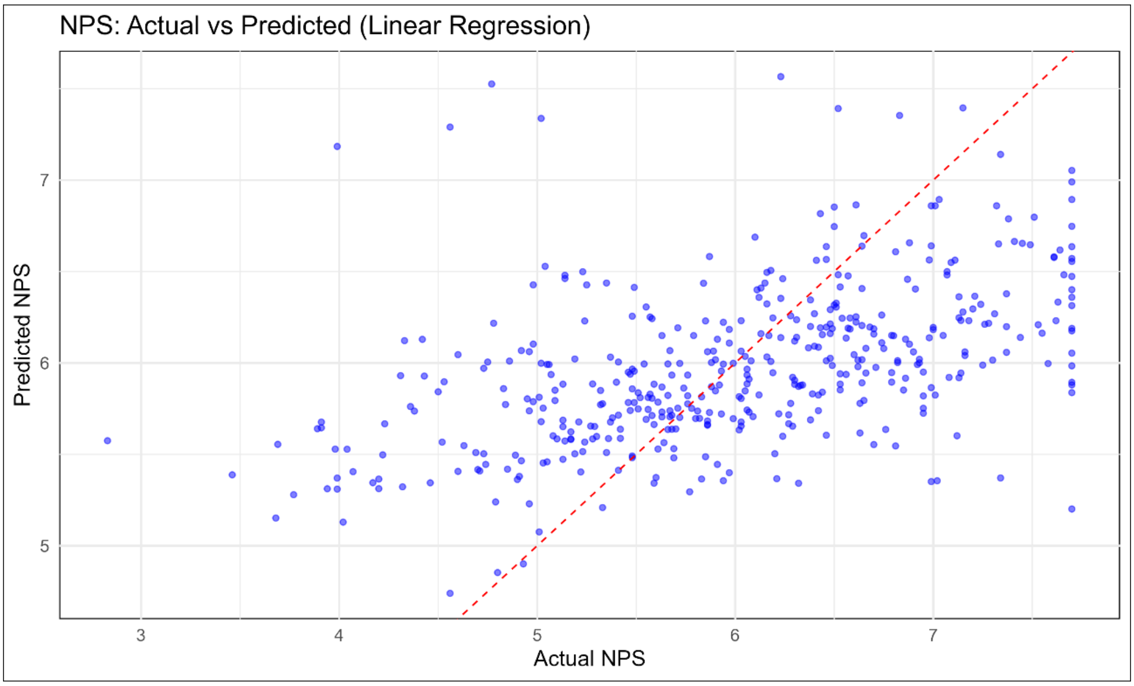
Metric	Selected Features
Sales Volume	Monthly_Sales_Volume_per_Country
	Polynomial_Term
	Number_of_Salespeople
	DEA_Efficiency
	Interaction_Term
	Regulatory_Environment_Score
	Number_of_Outlets
	Regional_Population_Density
	Cultural_Difference_Score
NPS	DEA_Efficiency
	Regional_Population_Density
	Monthly_Sales_Volume_per_Country
	Monthly_Sales_Volume_per_Dealer
	Local_Economic_Growth
	Cultural_Difference_Score
	Regulatory_Environment_Score
	Interaction_Term
DEA Efficiency	NPS_Score
	Regional_Population_Density
	Monthly_Sales_Volume_per_Country
	Monthly_Sales_Volume_per_Dealer
	Service_Completion_Time
	Local_Economic_Growth
	Regulatory_Environment_Score
	Cultural_Difference_Score
	Interaction_Term
	Number_of_Outlets

Appendix V. The Results from Every Predictive Models

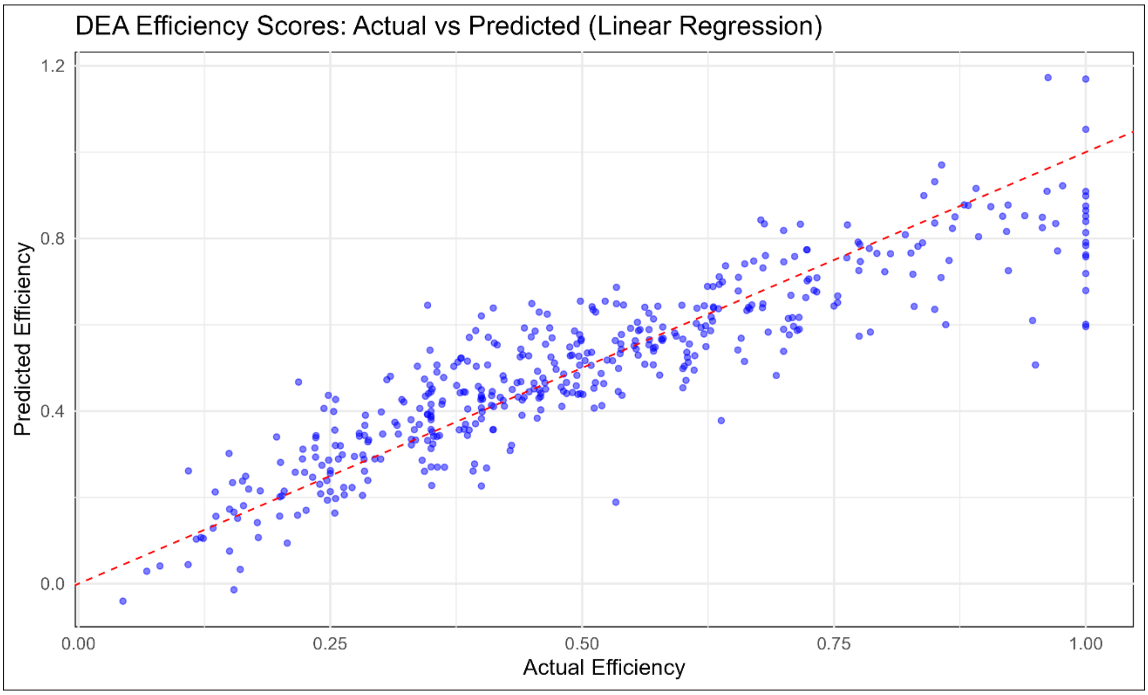
Appendix V.I. Monthly Sales Volume Prediction Using Linear Regression



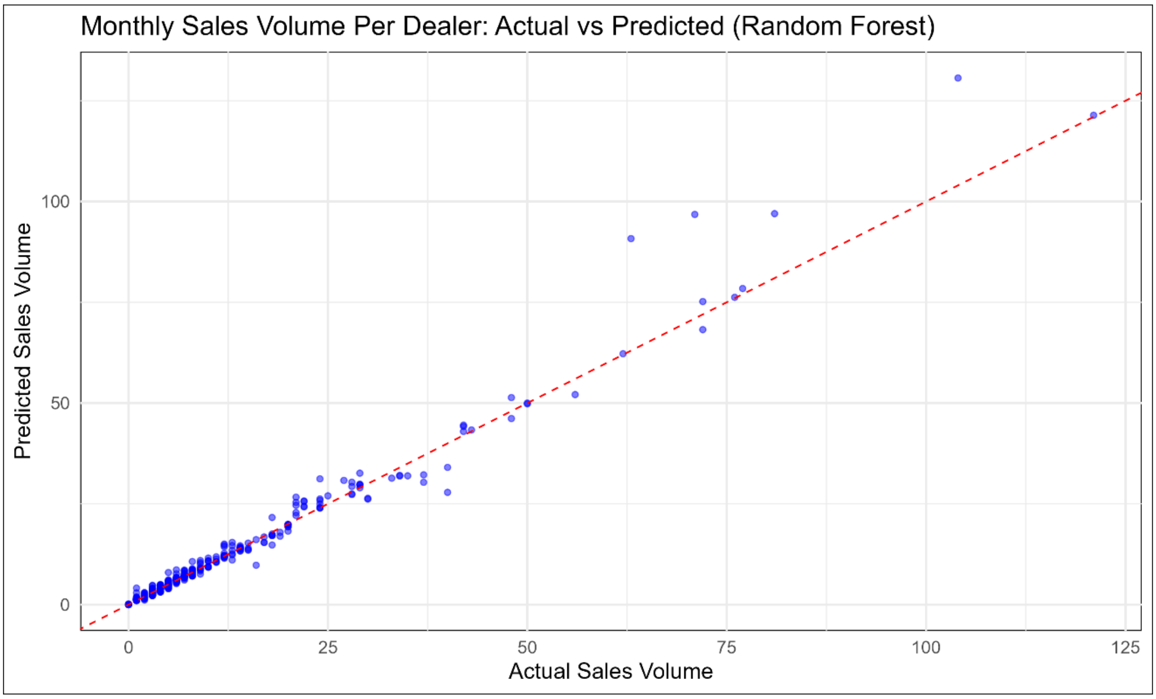
Appendix V.II. NPS Prediction Using Linear Regression



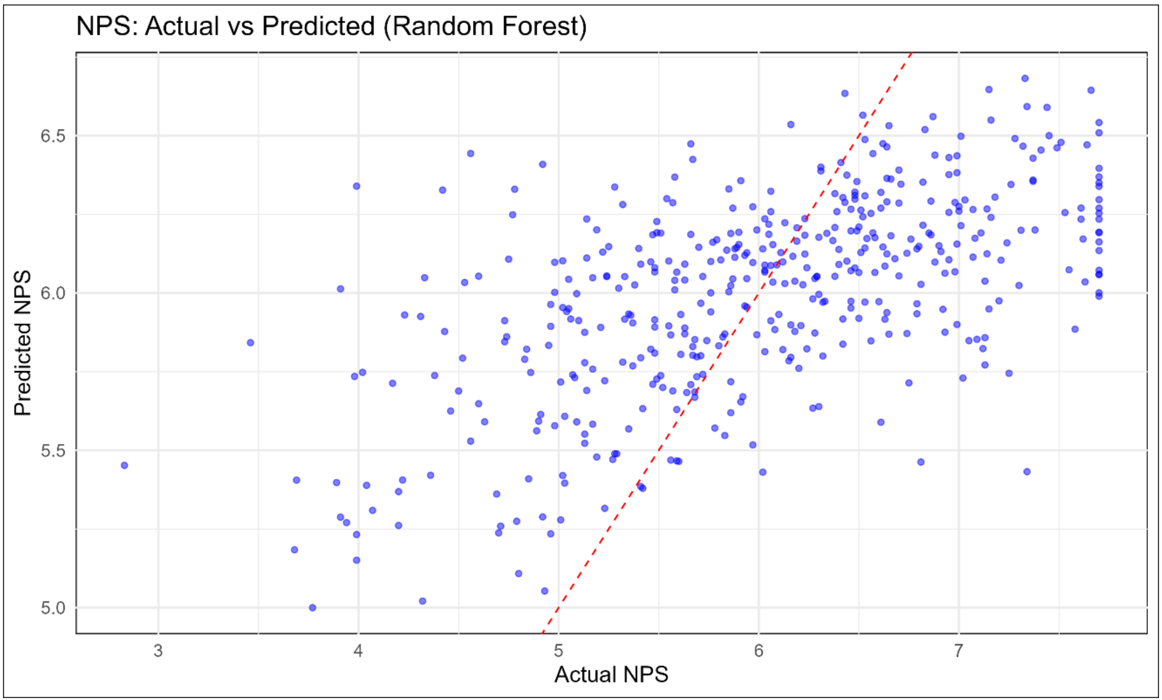
Appendix V.III. DEA Efficiency Scores Prediction Using Linear Regression



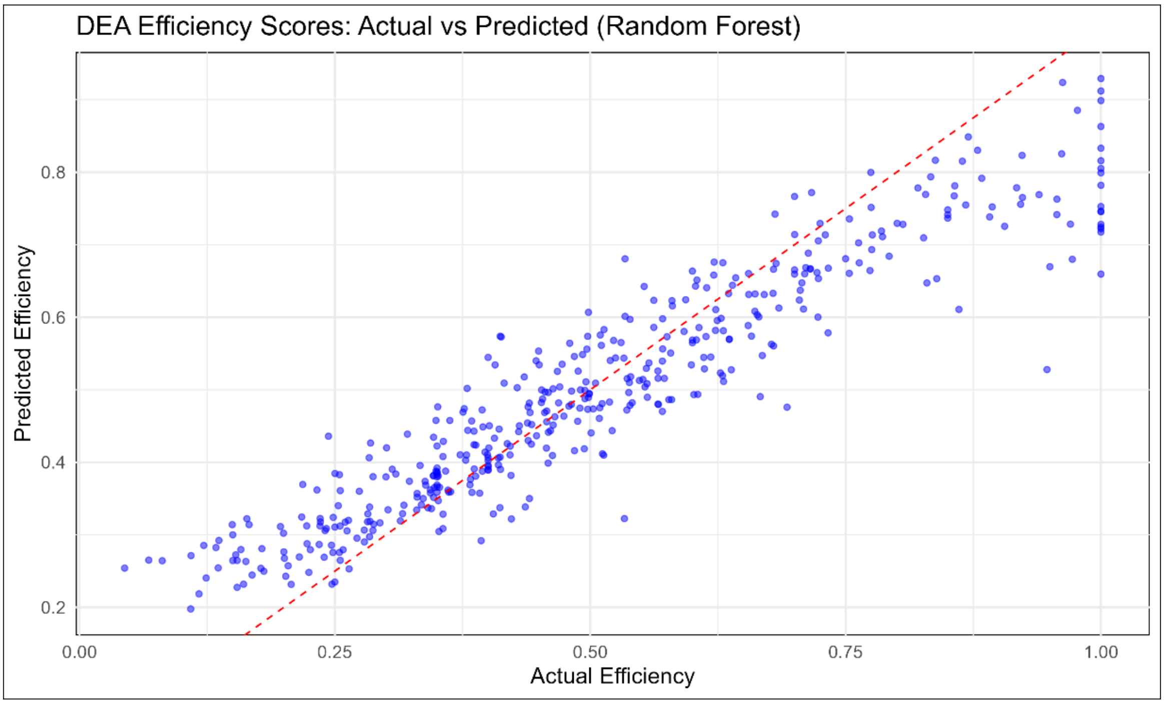
Appendix V.IV. Monthly Sales Volume Prediction Using Random Forest



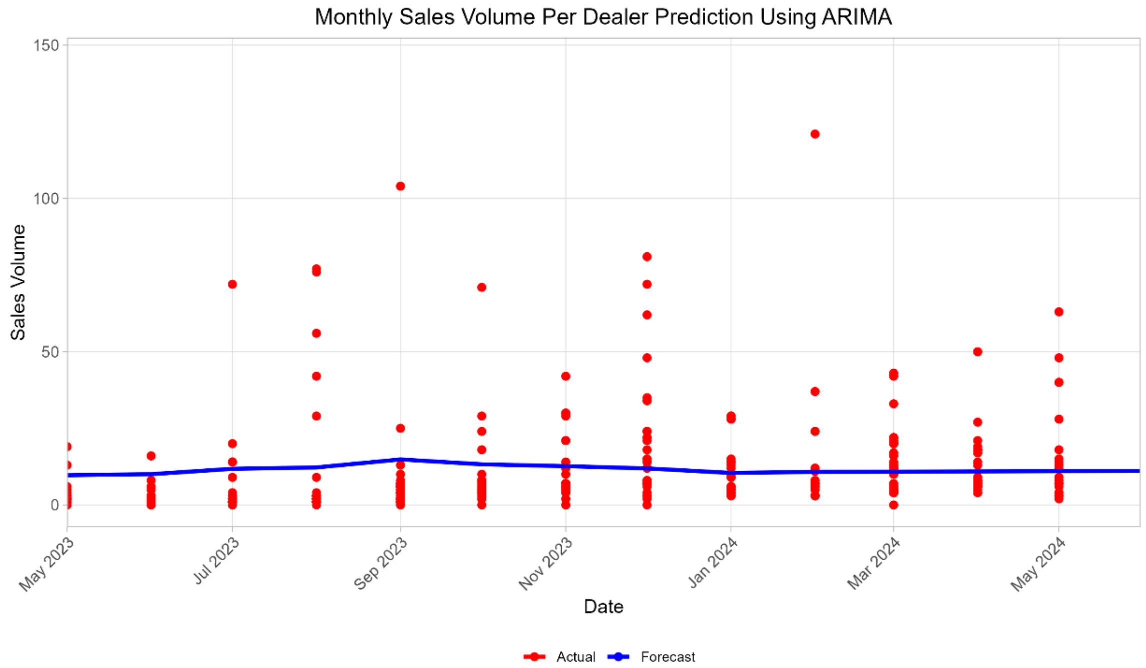
Appendix V.V. NPS Prediction Using Random Forest



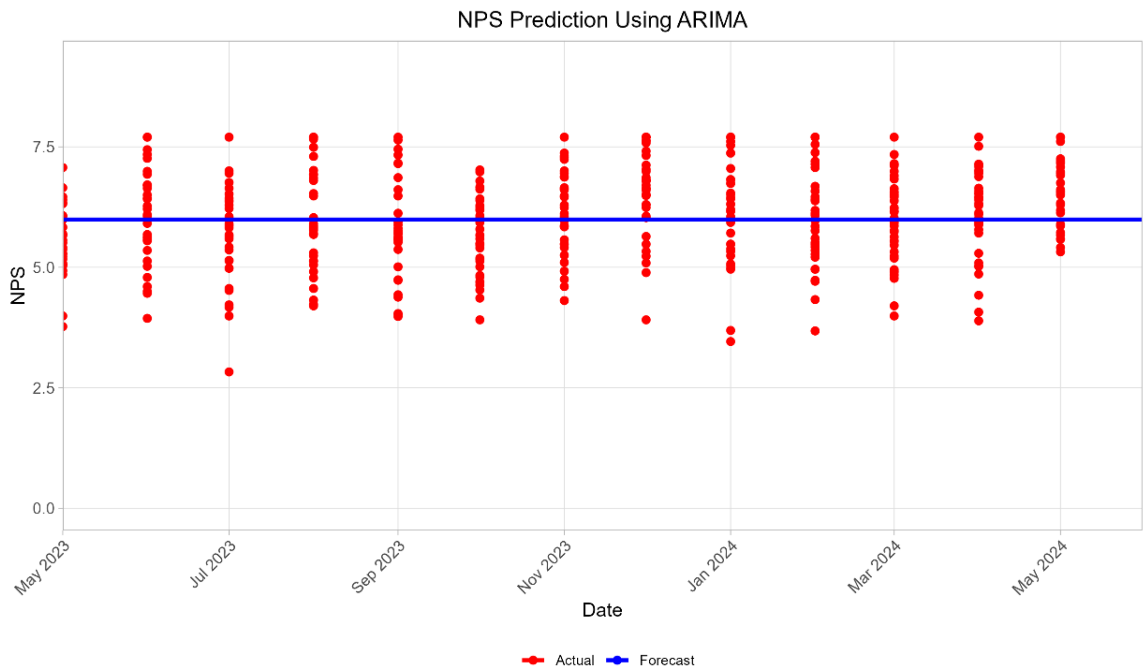
Appendix V.VI. DEA Efficiency Scores Prediction Using Random Forest



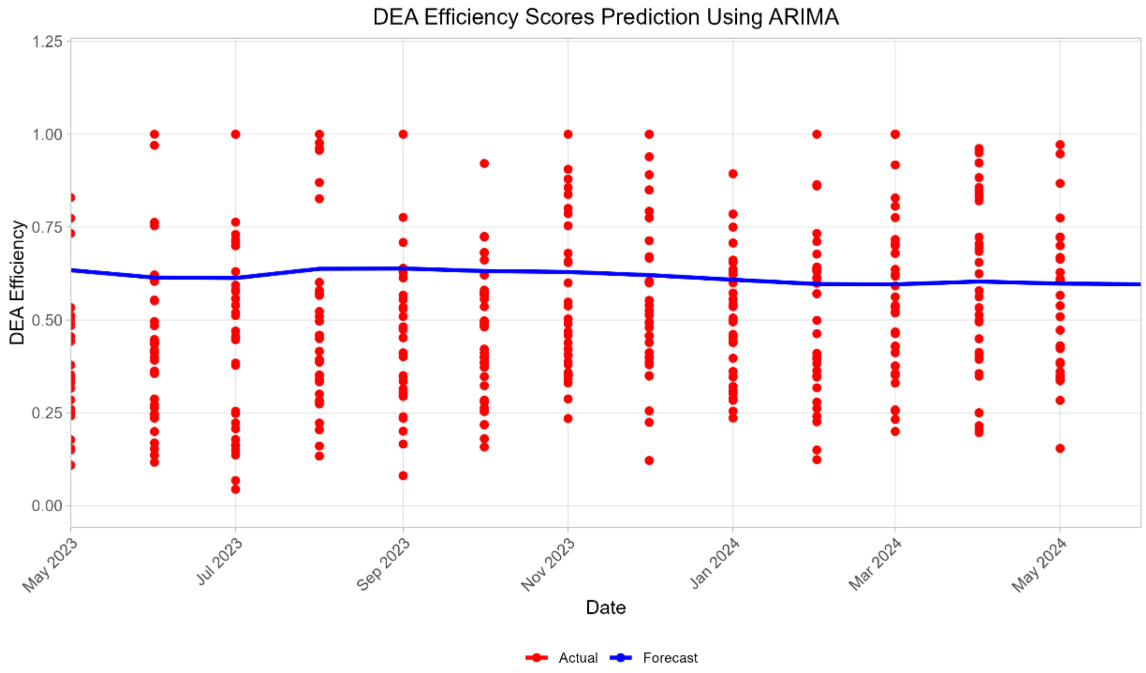
Appendix V.VII. Monthly Sales Volume Prediction Using ARIMA



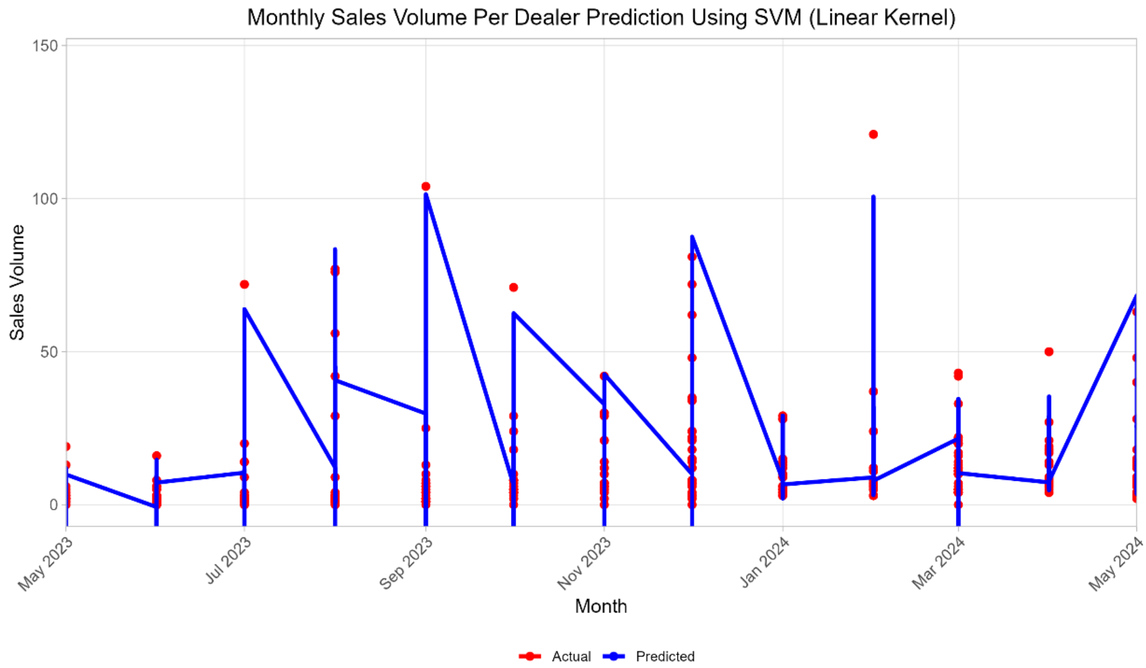
Appendix V.VIII. NPS Prediction Using ARIMA



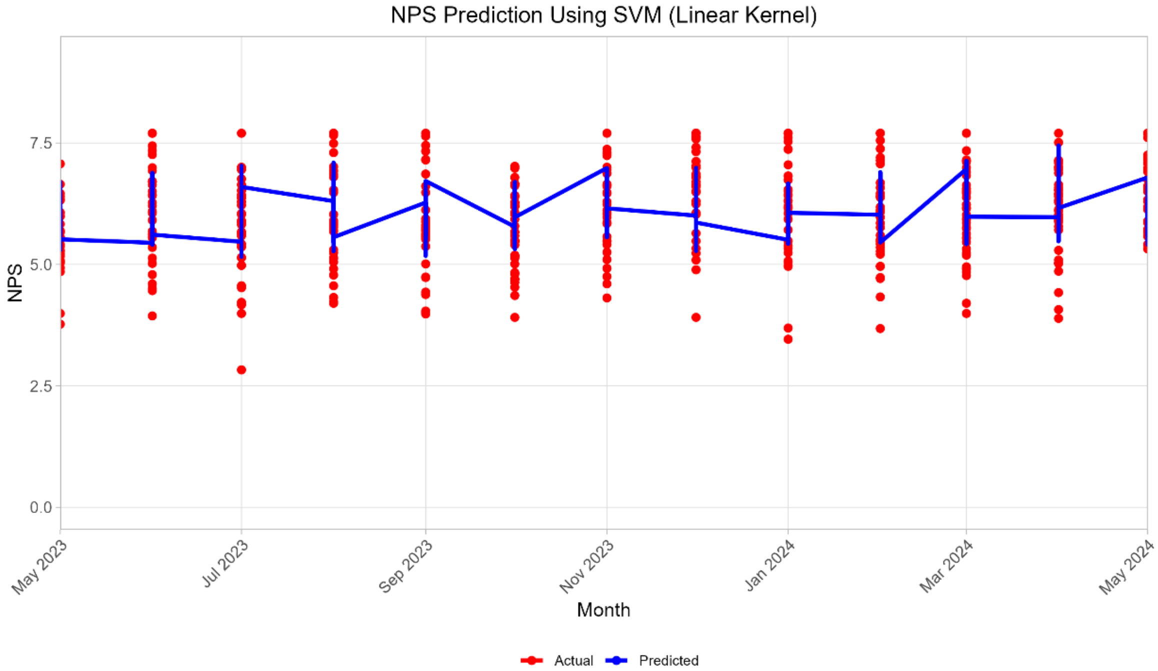
Appendix V.IX. DEA Efficiency Scores Prediction Using ARIMA



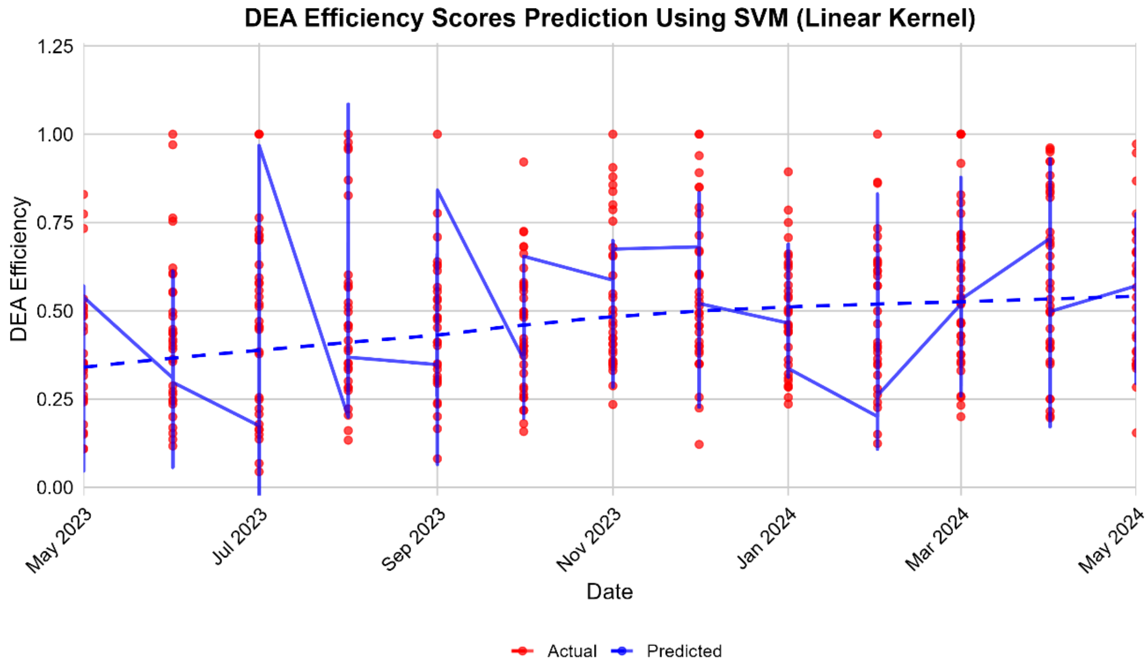
Appendix V.X. Monthly Sales Volume Prediction Using SVM



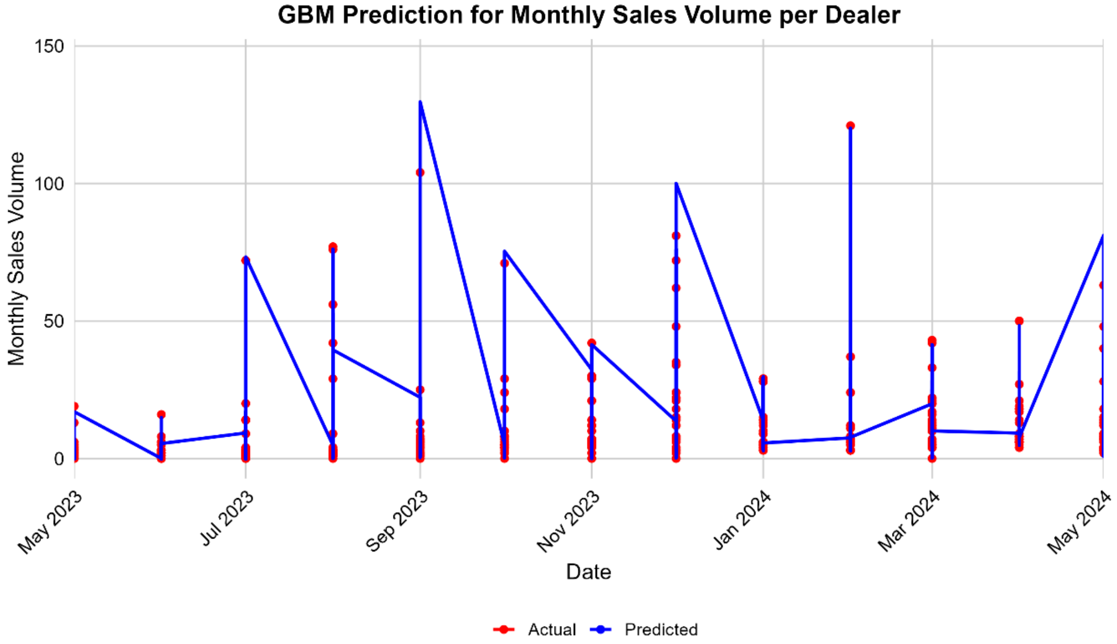
Appendix V.XI. NPS Prediction Using SVM



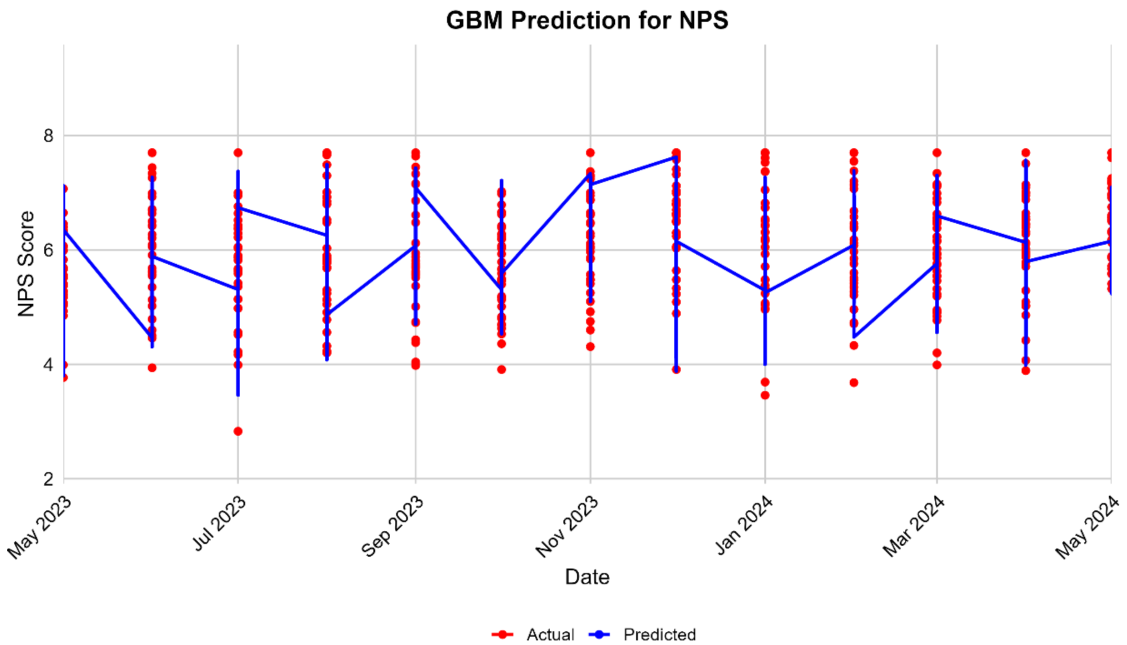
Appendix V.XII. DEA Efficiency Scores Prediction Using SVM



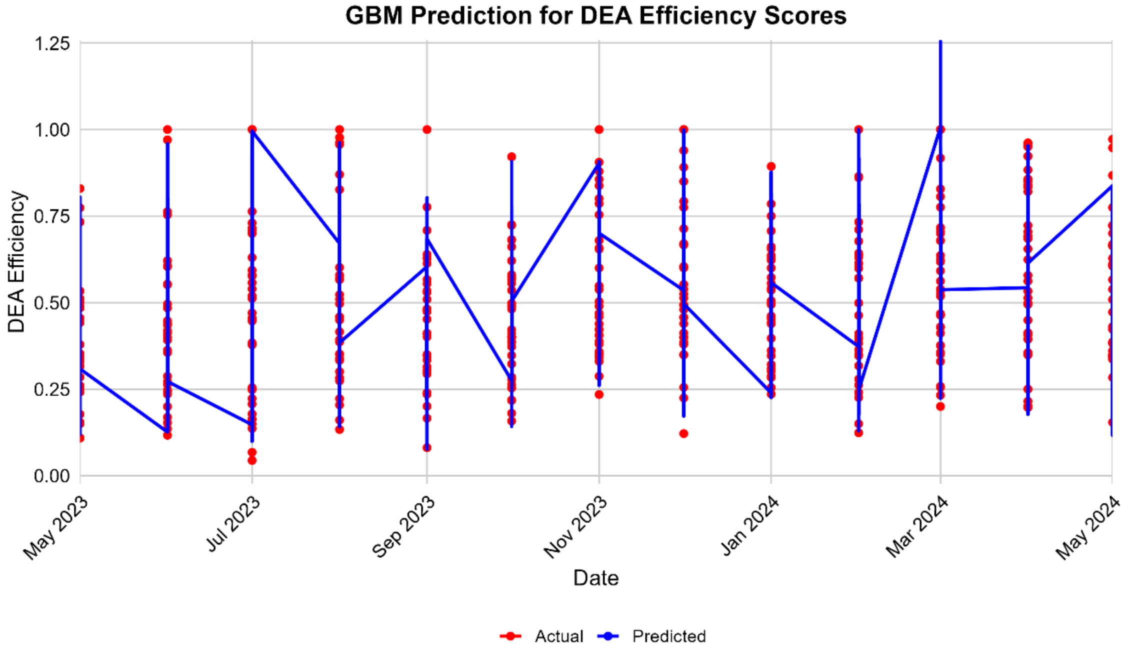
Appendix V.XIII. Monthly Sales Volume Prediction Using GBM



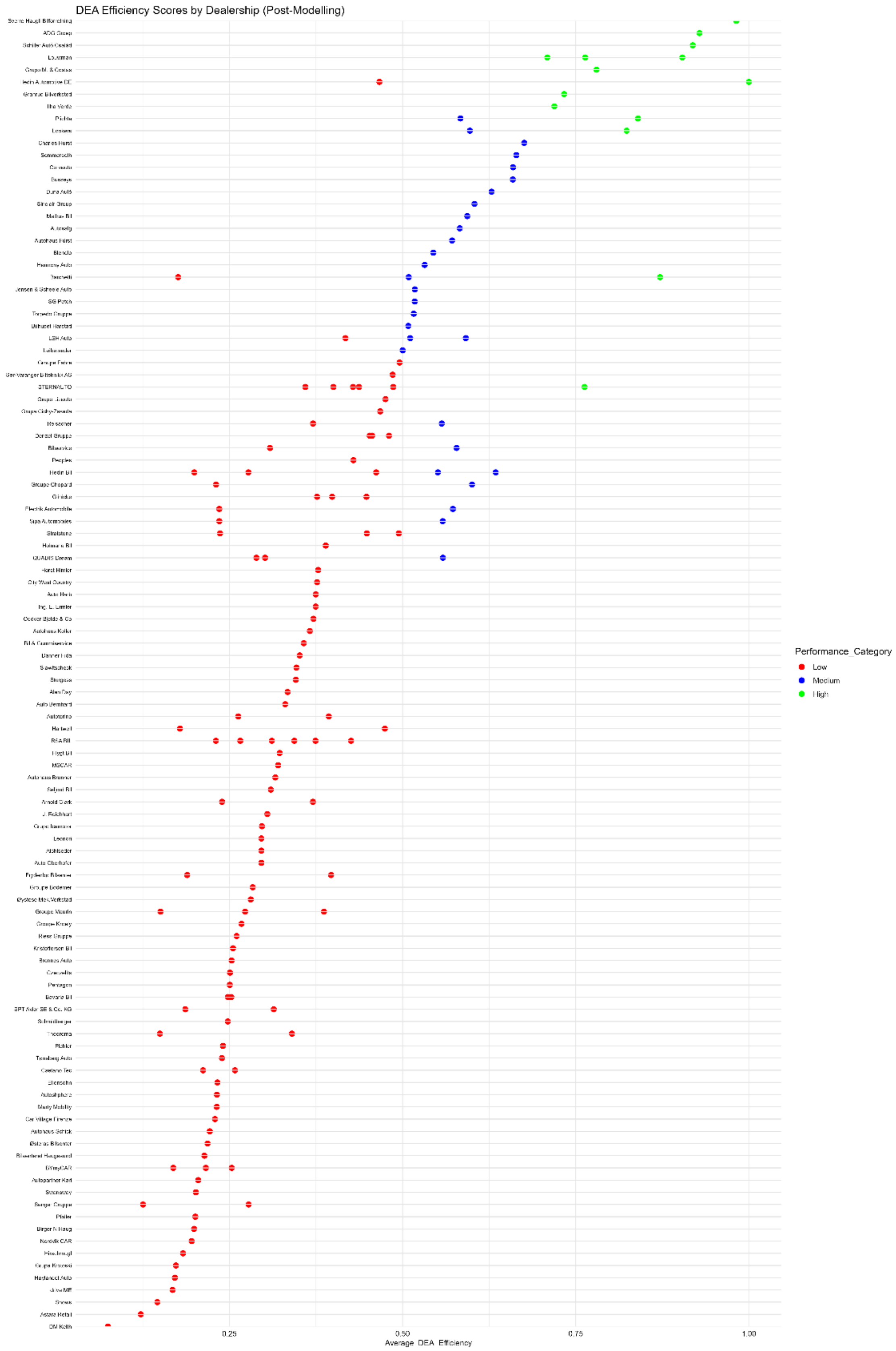
Appendix V.XIV. NPS Prediction Using GBM



Appendix V.XV. DEA Efficiency Scores Prediction Using GBM



Appendix VI. Average DEA Efficiency Scores for Every Dealership (Post-Modelling)



Appendix VII. Dealership Performance Data

Appendix VII.I. High Performing Dealerships

Dealership_Name	Country	Region	Average_DEA_ Efficiency	Regional_ Population_Density	Local_Economic_ Growth	Cultural_ Difference_Score	Regulatory_ Environment_Score	Performance_ Category
ADG Groep	Netherlands	Drenthe	0.928669781	0.03291714	0.252631579	0.1054	76.1	High
Barchetti	Italy	Veneto	0.871761273	0.049287032	0.363157895	0.1145	72.9	High
Granrud Bilverksted	Norway	Innlandet	0.733271709	0.001028661	0.294736842	0.0586	82.6	High
Grupo M. & Costas	Portugal	Norte (North)	0.779974228	0.030043984	0.4	0.0468	76.5	High
Hedin Automotive Dl	Germany	Rheinland-Pfalz	1	0.036889898	0.131578947	0.1682	79.7	High
Ilha Verde	Portugal	Açores (Azores)	0.719143399	0.018037032	0.463157895	0.0468	76.5	High
Lookers	UK	Yorkshire and The Humber	0.823520676	0.063564132	0.094736842	0.1211	83.5	High
Louwman	Netherlands	Noord-Brabant (North Brabant)	0.708947713	0.093022843	0.336842105	0.1054	76.1	High
Louwman	Netherlands	Noord-Holland (North Holland)	0.903846417	0.18849319	0.457894737	0.1054	76.1	High
Louwman	Netherlands	Zuid-Holland (South Holland)	0.763758042	0.232211266	0.289473684	0.1054	76.1	High
Plichta	Poland	Kujawsko-pomorskie (Kuyavian–Pomeranian)	0.839916888	0.019739642	0.363157895	0.1183	76.4	High
STERNAUTO	Germany	Thüringen (Thuringia)	0.762739289	0.022985244	0.168421053	0.1682	79.7	High
Schiller Autó Család	Hungary	Budapest	0.918956108	0.603770573	0.405263158	0.1522	73.4	High
Sverre Haugli Bilforre	Norway	Buskerud/Viken	0.981927526	0.003298808	0.221052632	0.0586	82.6	High

Appendix VII.II. Medium Performing Dealerships

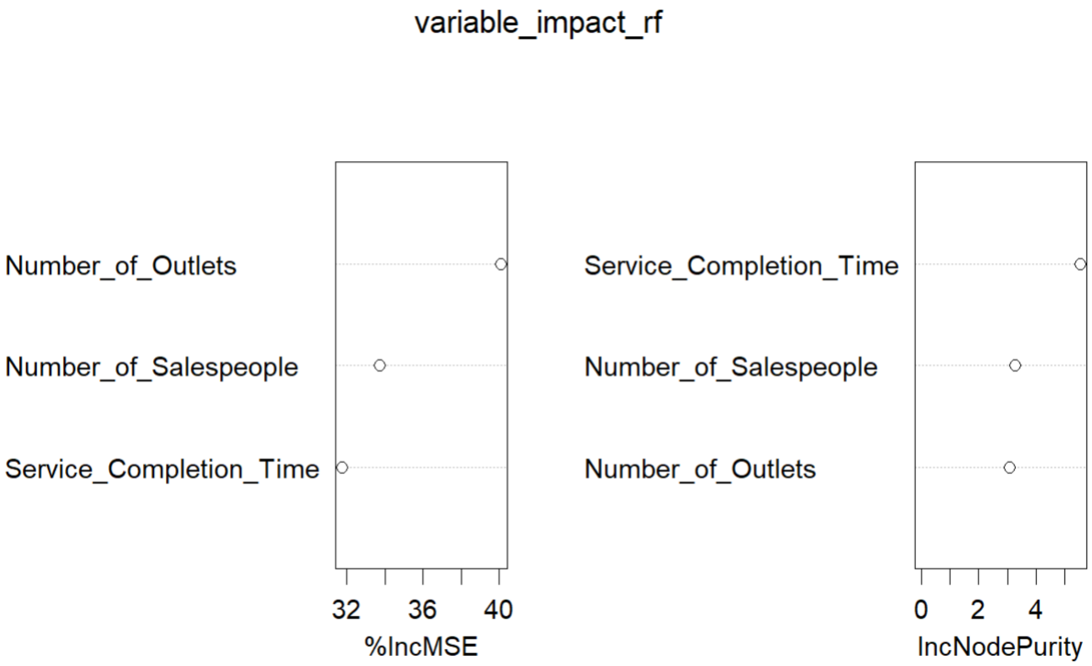
Dealership_Name	Country	Region	Average_DEA_ Efficiency	Regional_ Population_Density	Local_Economic_ Growth	Cultural_ Difference_Score	Regulatory_ Environment_Score	Performance_ Category
Autohaus Fürst	Austria	Burgenland	0.571552527	0.01376277	0.342105263	0.1068	78.7	Medium
Autosalg	Norway	Vestland	0.58260302	0.003103717	0.326315789	0.0586	82.6	Medium
Barchetti	Italy	Lombardia (Lombardy)	0.508939903	0.076351447	0.252631579	0.1145	72.9	Medium
Bilhuset Harstad	Norway	Troms	0.508285804	0.000886776	0.410526316	0.0586	82.6	Medium
Bilservice	Norway	Buskerud/Viken	0.578060145	0.003298808	0.221052632	0.0586	82.6	Medium
Blendio	Spain	País Vasco (Basque Country)	0.544518818	0.053898269	0.421052632	0.4165	77.9	Medium
Busseys	UK	East of England	0.659208307	0.05913025	0.068421053	0.1211	83.5	Medium
Charles Hurst	UK	Northern Ireland	0.675671296	0.024723326	0.105263158	0.1211	83.5	Medium
Corvauto	Portugal	Centro (Central)	0.659523038	0.013940125	0.305263158	0.0468	76.5	Medium
Duna Autó	Hungary	Budapest	0.628516628	0.603770573	0.405263158	0.1522	73.4	Medium
Electrik Automobile	France	Pays de la Loire	0.572696547	0.020644154	0.152631579	0.1032	76.8	Medium
Groupe Chopard	France	Provence-Alpes-Côte d'Azur	0.600356448	0.028447787	0.115789474	0.1032	76.8	Medium
Harmony Auto	UK	London	0.531976933	1	0.152631579	0.1211	83.5	Medium
Hedin Bil	Sweden	Småland och öarna (Småland and the islands)	0.551056011	0.004433882	0.184210526	0.06	82	Medium
Hedin Bil	Sweden	Västsverige (West Sweden)	0.634474809	0.012414869	0.363157895	0.06	82	Medium
Jensen & Scheele Auto	Norway	Østfold/Viken	0.51775121	0.013248439	0.221052632	0.0586	82.6	Medium
LSH Auto	UK	London	0.511094586	1	0.152631579	0.1211	83.5	Medium
LSH Auto	UK	North West	0.591304348	0.094246595	0.1	0.1211	83.5	Medium
Leibetseder	Austria	Oberösterreich (Upper Austria)	0.500140679	0.022630533	0.294736842	0.1068	78.7	Medium
Lookers	UK	North East	0.597222222	0.055228434	0.142105263	0.1211	83.5	Medium
Melhus Bil	Norway	Trøndelag	0.593421418	0.001844495	0.342105263	0.0586	82.6	Medium
Plichta	Poland	Pomorskie (Pomeranian)	0.583636364	0.02284336	0.415789474	0.1183	76.4	Medium
QUADIS Dream	Spain	Islas Baleares (Balearic Islands)	0.558251782	0.043132804	0.763157895	0.4165	77.9	Medium
Reisacher	Germany	Bayern (Bavaria)	0.556636227	0.033395999	0.147368421	0.1682	79.7	Medium
SG Petch	UK	North East	0.517509	0.055228434	0.142105263	0.1211	83.5	Medium
Sinclair Group	UK	Wales	0.603827373	0.026496879	0	0.1211	83.5	Medium
Sipa Automobiles	France	Nouvelle-Aquitaine	0.557977287	0.012308456	0.136842105	0.1032	76.8	Medium
Sommerseth	Norway	Nordland/Nordlánda	0.664277402	0.000886776	0.363157895	0.0586	82.6	Medium
Torpedo Gruppe	Germany	Hessen (Hesse)	0.516154807	0.053188848	0.110526316	0.1682	79.7	Medium

Appendix VII.III. Low Performing Dealerships

Dealership_Name	Country	Region	Average_DEA_ Efficiency	Regional_ Population_Density	Local_Economic_ Growth	Cultural_ Difference_Score	Regulatory_ Environment_Score	Performance_ Category
Aichlseder	Austria	Kärnten (Carinthia)	0.296190808	0.010446226	0.457894737	0.1068	78.7	Low
Alan Day	UK	London	0.334086422	1	0.152631579	0.1211	83.5	Low
Arnold Clark	UK	North East	0.37063271	0.055228434	0.142105263	0.1211	83.5	Low
Arnold Clark	UK	Scotland	0.23939922	0.012131101	0.089473684	0.1211	83.5	Low
Astara Retail	Spain	Comunidad de Madrid (Community of Madrid)	0.122095279	0.151461407	0.484210526	0.4165	77.9	Low
Auto Bernhard	Austria	Tirol (Tyrol)	0.330589618	0.010605846	0.6	0.1068	78.7	Low
Auto Harb	Austria	Steiermark (Styria)	0.37471571	0.013461266	0.289473684	0.1068	78.7	Low
Auto Oberhofer	Austria	Tirol (Tyrol)	0.296161428	0.010605846	0.6	0.1068	78.7	Low
Autohaus Brunner	Austria	Tirol (Tyrol)	0.316322008	0.010605846	0.6	0.1068	78.7	Low
Autohaus Koller	Austria	Niederösterreich (Lower Austria)	0.366179704	0.015749149	0.305263158	0.1068	78.7	Low
Autohaus Schick	Austria	Tirol (Tyrol)	0.221699544	0.010605846	0.6	0.1068	78.7	Low
Autopartner Karl	Austria	Niederösterreich (Lower Austria)	0.205025367	0.015749149	0.305263158	0.1068	78.7	Low
Autoshphere	France	Nouvelle-Aquitaine	0.232033346	0.012308456	0.136842105	0.1032	76.8	Low
Autotorino	Italy	Emilia-Romagna	0.393538813	0.0352937	0.278947368	0.1145	72.9	Low
Autotorino	Italy	Friuli-Venezia Giulia	0.262884655	0.027702894	0.310526316	0.1145	72.9	Low
BYmyCAR	France	Auvergne-Rhône-Alpes	0.168965139	0.019934733	0.147368421	0.1032	76.8	Low
BYmyCAR	France	Provence-Alpes-Côte d'Azur	0.25333906	0.028447787	0.115789474	0.1032	76.8	Low
BYmyCAR	France	Île-de-France	0.216022029	0.188244892	0.131578947	0.1032	76.8	Low
Barchetti	Italy	Trentino-Alto Adige (Trentino-Alto Adige/Südtirol)	0.176089108	0.015323496	0.394736842	0.1145	72.9	Low
Bavaria Bil	Sweden	Mellersta Norrland (Middle Norrland)	0.252751206	0.000656215	0.384210526	0.06	82	Low
Bavaria Bil	Sweden	Norra Mellansverige (North Middle Sweden)	0.24794362	0.002110528	0.305263158	0.06	82	Low
Bil & Gummiservice	Norway	Møre og Romsdal	0.357387759	0.002944098	0.478947368	0.0586	82.6	Low
Bilsenteret Haugesund	Norway	Rogaland	0.213930569	0.009311152	0.357894737	0.0586	82.6	Low
Bilservice	Norway	Vestfold	0.308647011	0.020555477	0.436842105	0.0586	82.6	Low
Birger N Haug	Norway	Oslo	0.199004985	0.281870743	0.331578947	0.0586	82.6	Low
Brennes Auto	Norway	Østfold/Viken	0.253179642	0.013248439	0.221052632	0.0586	82.6	Low
Caetano Tec	Portugal	Lisboa (Lisbon)	0.258069231	0.18178916	0.536842105	0.0468	76.5	Low
Caetano Tec	Spain	Andalucía (Andalusia)	0.211999988	0.017185726	0.378947368	0.4165	77.9	Low
Car Village Firenze	Italy	Toscana (Tuscany)	0.229189724	0.028199489	0.421052632	0.1145	72.9	Low
City West Country	UK	South West	0.376585522	0.042636209	0.126315789	0.1211	83.5	Low
Czeczelits	Austria	Niederösterreich (Lower Austria)	0.250915559	0.015749149	0.305263158	0.1068	78.7	Low
DM Keith	UK	Yorkshire and The Humber	0.074722149	0.063564132	0.094736842	0.1211	83.5	Low
Danner Fida	Austria	Oberösterreich (Upper Austria)	0.351507119	0.022630533	0.294736842	0.1068	78.7	Low
Denzel Gruppe	Austria	Niederösterreich (Lower Austria)	0.456108798	0.015749149	0.305263158	0.1068	78.7	Low
Denzel Gruppe	Austria	Steiermark (Styria)	0.480426576	0.013461266	0.289473684	0.1068	78.7	Low
Denzel Gruppe	Austria	Wien (Vienna)	0.452543158	0.876117338	0.305263158	0.1068	78.7	Low
Electrik Automobile	France	Bretagne	0.235431817	0.021353575	0.163157895	0.1032	76.8	Low
Ellensohn	Austria	Vorarlberg	0.232711056	0.028022134	0.310526316	0.1068	78.7	Low
Flygt Bil	Norway	Nordland/Nordlánda	0.322541417	0.000886776	0.363157895	0.0586	82.6	Low
Frydenbø Bilsenter	Norway	Agder	0.396846339	0.004558031	0.4	0.0586	82.6	Low
Frydenbø Bilsenter	Norway	Vestland	0.189086708	0.003103717	0.326315789	0.0586	82.6	Low
Glinicke	Germany	Hessen (Hesse)	0.398327751	0.053188848	0.110526316	0.1682	79.7	Low
Glinicke	Germany	Niedersachsen (Lower Saxony)	0.447882968	0.029990778	0.152631579	0.1682	79.7	Low
Glinicke	Germany	Nordrhein-Westfalen (North Rhine-Westphalia)	0.376599879	0.094211124	0.131578947	0.1682	79.7	Low
Groupe Bodemer	France	Pays de la Loire	0.283759198	0.020644154	0.152631579	0.1032	76.8	Low
Groupe Chopard	France	Auvergne-Rhône-Alpes	0.230785346	0.019934733	0.147368421	0.1032	76.8	Low
Groupe Fabre	France	Occitanie	0.495680675	0.014259364	0.157894737	0.1032	76.8	Low
Groupe Kroely	France	Grand Est	0.267472553	0.016848751	0.115789474	0.1032	76.8	Low
Groupe Maurin	France	Auvergne-Rhône-Alpes	0.272727273	0.019934733	0.147368421	0.1032	76.8	Low
Groupe Maurin	France	Occitanie	0.150528313	0.014259364	0.157894737	0.1032	76.8	Low
Groupe Maurin	France	Provence-Alpes-Côte d'Azur	0.386579067	0.028447787	0.115789474	0.1032	76.8	Low
Grupa Cichy-Zasada	Poland	Wielkopolskie (Greater Poland)	0.467745626	0.020520006	0.378947368	0.1183	76.4	Low
Grupa Krotoski	Poland	Warszawski Stołeczny (Warsaw Capital)	0.172839506	0.090823638	0.484210526	0.1183	76.4	Low
Grupo Icamotor	Spain	Canarias (Canary Islands)	0.297012449	0.053082435	0.615789474	0.4165	77.9	Low
Grupo Lizauto	Portugal	Centro (Central)	0.475384901	0.013940125	0.305263158	0.0468	76.5	Low
Hartwell	UK	East of England	0.178723404	0.05913025	0.068421053	0.1211	83.5	Low
Hartwell	UK	South East	0.474445311	0.086975028	0.1	0.1211	83.5	Low
Hedin Automotive DE	Germany	Baden-Württemberg	0.466544778	0.055902384	0.136842105	0.1682	79.7	Low
Hedin Bil	Sweden	Stockholm	0.19933881	0.065710131	0.184210526	0.06	82	Low
Hedin Bil	Sweden	Sydsverige (South Sweden)	0.277473988	0.019721907	0.194736842	0.06	82	Low
Hedin Bil	Sweden	Östra Mellansverige (East Middle Sweden)	0.461925057	0.007821368	0.326315789	0.06	82	Low
Hirschmugl	Austria	Steiermark (Styria)	0.183066791	0.013461266	0.289473684	0.1068	78.7	Low
Holmane Bil	Norway	Rogaland	0.389094467	0.009311152	0.357894737	0.0586	82.6	Low
Horst Himler	Austria	Steiermark (Styria)	0.378175143	0.013461266	0.289473684	0.1068	78.7	Low

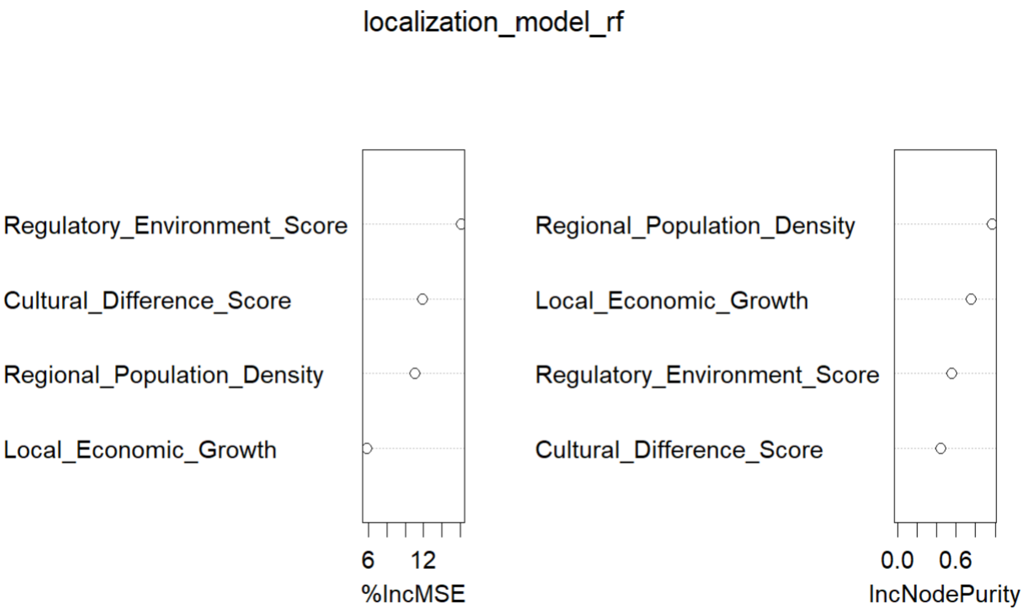
Dealership_Name	Country	Region	Average_DEA_ Efficiency	Regional_ Population_Density	Local_Economic_ Growth	Cultural_ Difference_Score	Regulatory_ Environment_Score	Performance_ Category
Høylandet Auto	Norway	Trøndelag	0.171309854	0.001844495	0.342105263	0.0586	82.6	Low
Ing. E. Ermler	Austria	Burgenland	0.37461864	0.01376277	0.342105263	0.1068	78.7	Low
J. Reichhart	Austria	Oberösterreich (Upper Austria)	0.304757587	0.022630533	0.294736842	0.1068	78.7	Low
Kristoffersen Bil	Norway	Trøndelag	0.255229017	0.001844495	0.342105263	0.0586	82.6	Low
LSH Auto	UK	West Midlands	0.41761507	0.081831725	0.073684211	0.1211	83.5	Low
Leonori	Italy	Lazio	0.296198402	0.059502696	0.3	0.1145	72.9	Low
MSCAR	Portugal	Algarve	0.320387833	0.016564983	1	0.0468	76.5	Low
Marty Mobility	Austria	Niederösterreich (Lower Austria)	0.231788123	0.015749149	0.305263158	0.1068	78.7	Low
Nordvik CAR	Norway	Nordland/Nordlánda	0.195511768	0.000886776	0.363157895	0.0586	82.6	Low
Oddvar Bjelde & Co	Norway	Vestland	0.37140665	0.003103717	0.326315789	0.0586	82.6	Low
Pentagon	UK	East Midlands	0.250636643	0.055760499	0.021052632	0.1211	83.5	Low
Peoples	UK	North West	0.429074228	0.094246595	0.1	0.1211	83.5	Low
Pfaller	Austria	Niederösterreich (Lower Austria)	0.200862444	0.015749149	0.305263158	0.1068	78.7	Low
Pichler	Austria	Oberösterreich (Upper Austria)	0.240642117	0.022630533	0.294736842	0.1068	78.7	Low
QUADIS Dream	Spain	Cataluña (Catalonia)	0.301571986	0.042937713	0.421052632	0.4165	77.9	Low
QUADIS Dream	Spain	Comunidad Valenciana (Valencian Community)	0.288992389	0.039160045	0.415789474	0.4165	77.9	Low
RSA BIL	Norway	Agder	0.230523743	0.004558031	0.4	0.0586	82.6	Low
RSA BIL	Norway	Akershus/Viken	0.374353693	0.023783343	0.221052632	0.0586	82.6	Low
RSA BIL	Norway	Oslo	0.343742101	0.281870743	0.331578947	0.0586	82.6	Low
RSA BIL	Norway	Rogaland	0.311267708	0.009311152	0.357894737	0.0586	82.6	Low
RSA BIL	Norway	Troms	0.42564268	0.000886776	0.410526316	0.0586	82.6	Low
RSA BIL	Norway	Østfold/Viken	0.265723029	0.013248439	0.221052632	0.0586	82.6	Low
Reisacher	Germany	Baden-Württemberg	0.370764737	0.055902384	0.136842105	0.1682	79.7	Low
Riess Gruppe	Germany	Baden-Württemberg	0.260424046	0.055902384	0.136842105	0.1682	79.7	Low
SPT Avior SE & Co. KG	Germany	Hamburg	0.314082838	0.467597191	0.105263158	0.1682	79.7	Low
SPT Avior SE & Co. KG	Germany	Niedersachsen (Lower Saxony)	0.186330109	0.029990778	0.152631579	0.1682	79.7	Low
STERNAUTO	Germany	Berlin	0.486474381	0.778820233	0.163157895	0.1682	79.7	Low
STERNAUTO	Germany	Brandenburg	0.428480157	0.015341232	0.147368421	0.1682	79.7	Low
STERNAUTO	Germany	Mecklenburg-Vorpommern	0.35965234	0.012450341	0.163157895	0.1682	79.7	Low
STERNAUTO	Germany	Sachsen (Saxony)	0.43720476	0.039372872	0.163157895	0.1682	79.7	Low
STERNAUTO	Germany	Sachsen-Anhalt (Saxony-Anhalt)	0.400218997	0.018799659	0.147368421	0.1682	79.7	Low
Schmidberger	Austria	Oberösterreich (Upper Austria)	0.247718993	0.022630533	0.294736842	0.1068	78.7	Low
Seljord Bil	Norway	Telemark	0.309858601	0.001879966	0.436842105	0.0586	82.6	Low
Senger Gruppe	Germany	Nordrhein-Westfalen (North Rhine-Westphalia)	0.125345732	0.094211124	0.131578947	0.1682	79.7	Low
Senger Gruppe	Germany	Schleswig-Holstein	0.277783278	0.033537883	0.152631579	0.1682	79.7	Low
Sipa Automobiles	France	Occitanie	0.235466008	0.014259364	0.157894737	0.1032	76.8	Low
Slawitscheck	Austria	Niederösterreich (Lower Austria)	0.34674784	0.015749149	0.305263158	0.1068	78.7	Low
Snows	UK	South East	0.145957253	0.086975028	0.1	0.1211	83.5	Low
Stratstone	UK	London	0.494496755	1	0.152631579	0.1211	83.5	Low
Stratstone	UK	South East	0.448343133	0.086975028	0.1	0.1211	83.5	Low
Stratstone	UK	West Midlands	0.236563874	0.081831725	0.073684211	0.1211	83.5	Low
Sturgess	UK	East Midlands	0.345993824	0.055760499	0.021052632	0.1211	83.5	Low
Swansway	UK	North West	0.201703704	0.094246595	0.1	0.1211	83.5	Low
Sør-Varanger Bilteknikk AS	Norway	Finnmark	0.485690874	0	0.410526316	0.0586	82.6	Low
Theorema	Italy	Liguria	0.340339156	0.049180619	0.378947368	0.1145	72.9	Low
Theorema	Italy	Piemonte (Piedmont)	0.149673727	0.029707009	0.247368421	0.1145	72.9	Low
Tønsberg Auto	Norway	Vestfold	0.239280744	0.020555477	0.436842105	0.0586	82.6	Low
drive ME	Austria	Oberösterreich (Upper Austria)	0.167893722	0.022630533	0.294736842	0.1068	78.7	Low
Østerås Bilsenter	Norway	Akershus/Viken	0.218487517	0.023783343	0.221052632	0.0586	82.6	Low
Øystese Mek.Verkstad	Norway	Vestland	0.280872503	0.003103717	0.326315789	0.0586	82.6	Low

Appendix VIII. Variable Importance of Internal Factors Using Random Forest

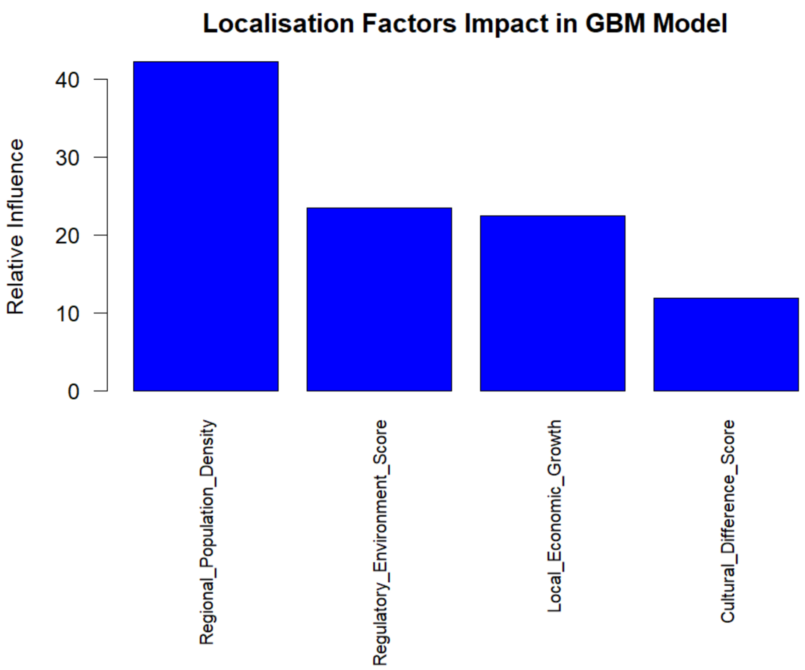


Appendix IX. The Results of Localisation Factors of Every Methods

Appendix IX.I. Impact of Localisation Factors Using Random Forest



Appendix IX.II. Impact of Localisation Factors Using GBM



Variables	Relative Importance (GBM)
Regional_Population_Density	42.62
Local_Economic_Growth	37.47
Regulatory_Environment_Score	11.73
Cultural_Difference_Score	8.18

Appendix X. Codes (Using R)

```
# Library Setup

```{r message=FALSE, warning=FALSE, include=FALSE}

options(error = recover)

library(readxl)

library(dplyr)

library(ggplot2)

library(fitdistrplus)

library(writexl)

library(caret)

library(randomForest)

library(e1071)

library(Metrics)

library(ROSE)

library(FSelector)

library(Benchmarking)

library(pROC)

library(randomForest)

library(gbm)

library(glmnet)

library(FSelectorRcpp)

library(infotheo)

library(forecast)

library(tseries)

library(lubridate)

library(reshape2)

library(gridExtra)

library(grid)

library(knitr)
```
```

library(kableExtra)

library(webshot)

library(ggpubr)

library(parallel)

library(foreach)

library(data.table)

library(tidyverse)

library(caTools)

library(tidyr)

library(mgcv)

library(ggcorrplot)

Read the Dataset File

```
# Set the seed for reproducibility
set.seed(123)

# Read the Excel dataset
data <- read_excel("BYD Dealership Data.xlsx", sheet = "Sheet1")
```

Pre-processing

```
# Clean column names by removing leading/trailing whitespace
colnames(data) <- trimws(colnames(data))

# Print the first few rows of the dataset to understand its structur
e
print(head(data))

# Check for missing values
missing_values <- colSums(is.na(data))
missing_values_table <- data.frame(Column = names(missing_values), M
issing_Values = missing_values)

# Print the table
print(missing_values_table)

# Save the table to Excel
write_xlsx(missing_values_table, "Missing Values.xlsx")

# Handle missing values by mean imputation (for numeric columns)
data <- data %>%
```

```
  mutate(`Monthly_Sales_Volume_per_Country` = ifelse(is.na(`Monthly_
Sales_Volume_per_Country`),
                                                            mean(`M
onthly_Sales_Volume_per_Country`, na.rm = TRUE),
                                                            `Monthl
y_Sales_Volume_per_Country`))

# Verify that there are no missing values left
missing_values_after <- colSums(is.na(data))
print(missing_values_after)

# Calculate outliers based on the IQR method
Q1 <- quantile(data$Monthly_Sales_Volume_per_Country, 0.25)
Q3 <- quantile(data$Monthly_Sales_Volume_per_Country, 0.75)
IQR_value <- Q3 - Q1

# Define the lower and upper bounds for outliers
lower_bound <- Q1 - 1.5 * IQR_value
upper_bound <- Q3 + 1.5 * IQR_value

# Identify the outliers
outliers <- data[data$Monthly_Sales_Volume_per_Country < lower_bound
| data$Monthly_Sales_Volume_per_Country > upper_bound, ]

# Check which countries and regions have outlier sales volumes
outlier_info <- outliers[, c("Country", "Region", "Monthly_Sales_Vol
ume_per_Country")]

# Print the outlier information
print(outlier_info)

# Create the boxplot for outlier identification
boxplot_outliers <- ggplot(data, aes(x = Country, y = `Monthly_Sales
_Volume_per_Country`)) +
  geom_boxplot() +
  ggtitle('Boxplot for Monthly Sales Volume per Country with Outlier
s') +
  theme(axis.text.x = element_text(angle = 90, hjust = 1))  # Rotate
x-axis labels for readability

print(boxplot_outliers)

# Save the boxplot to an image file
ggsave("Boxplot Outliers.png", plot = boxplot_outliers, device = "pn
g", width = 12, height = 8)

# Fit a normal distribution to the sales volume per country data
sales_volume <- data$`Monthly_Sales_Volume_per_Country`
fit <- fitdist(sales_volume, "norm")
mu <- fit$estimate['mean']
sigma <- fit$estimate['sd']
```

```
# Generate synthetic sales volume per Dealer
set.seed(42)  # for reproducibility
synthetic_country_sales <- rnorm(length(sales_volume), mean = mu, sd
= sigma)
synthetic_country_sales <- pmax(round(synthetic_country_sales), 0)
# Ensure non-negative integer values

# Ensure synthetic data adds up exactly and is non-negative
data <- data %>%
  group_by(Country, Year, Month) %>%
  mutate(
    synthetic_country_sales = synthetic_country_sales[match(paste(Co
untry, Year, Month),
                                                              paste(da
ta$Country, data$Year, data$Month))],
    proportional_sales = `Monthly_Sales_Volume_per_Country` * Number
_of_Outlets / sum(Number_of_Outlets),
    Monthly_Sales_Volume_per_Dealer = floor(proportional_sales),
    remaining_adjustment = `Monthly_Sales_Volume_per_Country` - sum(
Monthly_Sales_Volume_per_Dealer),
    adjustment = ifelse(row_number() <= remaining_adjustment, 1, 0),
    Monthly_Sales_Volume_per_Dealer = pmax(Monthly_Sales_Volume_per_
Dealer + adjustment, 0)
  ) %>%
  ungroup()

# Remove unnecessary columns by setting them to NULL
data <- data %>%
  mutate(synthetic_country_sales = NULL,
         proportional_sales = NULL,
         remaining_adjustment = NULL,
         adjustment = NULL)

# Generate Number_of_Salespeople using proportional scaling and numb
er of outlets
# Assume a base of 2 salespeople per outlet and scale proportionally
with sales volume
base_salespeople_per_outlet <- 2
units_per_salesperson <- 20
data <- data %>%
  mutate(Number_of_Salespeople = ceiling((Monthly_Sales_Volume_per_D
ealer / units_per_salesperson) +
                                         (Number_of_Outlets * base_s
alespeople_per_outlet)))

# Generate Service_Completion_Time using a Weibull distribution
# Assume shape parameter k = 1.5, scale parameter lambda = 25 (adjus
t these values based on insights)
shape_param <- 1.5  # Shape parameter
```

```
scale_param <- 2  # Scale parameter (assuming average service time a
round 2 hours)

# Generate Service_Completion_Time using a Weibull distribution in h
ours and round to 2 decimal places
data <- data %>%
  mutate(Service_Completion_Time = round(rweibull(n = n(), shape = s
hape_param, scale = scale_param), 2))

# Generate synthetic NPS using multiple factors including the genera
ted Service_Completion_Time
# Weights are arbitrary and should be adjusted based on actual data/
insights
# Adjust the weights to reflect a more realistic distribution of NPS
scores
data <- data %>%
  mutate(NPS_Score = pmin(5.0 +  # The baseline mean
                          0.002 * Monthly_Sales_Volume_per_Dealer -
                          0.1 * Service_Completion_Time +
                          0.01 * Local_Economic_Growth +
                          0.01 * Cultural_Difference_Score +
                          0.015 * Regulatory_Environment_Score +
                          rnorm(n(), mean = 0, sd = 1), 7.7))  # Adj
ust variability

# Ensure NPS_Score is within 0-10 range and round to 2 decimal place
s
data <- data %>%
  mutate(NPS_Score = round(pmax(pmin(NPS_Score, 7.7), 0), 2))

# Write the synthetic data to a new Excel file
output_file_path <- "BYD_Dealership_Data_Complete.xlsx"
write_xlsx(data, output_file_path)
```

Pre-analysis

Trend Analysis

```
# Convert Month column to numeric format if it contains month names
data <- data %>%
  mutate(Month = match(Month, month.name))

# Create a Date column from Year and Month
data <- data %>%
  mutate(Date = as.Date(paste(Year, Month, "01", sep = "-")))

# Plotting trends over time for Monthly Sales Volume per Country
trend_sales <- ggplot(data, aes(x = Date, y = `Monthly_Sales_Volume_
per_Country`)) +
```

```
  geom_line() +
  facet_wrap(~ Country, scales = "free_y") +
  ggtitle('Trend of Monthly Sales Volume per Country over Time') +
  xlab('Time') +
  ylab('Monthly Sales Volume per Country') +
  theme(axis.text.x = element_text(angle = 45, hjust = 1))

print(trend_sales)

# Save the trend plot to an image file
ggsave("Trend Monthly Sales Volume.png", plot = trend_sales, device
= "png")

## Saving 5 x 4 in image

# Plotting trends over time for NPS Scores
trend_nps_facet <- ggplot(data, aes(x = Date, y = NPS_Score)) +
  geom_line(aes(group = Dealership_Name), alpha = 0.5) +
  geom_smooth(se = FALSE, method = "loess", color = "blue") +
  facet_wrap(~ Country, scales = "free_y") +
  ggtitle('Trend of NPS over Time by Country') +
  xlab('Time') +
  ylab('NPS Score') +
  theme_minimal() +
  theme(axis.text.x = element_text(angle = 45, hjust = 1),
        strip.text = element_text(size = 10, face = "bold"))

print(trend_nps_facet)

## `geom_smooth()` using formula = 'y ~ x'

# Save the trend plot to an image file with a white background
ggsave("Trend NPS.png", plot = trend_nps_facet, device = "png", bg =
"white")

## Saving 5 x 4 in image
## `geom_smooth()` using formula = 'y ~ x'
```

Movement Analysis

```
# Plotting movement over time for Service Completion Time
movement_service_time <- ggplot(data, aes(x = Date, y = Service_Comp
letion_Time)) +
  geom_point(alpha = 0.6, size = 1) +  # Increase point size for bet
ter visibility
  geom_line(aes(group = Dealership_Name), alpha = 0.5) +
  geom_smooth(se = FALSE, method = "loess", color = "blue") +
  facet_wrap(~ Country, scales = "free_y") +
  ggtitle('Movement of Service Completion Time over Time by Country'
) +
  xlab('Time') +
```

```
  ylab('Service Completion Time (hours)') +
  theme_minimal() +
  theme(axis.text.x = element_text(angle = 45, hjust = 1),
        strip.text = element_text(size = 10, face = "bold"))

print(movement_service_time)

# Save the movement plot to an image file with a white background
ggsave("Movement Service Completion Time.png", plot = movement_servi
ce_time, device = "png", bg = "white")

# Plotting movement over time for Number of Salespeople
movement_salespeople <- ggplot(data, aes(x = Date, y = Number_of_Sal
espeople)) +
  geom_point(alpha = 0.6, size = 1) +  # Increase point size for bet
ter visibility
  geom_line(aes(group = Dealership_Name), alpha = 0.5) +
  geom_smooth(se = FALSE, method = "loess", color = "blue") +
  facet_wrap(~ Country, scales = "free_y") +
  ggtitle('Movement of Number of Salespeople over Time by Country')
+
  xlab('Time') +
  ylab('Number of Salespeople') +
  theme_minimal() +
  theme(axis.text.x = element_text(angle = 45, hjust = 1),
        strip.text = element_text(size = 10, face = "bold"))

print(movement_salespeople)

# Save the movement plot to an image file with a white background
ggsave("Movement Number of Salespeople.png", plot = movement_salespe
ople, device = "png", bg = "white")
```

Comparison Plots

```
# Bar plot for aggregate Monthly Sales Volume per Dealer by Region
agg_sales_region <- data %>%
  group_by(Region) %>%
  summarize(Aggregate_Sales = mean(Monthly_Sales_Volume_per_Dealer,
na.rm = TRUE)) %>%
  arrange(desc(Aggregate_Sales))

bar_sales_region <- ggplot(agg_sales_region, aes(x = reorder(Region,
Aggregate_Sales), y = Aggregate_Sales)) +
  geom_bar(stat = "identity", fill = "skyblue") +
  coord_flip() +
  ggtitle('Average Monthly Sales Volume per Dealer by Region') +
  xlab('Region') +
  ylab('Average Monthly Sales Volume per Dealer') +
  theme_minimal() +
```

```
  theme(axis.text.x = element_text(angle = 90, hjust = 1, size = 8),
        axis.text.y = element_text(size = 8),
        plot.title = element_text(hjust = 0.5))

print(bar_sales_region)

# Save the bar plot to an image file
ggsave("Bar Sales Volume by Region.png", plot = bar_sales_region, de
vice = "png", bg = "white", width = 10, height = 12)

# Bar plot for aggregate NPS Scores by Dealership
agg_nps_dealership <- data %>%
  group_by(Dealership_Name) %>%
  summarize(Aggregate_NPS = mean(NPS_Score, na.rm = TRUE)) %>%
  arrange(desc(Aggregate_NPS))

bar_nps_dealership <- ggplot(agg_nps_dealership, aes(x = reorder(Dea
lership_Name, Aggregate_NPS), y = Aggregate_NPS)) +
  geom_bar(stat = "identity", fill = "lightgreen") +
  coord_flip() +
  ggtitle('Average NPS by Dealership') +
  xlab('Dealership Name') +
  ylab('Average NPS') +
  theme_minimal() +
  theme(axis.text.x = element_text(angle = 90, hjust = 1, size = 8),
        axis.text.y = element_text(size = 8),
        plot.title = element_text(hjust = 0.5))

print(bar_nps_dealership)

# Save the bar plot to an image file
ggsave("Bar NPS by Dealership.png", plot = bar_nps_dealership, devic
e = "png", bg = "white", width = 10, height = 12)
```

Efficiency Analysis using DEA

```
# Convert data to data.table for faster operations
data <- as.data.table(data)

# Ensure relevant columns are numeric
data[, `:=`(Number_of_Salespeople = as.numeric(Number_of_Salespeople
),
            Number_of_Outlets = as.numeric(Number_of_Outlets),
            Local_Economic_Growth = as.numeric(Local_Economic_Growth
),
            Regional_Population_Density = as.numeric(Regional_Popula
tion_Density),
            Service_Completion_Time = as.numeric(Service_Completion_
Time),
```

```
            Monthly_Sales_Volume_per_Dealer = as.numeric(Monthly_Sal
es_Volume_per_Dealer),
            NPS_Score = as.numeric(NPS_Score),
            Monthly_Sales_Volume_per_Country = as.numeric(Monthly_Sa
les_Volume_per_Country))]

# Normalize data (optional, helps in better discrimination)
normalize <- function(x) {
  return((x - min(x)) / (max(x) - min(x)))
}

# Normalize inputs and outputs
data_normalized <- data[, .(
  Number_of_Salespeople = normalize(Number_of_Salespeople),
  Number_of_Outlets = normalize(Number_of_Outlets),
  Local_Economic_Growth = normalize(Local_Economic_Growth),
  Regional_Population_Density = normalize(Regional_Population_Densit
y),
  Service_Completion_Time = normalize(Service_Completion_Time),
  Monthly_Sales_Volume_per_Dealer = normalize(Monthly_Sales_Volume_p
er_Dealer),
  NPS_Score = normalize(NPS_Score),
  Monthly_Sales_Volume_per_Country = normalize(Monthly_Sales_Volume_
per_Country)
)]

# Define inputs and outputs for DEA using normalized data
inputs <- as.matrix(data_normalized[, .(Number_of_Salespeople, Numbe
r_of_Outlets,
                                        Local_Economic_Growth, Regio
nal_Population_Density,
                                        Service_Completion_Time)])
outputs <- as.matrix(data_normalized[, .(Monthly_Sales_Volume_per_De
aler, NPS_Score,
                                         Monthly_Sales_Volume_per_Co
untry)])

# Perform DEA analysis using CRS model for simplicity
dea_model <- dea(inputs, outputs, RTS = "crs", ORIENTATION = "in")

# Extract DEA efficiency scores
data[, DEA_Efficiency := dea_model$eff]
data <- as.data.frame(data)

# Plot 1: Distribution of DEA Efficiency Scores with White Backgroun
d
dea_efficiency_plot <- ggplot(data, aes(x = DEA_Efficiency)) +
  geom_histogram(binwidth = 0.05, fill = "blue", color = "white", al
pha = 0.7) +
```

```
  ggtitle("Distribution of DEA Efficiency Scores (Pre-Modelling)") +
  xlab("DEA Efficiency Score") +
  ylab("Frequency") +
  theme_minimal() +
  theme(
    plot.background = element_rect(fill = "white"),
    panel.background = element_rect(fill = "white", color = "white")
,
    panel.grid = element_line(color = "gray90"),
    plot.title = element_text(color = "black", size = 14, face = "bo
ld"),
    axis.title.x = element_text(color = "black", size = 12),
    axis.title.y = element_text(color = "black", size = 12),
    axis.text = element_text(color = "black")
  )

# Display the plot
print(dea_efficiency_plot)

# Save the plot as an image file with a white background
ggsave("DEA Efficiency Distribution Pre-Modelling.png", plot = dea_e
fficiency_plot, device = "png", bg = "white")

# Plot 2: Average DEA Efficiency by Country with White Background
# Aggregate average DEA Efficiency by Country
dea_efficiency_by_country <- data %>%
  group_by(Country) %>%
  summarize(Average_DEA_Efficiency = mean(DEA_Efficiency, na.rm = TR
UE))

# Create a bar plot of average DEA Efficiency by Country
dea_efficiency_country_plot <- ggplot(dea_efficiency_by_country, aes
(x = reorder(Country, Average_DEA_Efficiency), y = Average_DEA_Effic
iency)) +
  geom_bar(stat = "identity", fill = "skyblue") +
  coord_flip() +
  ggtitle("Average DEA Efficiency by Country (Pre-Modelling)") +
  xlab("Country") +
  ylab("Average DEA Efficiency Score") +
  theme_minimal() +
  theme(
    plot.background = element_rect(fill = "white"),
    panel.background = element_rect(fill = "white", color = "white")
,
    panel.grid = element_line(color = "gray90"),
    plot.title = element_text(color = "black", size = 14, face = "bo
ld"),
    axis.title.x = element_text(color = "black", size = 12),
    axis.title.y = element_text(color = "black", size = 12),
```

```
    axis.text = element_text(color = "black")
  )

# Display the plot
print(dea_efficiency_country_plot)

# Save the plot as an image file with a white background
ggsave("DEA Efficiency by Country Pre-Modelling.png", plot = dea_eff
iciency_country_plot, device = "png", bg = "white")
```

Predictive Modelling Preparation

```
# Engineer new features if necessary (Feature Engineering)
data <- data %>%
  mutate(Interaction_Term = Number_of_Salespeople * Number_of_Outlet
s,
         Polynomial_Term = I(Number_of_Salespeople^2))

# Display the first few rows to confirm changes
head(data)

# Set seed for reproducibility
set.seed(123)

# Create a single partition index for the training and test split
train_index <- createDataPartition(data$Monthly_Sales_Volume_per_Dea
ler, p = 0.8, list = FALSE)

# Split the dataset into training and test sets using the same index
train_data_sales <- data[train_index, ]
test_data_sales <- data[-train_index, ]

# Since 'data' contains all necessary columns, use the same index fo
r NPS and efficiency
train_data_nps <- data[train_index, ]  # No need to separate as data
is the same
test_data_nps <- data[-train_index, ]  # No need to separate as data
is the same

train_data_efficiency <- data[train_index, ]  # No need to separate
as data is the same
test_data_efficiency <- data[-train_index, ]  # No need to separate
as data is the same

# Verify that the dimensions are consistent
cat("Train Data Sales Dimensions:", dim(train_data_sales), "\n")

## Train Data Sales Dimensions: 1758 19

cat("Test Data Sales Dimensions:", dim(test_data_sales), "\n")
```

```
## Test Data Sales Dimensions: 439 19
cat("Train Data NPS Dimensions:", dim(train_data_nps), "\n")
## Train Data NPS Dimensions: 1758 19
cat("Test Data NPS Dimensions:", dim(test_data_nps), "\n")
## Test Data NPS Dimensions: 439 19
cat("Train Data Efficiency Dimensions:", dim(train_data_efficiency),
"\n")
## Train Data Efficiency Dimensions: 1758 19
cat("Test Data Efficiency Dimensions:", dim(test_data_efficiency), "
\n")
## Test Data Efficiency Dimensions: 439 19
# Validate that the train and test data have consistent sizes
stopifnot(
  nrow(train_data_sales) == nrow(train_data_nps),
  nrow(test_data_sales) == nrow(test_data_nps),
  nrow(train_data_sales) == nrow(train_data_efficiency),
  nrow(test_data_sales) == nrow(test_data_efficiency)
)
```

Predictive Modelling: Linear Regression

```
# Feature selection using information gain for each target

# For Monthly Sales Volume per Dealer
weights_sales <- information.gain(Monthly_Sales_Volume_per_Dealer ~
., data = train_data_sales)
weights_sales$Feature <- rownames(weights_sales)
weights_sales <- weights_sales[order(weights_sales$attr_importance,
decreasing = TRUE), ]

# For NPS Score
weights_nps <- information.gain(NPS_Score ~ ., data = train_data_nps
)
weights_nps$Feature <- rownames(weights_nps)
weights_nps <- weights_nps[order(weights_nps$attr_importance, decrea
sing = TRUE), ]

# For DEA Efficiency
weights_efficiency <- information.gain(DEA_Efficiency ~ ., data = tr
ain_data_efficiency)
weights_efficiency$Feature <- rownames(weights_efficiency)
weights_efficiency <- weights_efficiency[order(weights_efficiency$at
```

```
tr_importance, decreasing = TRUE), ]

# Filter features with significant information gain

# For Monthly Sales Volume per Dealer
significant_features_sales <- filter(weights_sales, attr_importance
> 0.001)$Feature
modeling_data_sales <- train_data_sales[, significant_features_sales
, drop = FALSE]
modeling_data_sales$Monthly_Sales_Volume_per_Dealer <- train_data_sa
les$Monthly_Sales_Volume_per_Dealer

# For NPS Score
significant_features_nps <- filter(weights_nps, attr_importance > 0.
001)$Feature
modeling_data_nps <- train_data_nps[, significant_features_nps, drop
= FALSE]
modeling_data_nps$NPS_Score <- train_data_nps$NPS_Score

# For DEA Efficiency
significant_features_efficiency <- filter(weights_efficiency, attr_i
mportance > 0.001)$Feature
modeling_data_efficiency <- train_data_efficiency[, significant_feat
ures_efficiency, drop = FALSE]
modeling_data_efficiency$DEA_Efficiency <- train_data_efficiency$DEA
_Efficiency

# Print out the significant features for each model
cat("Significant Features for Sales Volume:\n")

## Significant Features for Sales Volume:

print(significant_features_sales)

cat("\nSignificant Features for NPS Score:\n")

##
## Significant Features for NPS Score:

print(significant_features_nps)

## [1] "Dealership_Name" "Region"          "DEA_Efficiency"  "Countr
y"

cat("\nSignificant Features for DEA Efficiency:\n")

##
## Significant Features for DEA Efficiency:

print(significant_features_efficiency)
```

```
# Define hyperparameter grid for tuning
tune_grid <- expand.grid(.alpha = seq(0, 1, length = 10), .lambda =
seq(0.0001, 0.1, length = 10))

# K-fold Cross-Validation
control <- trainControl(method = "cv", number = 10)
```

Linear Regression for Sales Volume

```
# Hyperparameter tuning for Sales Volume
model_sales_tuned <- train(Monthly_Sales_Volume_per_Dealer ~ ., data
= modeling_data_sales, method = "glmnet", tuneGrid = tune_grid, trCo
ntrol = control)
print(model_sales_tuned)

# Make predictions on the test set using the tuned model
pred_sales_tuned <- predict(model_sales_tuned, test_data_sales)

# Evaluate the tuned model using MAE and RMSE
train_mae_sales_tuned <- mae(train_data_sales$Monthly_Sales_Volume_p
er_Dealer, predict(model_sales_tuned, train_data_sales))
test_mae_sales_tuned <- mae(test_data_sales$Monthly_Sales_Volume_per
_Dealer, pred_sales_tuned)
train_rmse_sales_tuned <- rmse(train_data_sales$Monthly_Sales_Volume
_per_Dealer, predict(model_sales_tuned, train_data_sales))
test_rmse_sales_tuned <- rmse(test_data_sales$Monthly_Sales_Volume_p
er_Dealer, pred_sales_tuned)

print(paste("Train MAE Sales (Tuned): ", train_mae_sales_tuned))

## [1] "Train MAE Sales (Tuned):  2.07639527078427"

print(paste("Test MAE Sales (Tuned): ", test_mae_sales_tuned))

## [1] "Test MAE Sales (Tuned):  2.28680158430111"

print(paste("Train RMSE Sales (Tuned): ", train_rmse_sales_tuned))

## [1] "Train RMSE Sales (Tuned):  3.02918835166912"

print(paste("Test RMSE Sales (Tuned): ", test_rmse_sales_tuned))

## [1] "Test RMSE Sales (Tuned):  3.14948900598878"

# Contextualization of MAE and RMSE for Sales Volume
mean_sales <- mean(test_data_sales$Monthly_Sales_Volume_per_Dealer)
train_mae_sales_pct_tuned <- (train_mae_sales_tuned / mean_sales) *
100
test_mae_sales_pct_tuned <- (test_mae_sales_tuned / mean_sales) * 10
0
train_rmse_sales_pct_tuned <- (train_rmse_sales_tuned / mean_sales)
* 100
```

```
test_rmse_sales_pct_tuned <- (test_rmse_sales_tuned / mean_sales) *
100

print(paste("Train MAE as a percentage of Mean Sales (Tuned): ", tra
in_mae_sales_pct_tuned))

## [1] "Train MAE as a percentage of Mean Sales (Tuned):  20.3015038
724787"

print(paste("Test MAE as a percentage of Mean Sales (Tuned): ", test
_mae_sales_pct_tuned))

## [1] "Test MAE as a percentage of Mean Sales (Tuned):  22.35870591
33226"

print(paste("Train RMSE as a percentage of Mean Sales (Tuned): ", tr
ain_rmse_sales_pct_tuned))

## [1] "Train RMSE as a percentage of Mean Sales (Tuned):  29.617231
3225555"

print(paste("Test RMSE as a percentage of Mean Sales (Tuned): ", tes
t_rmse_sales_pct_tuned))

## [1] "Test RMSE as a percentage of Mean Sales (Tuned):  30.7934448
469727"

# Visualization for Sales Volume Prediction
results_sales_tuned <- data.frame(Actual = test_data_sales$Monthly_S
ales_Volume_per_Dealer, Predicted = pred_sales_tuned)
plot_sales <- ggplot(results_sales_tuned, aes(x = Actual, y = Predic
ted)) +
  geom_point(color = 'blue', alpha = 0.5) +
  geom_abline(slope = 1, intercept = 0, color = 'red', linetype = 'd
ashed') +
  ggtitle('Monthly Sales Volume Per Dealer: Actual vs Predicted (Lin
ear Regression)') +
  xlab('Actual Sales Volume') +
  ylab('Predicted Sales Volume') +
  theme_minimal(base_family = "Arial", base_size = 14) +
  theme(
    panel.background = element_rect(fill = "white"),
    plot.background = element_rect(fill = "white"),
    legend.background = element_rect(fill = "white"),
    legend.key = element_rect(fill = "white"),
    strip.background = element_rect(fill = "white")
  )
print(plot_sales)

# Save Sales Volume plot
ggsave("Sales Volume Prediction LR.png", plot = plot_sales, width =
10, height = 6)
```

Linear Regression for NPS

```
# Hyperparameter tuning for NPS
model_nps_tuned <- train(NPS_Score ~ ., data = modeling_data_nps, me
thod = "glmnet", tuneGrid = tune_grid, trControl = control)
print(model_nps_tuned)

# Make predictions on the test set using the tuned model
pred_nps_tuned <- predict(model_nps_tuned, test_data_nps)

# Evaluate the tuned model using MAE and RMSE
train_mae_nps_tuned <- mae(train_data_nps$NPS_Score, predict(model_n
ps_tuned, train_data_nps))
test_mae_nps_tuned <- mae(test_data_nps$NPS_Score, pred_nps_tuned)
train_rmse_nps_tuned <- rmse(train_data_nps$NPS_Score, predict(model
_nps_tuned, train_data_nps))
test_rmse_nps_tuned <- rmse(test_data_nps$NPS_Score, pred_nps_tuned)

print(paste("Train MAE NPS (Tuned): ", train_mae_nps_tuned))

## [1] "Train MAE NPS (Tuned):  0.645623906799354"

print(paste("Test MAE NPS (Tuned): ", test_mae_nps_tuned))

## [1] "Test MAE NPS (Tuned):  0.650434929565623"

print(paste("Train RMSE NPS (Tuned): ", train_rmse_nps_tuned))

## [1] "Train RMSE NPS (Tuned):  0.809883248237703"

print(paste("Test RMSE NPS (Tuned): ", test_rmse_nps_tuned))

## [1] "Test RMSE NPS (Tuned):  0.835360160121599"

# Contextualization of MAE and RMSE for NPS
mean_nps <- mean(test_data_nps$NPS_Score)
train_mae_nps_pct_tuned <- (train_mae_nps_tuned / mean_nps) * 100
test_mae_nps_pct_tuned <- (test_mae_nps_tuned / mean_nps) * 100
train_rmse_nps_pct_tuned <- (train_rmse_nps_tuned / mean_nps) * 100
test_rmse_nps_pct_tuned <- (test_rmse_nps_tuned / mean_nps) * 100

print(paste("Train MAE as a percentage of Mean NPS (Tuned): ", train
_mae_nps_pct_tuned))

## [1] "Train MAE as a percentage of Mean NPS (Tuned):  10.748034534
4921"

print(paste("Test MAE as a percentage of Mean NPS (Tuned): ", test_m
ae_nps_pct_tuned))

## [1] "Test MAE as a percentage of Mean NPS (Tuned):  10.8281261145
8"
```

```
print(paste("Train RMSE as a percentage of Mean NPS (Tuned): ", trai
n_rmse_nps_pct_tuned))
```

```
## [1] "Train RMSE as a percentage of Mean NPS (Tuned):  13.48254460
42082"
```

```
print(paste("Test RMSE as a percentage of Mean NPS (Tuned): ", test_
rmse_nps_pct_tuned))
```

```
## [1] "Test RMSE as a percentage of Mean NPS (Tuned):  13.906671910
9522"
```

```
# Visualization for NPS Prediction
results_nps_tuned <- data.frame(Actual = test_data_nps$NPS_Score, Pr
edicted = pred_nps_tuned)
plot_nps <- ggplot(results_nps_tuned, aes(x = Actual, y = Predicted)
) +
  geom_point(color = 'blue', alpha = 0.5) +
  geom_abline(slope = 1, intercept = 0, color = 'red', linetype = 'd
ashed') +
  ggtitle('NPS: Actual vs Predicted (Linear Regression)') +
  xlab('Actual NPS') +
  ylab('Predicted NPS') +
  theme_minimal(base_family = "Arial", base_size = 14) +
  theme(
    panel.background = element_rect(fill = "white"),
    plot.background = element_rect(fill = "white"),
    legend.background = element_rect(fill = "white"),
    legend.key = element_rect(fill = "white"),
    strip.background = element_rect(fill = "white")
  )
print(plot_nps)

# Save NPS plot
ggsave("NPS Prediction LR.png", plot = plot_nps, width = 10, height
= 6)
```

Linear Regression for Efficiency

```
# Hyperparameter tuning for Efficiency
model_efficiency_tuned <- train(DEA_Efficiency ~ ., data = modeling_
data_efficiency, method = "glmnet", tuneGrid = tune_grid, trControl
= control)
print(model_efficiency_tuned)

# Make predictions on the test set using the tuned model
pred_efficiency_tuned <- predict(model_efficiency_tuned, test_data_e
fficiency)

# Evaluate the tuned model using MAE and RMSE
train_mae_efficiency_tuned <- mae(train_data_efficiency$DEA_Efficien
```

```
cy, predict(model_efficiency_tuned, train_data_efficiency))
test_mae_efficiency_tuned <- mae(test_data_efficiency$DEA_Efficiency
, pred_efficiency_tuned)
train_rmse_efficiency_tuned <- rmse(train_data_efficiency$DEA_Effici
ency, predict(model_efficiency_tuned, train_data_efficiency))
test_rmse_efficiency_tuned <- rmse(test_data_efficiency$DEA_Efficien
cy, pred_efficiency_tuned)

print(paste("Train MAE Efficiency (Tuned): ", train_mae_efficiency_t
uned))

## [1] "Train MAE Efficiency (Tuned):  0.0741291532489542"

print(paste("Test MAE Efficiency (Tuned): ", test_mae_efficiency_tun
ed))

## [1] "Test MAE Efficiency (Tuned):  0.0745621877581563"

print(paste("Train RMSE Efficiency (Tuned): ", train_rmse_efficiency
_tuned))

## [1] "Train RMSE Efficiency (Tuned):  0.0999637265506097"

print(paste("Test RMSE Efficiency (Tuned): ", test_rmse_efficiency_t
uned))

## [1] "Test RMSE Efficiency (Tuned):  0.100592918218228"

# Contextualization of MAE and RMSE for Efficiency
mean_efficiency <- mean(test_data_efficiency$DEA_Efficiency)
train_mae_efficiency_pct_tuned <- (train_mae_efficiency_tuned / mean
_efficiency) * 100
test_mae_efficiency_pct_tuned <- (test_mae_efficiency_tuned / mean_e
fficiency) * 100
train_rmse_efficiency_pct_tuned <- (train_rmse_efficiency_tuned / me
an_efficiency) * 100
test_rmse_efficiency_pct_tuned <- (test_rmse_efficiency_tuned / mean
_efficiency) * 100

print(paste("Train MAE as a percentage of Mean Efficiency (Tuned): "
, train_mae_efficiency_pct_tuned))

## [1] "Train MAE as a percentage of Mean Efficiency (Tuned):  14.69
8696582262"

print(paste("Test MAE as a percentage of Mean Efficiency (Tuned): ",
test_mae_efficiency_pct_tuned))

## [1] "Test MAE as a percentage of Mean Efficiency (Tuned):  14.784
5608149079"

print(paste("Train RMSE as a percentage of Mean Efficiency (Tuned):
", train_rmse_efficiency_pct_tuned))
```

```
## [1] "Train RMSE as a percentage of Mean Efficiency (Tuned):  19.8
213040538184"
```

```r
print(paste("Test RMSE as a percentage of Mean Efficiency (Tuned): "
, test_rmse_efficiency_pct_tuned))
```

```
## [1] "Test RMSE as a percentage of Mean Efficiency (Tuned):  19.94
6063301821"
```

```r
# Visualization for Efficiency Prediction
results_efficiency_tuned <- data.frame(Actual = test_data_efficiency
$DEA_Efficiency, Predicted = pred_efficiency_tuned)
plot_efficiency <- ggplot(results_efficiency_tuned, aes(x = Actual,
y = Predicted)) +
  geom_point(color = 'blue', alpha = 0.5) +
  geom_abline(slope = 1, intercept = 0, color = 'red', linetype = 'd
ashed') +
  ggtitle('DEA Efficiency Scores: Actual vs Predicted (Linear Regres
sion)') +
  xlab('Actual Efficiency') +
  ylab('Predicted Efficiency') +
  theme_minimal(base_family = "Arial", base_size = 14) +
  theme(
    panel.background = element_rect(fill = "white"),
    plot.background = element_rect(fill = "white"),
    legend.background = element_rect(fill = "white"),
    legend.key = element_rect(fill = "white"),
    strip.background = element_rect(fill = "white")
  )
print(plot_efficiency)

# Save Efficiency plot
ggsave("Efficiency Prediction LR.png", plot = plot_efficiency, width
= 10, height = 6)
```

Predictive Modelling: Random Forest

Random Forest for Sales Volume

```r
# Set seed for reproducibility
set.seed(123)

# Feature Selection using Random Forest for Sales Volume Prediction
# Build a preliminary Random Forest model for Sales Volume
rf_model_prel_sales <- randomForest(Monthly_Sales_Volume_per_Dealer
~ ., data = train_data_sales, ntree = 100, importance = TRUE)

# Get variable importance for Sales Volume
var_importance_sales <- importance(rf_model_prel_sales)
```

```
# Create a data frame with feature importance for Sales Volume
importance_df_sales <- data.frame(Feature = rownames(var_importance_
sales), Importance = var_importance_sales[, "IncNodePurity"])

# Filter features with significant importance for Sales Volume
significant_features_rf_sales <- importance_df_sales %>%
  filter(Importance > quantile(Importance, 0.25)) %>%  # Retain top
75% important features
  pull(Feature)

# Select columns using the significant features vector for Sales Vol
ume
modeling_data_sales_rf <- train_data_sales[, significant_features_rf
_sales, drop = FALSE]

# Add the target variable back to the modeling data
modeling_data_sales_rf$Monthly_Sales_Volume_per_Dealer <- train_data
_sales$Monthly_Sales_Volume_per_Dealer

# Print the selected features for modeling
print("Selected Features for Sales Volume Prediction:")

## [1] "Selected Features for Sales Volume Prediction:"

print(significant_features_rf_sales)

##  [1] "Country"                          "Number_of_Outlets"
##  [3] "Month"                            "Monthly_Sales_Volume_per
_Country"
##  [5] "Regional_Population_Density"      "Cultural_Difference_Scor
e"
##  [7] "Regulatory_Environment_Score"     "Number_of_Salespeople"
##  [9] "Service_Completion_Time"          "Date"
## [11] "DEA_Efficiency"                   "Interaction_Term"
## [13] "Polynomial_Term"

# Define a hyperparameter grid for tuning only mtry
tune_grid_rf_sales <- expand.grid(
  mtry = seq(2, length(significant_features_rf_sales), by = 2) # Use
length(significant_features_rf_sales) to dynamically adapt to number
of features
)

# K-fold Cross-Validation setup
control_rf_sales <- trainControl(method = "cv", number = 10)

# Train Random Forest model with hyperparameter tuning for sales vol
ume
rf_model_tuned_sales <- train(
  Monthly_Sales_Volume_per_Dealer ~ .,
```

```r
  data = modeling_data_sales_rf,
  method = "rf",
  tuneGrid = tune_grid_rf_sales,
  trControl = control_rf_sales,
  ntree = 200,  # Set ntree directly in the train function
  importance = TRUE
)

# Print the best model from tuning
print("Best Random Forest Model for Sales Volume Prediction:")

## [1] "Best Random Forest Model for Sales Volume Prediction:"

print(rf_model_tuned_sales)

## Random Forest
##
## 1758 samples
##   13 predictor
##
## No pre-processing
## Resampling: Cross-Validated (10 fold)
## Summary of sample sizes: 1582, 1583, 1581, 1583, 1581, 1583, ...
## Resampling results across tuning parameters:
##
##   mtry  RMSE      Rsquared   MAE
##    2    6.918234  0.9336429  2.878141
##    4    4.205819  0.9678190  1.383026
##    6    3.786112  0.9727759  1.165131
##    8    3.489348  0.9765420  1.075708
##   10    3.443122  0.9761186  1.035317
##   12    3.454327  0.9748865  1.035246
##
## RMSE was used to select the optimal model using the smallest valu
e.
## The final value used for the model was mtry = 10.

# Make predictions on the test set using the tuned model
pred_sales_rf_tuned <- predict(rf_model_tuned_sales, test_data_sales
)

# Evaluate the tuned model using MAE and RMSE
train_mae_sales_rf <- mae(train_data_sales$Monthly_Sales_Volume_per_
Dealer, predict(rf_model_tuned_sales, train_data_sales))
test_mae_sales_rf <- mae(test_data_sales$Monthly_Sales_Volume_per_De
aler, pred_sales_rf_tuned)
train_rmse_sales_rf <- rmse(train_data_sales$Monthly_Sales_Volume_pe
r_Dealer, predict(rf_model_tuned_sales, train_data_sales))
test_rmse_sales_rf <- rmse(test_data_sales$Monthly_Sales_Volume_per_
Dealer, pred_sales_rf_tuned)
```

```
# Contextualization of MAE and RMSE for Sales Volume
mean_sales <- mean(test_data_sales$Monthly_Sales_Volume_per_Dealer)
train_mae_sales_pct_rf <- (train_mae_sales_rf / mean_sales) * 100
test_mae_sales_pct_rf <- (test_mae_sales_rf / mean_sales) * 100
train_rmse_sales_pct_rf <- (train_rmse_sales_rf / mean_sales) * 100
test_rmse_sales_pct_rf <- (test_rmse_sales_rf / mean_sales) * 100

# Print evaluation metrics
print(paste("Train MAE Sales (RF):", train_mae_sales_rf, "(", train_
mae_sales_pct_rf, "% of Mean Sales)"))

## [1] "Train MAE Sales (RF): 0.480428405130457 ( 4.69728440650936 %
of Mean Sales)"

print(paste("Test MAE Sales (RF):", test_mae_sales_rf, "(", test_mae
_sales_pct_rf, "% of Mean Sales)"))

## [1] "Test MAE Sales (RF): 0.945362823982429 ( 9.24307972668789 %
of Mean Sales)"

print(paste("Train RMSE Sales (RF):", train_rmse_sales_rf, "(", trai
n_rmse_sales_pct_rf, "% of Mean Sales)"))

## [1] "Train RMSE Sales (RF): 1.9496787091276 ( 19.0625602072832 %
of Mean Sales)"

print(paste("Test RMSE Sales (RF):", test_rmse_sales_rf, "(", test_r
mse_sales_pct_rf, "% of Mean Sales)"))

## [1] "Test RMSE Sales (RF): 2.71200235602083 ( 26.5160141267961 %
of Mean Sales)"

# Visualization for Sales Volume Prediction
results_sales_rf_tuned <- data.frame(Actual = test_data_sales$Monthl
y_Sales_Volume_per_Dealer, Predicted = pred_sales_rf_tuned)
plot_sales_rf <- ggplot(results_sales_rf_tuned, aes(x = Actual, y =
Predicted)) +
  geom_point(color = 'blue', alpha = 0.5) +
  geom_abline(slope = 1, intercept = 0, color = 'red', linetype = 'd
ashed') +
  ggtitle('Monthly Sales Volume Per Dealer: Actual vs Predicted (Ran
dom Forest)') +
  xlab('Actual Sales Volume') +
  ylab('Predicted Sales Volume') +
  theme_minimal(base_family = "Arial", base_size = 14) +
  theme(
    panel.background = element_rect(fill = "white"),
    plot.background = element_rect(fill = "white"),
    legend.background = element_rect(fill = "white"),
    legend.key = element_rect(fill = "white"),
```

```
    strip.background = element_rect(fill = "white")
  )
print(plot_sales_rf)

# Save Sales Volume plot
ggsave("Sales Volume Prediction RF.png", plot = plot_sales_rf, width
= 10, height = 6)
```

Random Forest for NPS

```
# Set seed for reproducibility
set.seed(123)

# Feature Selection using Random Forest for NPS Prediction
# Build a preliminary Random Forest model for NPS Score
rf_model_prel_nps <- randomForest(NPS_Score ~ ., data = train_data_n
ps, ntree = 100, importance = TRUE)

# Get variable importance for NPS
var_importance_nps <- importance(rf_model_prel_nps)

# Create a data frame with feature importance for NPS
importance_df_nps <- data.frame(Feature = rownames(var_importance_np
s), Importance = var_importance_nps[, "IncNodePurity"])

# Filter features with significant importance for NPS
significant_features_rf_nps <- importance_df_nps %>%
  filter(Importance > quantile(Importance, 0.25)) %>%  # Retain top
75% important features
  pull(Feature)

# Select columns using the significant features vector for NPS
modeling_data_nps_rf <- train_data_nps[, significant_features_rf_nps
, drop = FALSE]

# Add target variable to modeling data
modeling_data_nps_rf$NPS_Score <- train_data_nps$NPS_Score

# Define hyperparameter grid for tuning (only mtry is used)
tune_grid_rf_nps <- expand.grid(mtry = seq(2, length(significant_fea
tures_rf_nps), by = 2))

# Define cross-validation method
control_rf_nps <- trainControl(method = "cv", number = 5)

# Train Random Forest model with hyperparameter tuning for NPS
rf_model_tuned_nps <- train(
  NPS_Score ~ .,
  data = modeling_data_nps_rf,
  method = "rf",
```

```
  tuneGrid = tune_grid_rf_nps,
  trControl = control_rf_nps,
  ntree = 200,  # Set ntree directly in the train function
  importance = TRUE
)

# Print the best model from tuning
print("Best Random Forest Model for NPS Prediction:")

## [1] "Best Random Forest Model for NPS Prediction:"

print(rf_model_tuned_nps)

## Random Forest
##
## 1758 samples
##   13 predictor
##
## No pre-processing
## Resampling: Cross-Validated (5 fold)
## Summary of sample sizes: 1405, 1406, 1407, 1407, 1407
## Resampling results across tuning parameters:
##
##   mtry  RMSE       Rsquared    MAE
##    2    0.9471641  0.09123379  0.7692335
##    4    0.9213800  0.14128059  0.7488783
##    6    0.8892098  0.21301587  0.7201584
##    8    0.8695109  0.24819742  0.7016500
##   10    0.8526873  0.27673286  0.6858250
##   12    0.8357788  0.30577306  0.6691705
##
## RMSE was used to select the optimal model using the smallest valu
e.
## The final value used for the model was mtry = 12.

# Make predictions on the test set using the tuned model
pred_nps_rf_tuned <- predict(rf_model_tuned_nps, test_data_nps)

# Evaluate the tuned model using MAE and RMSE
train_mae_nps_rf <- mae(train_data_nps$NPS_Score, predict(rf_model_t
uned_nps, train_data_nps))
test_mae_nps_rf <- mae(test_data_nps$NPS_Score, pred_nps_rf_tuned)
train_rmse_nps_rf <- rmse(train_data_nps$NPS_Score, predict(rf_model
_tuned_nps, train_data_nps))
test_rmse_nps_rf <- rmse(test_data_nps$NPS_Score, pred_nps_rf_tuned)

# Print evaluation metrics
print(paste("Train MAE NPS (RF):", train_mae_nps_rf))

## [1] "Train MAE NPS (RF): 0.502955744866378"
```

```
print(paste("Test MAE NPS (RF):", test_mae_nps_rf))

## [1] "Test MAE NPS (RF): 0.645164760746155"

print(paste("Train RMSE NPS (RF):", train_rmse_nps_rf))

## [1] "Train RMSE NPS (RF): 0.628771632621638"

print(paste("Test RMSE NPS (RF):", test_rmse_nps_rf))

## [1] "Test RMSE NPS (RF): 0.81022007034307"

# Contextualization of MAE and RMSE for NPS
mean_nps <- mean(test_data_nps$NPS_Score)
train_mae_nps_pct_rf <- (train_mae_nps_rf / mean_nps) * 100
test_mae_nps_pct_rf <- (test_mae_nps_rf / mean_nps) * 100
train_rmse_nps_pct_rf <- (train_rmse_nps_rf / mean_nps) * 100
test_rmse_nps_pct_rf <- (test_rmse_nps_rf / mean_nps) * 100

# Print contextualized evaluation metrics
print(paste("Train MAE as a percentage of Mean NPS (RF):", train_mae
_nps_pct_rf))

## [1] "Train MAE as a percentage of Mean NPS (RF): 8.37296397827632
"

print(paste("Test MAE as a percentage of Mean NPS (RF):", test_mae_n
ps_pct_rf))

## [1] "Test MAE as a percentage of Mean NPS (RF): 10.7403908930714"

print(paste("Train RMSE as a percentage of Mean NPS (RF):", train_rm
se_nps_pct_rf))

## [1] "Train RMSE as a percentage of Mean NPS (RF): 10.467486024842
3"

print(paste("Test RMSE as a percentage of Mean NPS (RF):", test_rmse
_nps_pct_rf))

## [1] "Test RMSE as a percentage of Mean NPS (RF): 13.4881518557092
"

# Visualization for NPS Prediction using Random Forest
results_nps_rf_tuned <- data.frame(Actual = test_data_nps$NPS_Score,
Predicted = pred_nps_rf_tuned)
plot_nps_rf_tuned <- ggplot(results_nps_rf_tuned, aes(x = Actual, y
= Predicted)) +
  geom_point(color = 'blue', alpha = 0.5) +
  geom_abline(slope = 1, intercept = 0, color = 'red', linetype = 'd
ashed') +
  ggtitle('NPS: Actual vs Predicted (Random Forest)') +
  xlab('Actual NPS') +
```

```
  ylab('Predicted NPS') +
  theme_minimal(base_family = "Arial", base_size = 14) +
  theme(
    panel.background = element_rect(fill = "white"),
    plot.background = element_rect(fill = "white"),
    legend.background = element_rect(fill = "white"),
    legend.key = element_rect(fill = "white"),
    strip.background = element_rect(fill = "white")
  )
print(plot_nps_rf_tuned)

# Save NPS plot
ggsave("NPS Prediction RF.png", plot = plot_nps_rf_tuned, width = 10
, height = 6)
```

Random Forest for Efficiency

```
# Set seed for reproducibility
set.seed(123)

# Feature Selection using Random Forest for DEA Efficiency Predictio
n
# Build a preliminary Random Forest model for DEA Efficiency
rf_model_prel_efficiency <- randomForest(DEA_Efficiency ~ ., data =
train_data_efficiency, ntree = 100, importance = TRUE)

# Get variable importance for DEA Efficiency
var_importance_efficiency <- importance(rf_model_prel_efficiency)

# Create a data frame with feature importance for DEA Efficiency
importance_df_efficiency <- data.frame(
  Feature = rownames(var_importance_efficiency),
  Importance = var_importance_efficiency[, "IncNodePurity"]
)

# Filter features with significant importance for DEA Efficiency
significant_features_rf_efficiency <- importance_df_efficiency %>%
  filter(Importance > quantile(Importance, 0.25)) %>%  # Retain top
75% important features
  pull(Feature)

# Select columns using the significant features vector for DEA Effic
iency
modeling_data_efficiency_rf <- train_data_efficiency[, significant_f
eatures_rf_efficiency, drop = FALSE]

# Add the target variable DEA_Efficiency to the modeling data
modeling_data_efficiency_rf$DEA_Efficiency <- train_data_efficiency$
DEA_Efficiency
```

```r
# Define a hyperparameter grid for tuning only mtry
tune_grid_rf_efficiency <- expand.grid(
  mtry = seq(2, length(significant_features_rf_efficiency), by = 2)
# Use length(significant_features_rf_efficiency) to dynamically adap
t to number of features
)

# Define cross-validation method with more folds
control_rf_efficiency <- trainControl(method = "cv", number = 10)

# Train Random Forest model with hyperparameter tuning for efficienc
y
rf_model_tuned_efficiency <- train(
  DEA_Efficiency ~ .,
  data = modeling_data_efficiency_rf,
  method = "rf",
  tuneGrid = tune_grid_rf_efficiency,
  trControl = control_rf_efficiency,
  ntree = 200,  # Set ntree directly in the train function
  importance = TRUE
)

# Print the best model from tuning
print("Best Random Forest Model for Efficiency Prediction:")

## [1] "Best Random Forest Model for Efficiency Prediction:"

print(rf_model_tuned_efficiency)

## Random Forest
##
## 1758 samples
##   13 predictor
##
## No pre-processing
## Resampling: Cross-Validated (10 fold)
## Summary of sample sizes: 1582, 1583, 1582, 1582, 1582, 1583, ...
## Resampling results across tuning parameters:
##
##   mtry  RMSE        Rsquared   MAE
##    2    0.17825950  0.6620336  0.14374415
##    4    0.14658744  0.7439215  0.11521167
##    6    0.12699302  0.7990849  0.09772343
##    8    0.11345565  0.8307431  0.08537880
##   10    0.10442097  0.8514819  0.07678523
##   12    0.09686539  0.8693385  0.06998505
##
## RMSE was used to select the optimal model using the smallest valu
e.
## The final value used for the model was mtry = 12.
```

```
# Make predictions on the test set using the tuned model
pred_efficiency_rf_tuned <- predict(rf_model_tuned_efficiency, test_
data_efficiency)

# Evaluate the tuned model using MAE and RMSE
train_mae_efficiency_rf <- mae(train_data_efficiency$DEA_Efficiency,
predict(rf_model_tuned_efficiency, train_data_efficiency))
test_mae_efficiency_rf <- mae(test_data_efficiency$DEA_Efficiency, p
red_efficiency_rf_tuned)
train_rmse_efficiency_rf <- rmse(train_data_efficiency$DEA_Efficienc
y, predict(rf_model_tuned_efficiency, train_data_efficiency))
test_rmse_efficiency_rf <- rmse(test_data_efficiency$DEA_Efficiency,
pred_efficiency_rf_tuned)

# Contextualization of MAE and RMSE for Efficiency
mean_efficiency <- mean(test_data_efficiency$DEA_Efficiency)
train_mae_efficiency_pct_rf <- (train_mae_efficiency_rf / mean_effic
iency) * 100
test_mae_efficiency_pct_rf <- (test_mae_efficiency_rf / mean_efficie
ncy) * 100
train_rmse_efficiency_pct_rf <- (train_rmse_efficiency_rf / mean_eff
iciency) * 100
test_rmse_efficiency_pct_rf <- (test_rmse_efficiency_rf / mean_effic
iency) * 100

# Print evaluation metrics
print(paste("Train MAE Efficiency (RF):", train_mae_efficiency_rf, "
(", train_mae_efficiency_pct_rf, "% of Mean Efficiency)"))

## [1] "Train MAE Efficiency (RF): 0.0497600806623667 ( 9.8666758691
9089 % of Mean Efficiency)"

print(paste("Test MAE Efficiency (RF):", test_mae_efficiency_rf, "("
, test_mae_efficiency_pct_rf, "% of Mean Efficiency)"))

## [1] "Test MAE Efficiency (RF): 0.0683742230991392 ( 13.5575804570
021 % of Mean Efficiency)"

print(paste("Train RMSE Efficiency (RF):", train_rmse_efficiency_rf,
"(", train_rmse_efficiency_pct_rf, "% of Mean Efficiency)"))

## [1] "Train RMSE Efficiency (RF): 0.0682711753784813 ( 13.53714764
32836 % of Mean Efficiency)"

print(paste("Test RMSE Efficiency (RF):", test_rmse_efficiency_rf, "
(", test_rmse_efficiency_pct_rf, "% of Mean Efficiency)"))

## [1] "Test RMSE Efficiency (RF): 0.0918873711247082 ( 18.219884198
1625 % of Mean Efficiency)"
```

```r
# Visualization for Efficiency Prediction
results_efficiency_rf_tuned <- data.frame(Actual = test_data_efficie
ncy$DEA_Efficiency, Predicted = pred_efficiency_rf_tuned)
plot_efficiency_rf <- ggplot(results_efficiency_rf_tuned, aes(x = Ac
tual, y = Predicted)) +
  geom_point(color = 'blue', alpha = 0.5) +
  geom_abline(slope = 1, intercept = 0, color = 'red', linetype = 'd
ashed') +
  ggtitle('DEA Efficiency Scores: Actual vs Predicted (Random Forest
)') +
  xlab('Actual Efficiency') +
  ylab('Predicted Efficiency') +
  theme_minimal(base_family = "Arial", base_size = 14) +
  theme(
    panel.background = element_rect(fill = "white"),
    plot.background = element_rect(fill = "white"),
    legend.background = element_rect(fill = "white"),
    legend.key = element_rect(fill = "white"),
    strip.background = element_rect(fill = "white")
  )
print(plot_efficiency_rf)

# Save Efficiency plot
ggsave("Efficiency Prediction RF.png", plot = plot_efficiency_rf, wi
dth = 10, height = 6)
```

Predictive Modelling: ARIMA

```r
# Set seed for reproducibility
set.seed(123)

# Create copies for ARIMA-specific modifications
train_data_sales_arima <- train_data_sales
test_data_sales_arima <- test_data_sales
train_data_nps_arima <- train_data_nps
test_data_nps_arima <- test_data_nps
train_data_efficiency_arima <- train_data_efficiency
test_data_efficiency_arima <- test_data_efficiency

# Convert 'Date' column to Date type if not already
train_data_sales_arima$Date <- as.Date(train_data_sales_arima$Date)
test_data_sales_arima$Date <- as.Date(test_data_sales_arima$Date)

train_data_nps_arima$Date <- as.Date(train_data_nps_arima$Date)
test_data_nps_arima$Date <- as.Date(test_data_nps_arima$Date)

train_data_efficiency_arima$Date <- as.Date(train_data_efficiency_ar
ima$Date)
test_data_efficiency_arima$Date <- as.Date(test_data_efficiency_arim
```

```
a$Date)

# Verify that dates are of Date class
print(class(train_data_sales_arima$Date))

## [1] "Date"

print(class(test_data_sales_arima$Date))

## [1] "Date"

print(class(train_data_nps_arima$Date))

## [1] "Date"

print(class(test_data_nps_arima$Date))

## [1] "Date"

print(class(train_data_efficiency_arima$Date))

## [1] "Date"

print(class(test_data_efficiency_arima$Date))

## [1] "Date"
```

ARIMA for Sales Volume

```
# Convert the training data to a time series object for ARIMA
sales_ts_train_arima <- ts(
  train_data_sales_arima$Monthly_Sales_Volume_per_Dealer,
  frequency = 12,
  start = c(year(min(train_data_sales_arima$Date)), month(min(train_
data_sales_arima$Date)))
)

# Use auto.arima to select the best ARIMA model parameters
best_arima_model_sales <- auto.arima(sales_ts_train_arima, seasonal
= TRUE, stepwise = TRUE, approximation = FALSE)
summary(best_arima_model_sales)

## Series: sales_ts_train_arima
## ARIMA(1,0,1)(2,0,2)[12] with non-zero mean
##
## Coefficients:
##          ar1      ma1    sar1     sar2     sma1    sma2     mean
##       0.7394  -0.3270  1.5677  -0.7320  -1.4692  0.6463  11.1495
## s.e.  0.0292   0.0405  0.1123   0.0902   0.1169  0.1063   1.1034
##
## sigma^2 = 274.9:  log likelihood = -7428.33
## AIC=14872.66   AICc=14872.74   BIC=14916.44
##
```

```
## Training set error measures:
##                           ME     RMSE      MAE  MPE MAPE      MASE
ACF1
## Training set 0.002464475 16.54745 7.280049 -Inf  Inf 0.7371667 -0
.006953096

# Determine the number of periods to forecast based on the test data
forecast_horizon_arima <- nrow(test_data_sales_arima)

# Forecast using the fitted ARIMA model, limited to the length of th
e test data
forecast_sales_arima <- forecast(best_arima_model_sales, h = forecas
t_horizon_arima)

# Create time series objects
sales_ts_train_arima <- ts(
  train_data_sales_arima$Monthly_Sales_Volume_per_Dealer,
  frequency = 12,
  start = c(year(min(train_data_sales_arima$Date)), month(min(train_
data_sales_arima$Date)))
)

sales_ts_test_arima <- ts(
  test_data_sales_arima$Monthly_Sales_Volume_per_Dealer,
  frequency = 12,
  start = c(year(min(test_data_sales_arima$Date)), month(min(test_da
ta_sales_arima$Date)))
)

# Forecast based on ARIMA model
forecast_sales_arima <- forecast(auto.arima(sales_ts_train_arima), h
= length(sales_ts_test_arima))

# Combine forecast with dates
forecast_data_arima <- data.frame(
  Date = seq.Date(
    from = min(test_data_sales_arima$Date),
    by = "month",
    length.out = length(forecast_sales_arima$mean)
  ),
  Forecast = forecast_sales_arima$mean
)

# Combine actual data with dates
actual_data_arima <- data.frame(
  Date = test_data_sales_arima$Date,
  Actual = test_data_sales_arima$Monthly_Sales_Volume_per_Dealer
)
```

```r
# Plot with ggplot
ggplot() +
  geom_point(data = actual_data_arima, aes(x = Date, y = Actual, col
or = "Actual"), size = 2) +
  geom_line(data = forecast_data_arima, aes(x = Date, y = Forecast,
color = "Forecast"), size = 1.2) +
  scale_color_manual(values = c("Actual" = "red", "Forecast" = "blue
")) +
  labs(title = "Monthly Sales Volume Per Dealer Prediction Using ARI
MA",
       x = "Date",
       y = "Sales Volume",
       color = "Series") +
  theme_light() +
  theme(
    axis.text.x = element_text(angle = 45, hjust = 1, vjust = 1, siz
e = 10), # Adjust text size
    axis.text.y = element_text(size = 10),
    axis.title.x = element_text(size = 12),
    axis.title.y = element_text(size = 12),
    plot.title = element_text(hjust = 0.5, size = 14),
    legend.position = "bottom",
    legend.title = element_blank(),
    panel.grid.minor = element_blank()
  ) +
  scale_x_date(
    date_labels = "%b %Y",
    date_breaks = "2 months",  # Show fewer x-axis labels to avoid o
verlap
    expand = c(0, 0)           # Remove extra space
  ) +
  coord_cartesian(xlim = as.Date(c("2023-05-01", "2024-05-31")), yli
m = c(0, max(actual_data_arima$Actual, na.rm = TRUE) * 1.2))  # Adju
st y-limits to provide buffer

# Save the plot
ggsave("Sales Volume Prediction ARIMA.png", width = 10, height = 6)

# Print the first few values of the test and forecast series
cat("First few actual values:\n")

## First few actual values:

print(head(sales_ts_test_arima))

##      May Jun Jul Aug Sep Oct
## 2023   3   4  25  29  63   1

cat("First few forecast values:\n")

## First few forecast values:
```

```
print(head(forecast_sales_arima$mean))

##             Jan       Feb       Mar       Apr May Jun Jul Aug Sep
Oct       Nov
## 2169
9.705032
## 2170 11.784870 12.230829 14.849592 13.258871
##             Dec
## 2169 10.038214
## 2170

# Check for non-numeric values
cat("Checking data types:\n")

## Checking data types:

cat("Actual series type:", typeof(sales_ts_test_arima), "\n")

## Actual series type: double

cat("Forecast series type:", typeof(forecast_sales_arima$mean), "\n"
)

## Forecast series type: double

# Ensure data is numeric
sales_ts_test_arima <- as.numeric(sales_ts_test_arima)
forecast_sales_arima$mean <- as.numeric(forecast_sales_arima$mean)

# Check for infinite values
cat("Checking for Inf values:\n")

## Checking for Inf values:

inf_in_actual <- any(is.infinite(sales_ts_test_arima))
inf_in_forecast <- any(is.infinite(forecast_sales_arima$mean))
cat("Inf in actual:", inf_in_actual, "\n")

## Inf in actual: FALSE

cat("Inf in forecast:", inf_in_forecast, "\n")

## Inf in forecast: FALSE

# Check for matching start and end dates
cat("Actual start:", start(sales_ts_test_arima), "\n")

## Actual start: 1 1

cat("Actual end:", end(sales_ts_test_arima), "\n")

## Actual end: 439 1

cat("Forecast start:", start(forecast_sales_arima$mean), "\n")
```

```
## Forecast start: 1 1
cat("Forecast end:", end(forecast_sales_arima$mean), "\n")
## Forecast end: 439 1
# Compute MAE and RMSE if lengths match
actual_length <- length(sales_ts_test_arima)
forecast_length <- length(forecast_sales_arima$mean)

if (actual_length == forecast_length) {
  mae_sales_arima <- mean(abs(sales_ts_test_arima - forecast_sales_a
rima$mean), na.rm = TRUE)
  rmse_sales_arima <- sqrt(mean((sales_ts_test_arima - forecast_sale
s_arima$mean)^2, na.rm = TRUE))

  print(paste("MAE for ARIMA model (Sales Volume):", mae_sales_arima
))
  print(paste("RMSE for ARIMA model (Sales Volume):", rmse_sales_ari
ma))
} else {
  print("Error: Length of actual and forecasted series do not match.
")
}
## [1] "MAE for ARIMA model (Sales Volume): 9.29801369596033"
## [1] "RMSE for ARIMA model (Sales Volume): 14.4416291652584"
```

ARIMA for NPS Score

```
# Convert the training data to a time series object for ARIMA
nps_ts_train_arima <- ts(
  train_data_nps_arima$NPS_Score,
  frequency = 12,
  start = c(year(min(train_data_nps_arima$Date)), month(min(train_da
ta_nps_arima$Date)))
)

# Use auto.arima to select the best ARIMA model parameters
best_arima_model_nps <- auto.arima(nps_ts_train_arima, seasonal = TR
UE, stepwise = TRUE, approximation = FALSE)
summary(best_arima_model_nps)
## Series: nps_ts_train_arima
## ARIMA(0,0,0) with non-zero mean
##
## Coefficients:
##         mean
##       5.9903
## s.e.  0.0231
##
```

```
## sigma^2 = 0.9426:  log likelihood = -2442
## AIC=4887.99   AICc=4888   BIC=4898.93
##
## Training set error measures:
##                         ME      RMSE       MAE       MPE     MAPE
MASE
## Training set -9.083954e-14 0.9705788 0.7872952 -2.993051 14.14354
0.7181046
##                     ACF1
## Training set -0.01223234
```

```
# Determine the number of periods to forecast based on the test data
forecast_horizon_arima <- nrow(test_data_nps_arima)

# Forecast using the fitted ARIMA model, limited to the length of th
e test data
forecast_nps_arima <- forecast(best_arima_model_nps, h = forecast_ho
rizon_arima)

# Create time series objects for the test data
nps_ts_test_arima <- ts(
  test_data_nps_arima$NPS_Score,
  frequency = 12,
  start = c(year(min(test_data_nps_arima$Date)), month(min(test_data
_nps_arima$Date)))
)

# Combine forecast with dates
forecast_data_arima <- data.frame(
  Date = seq.Date(
    from = min(test_data_nps_arima$Date),
    by = "month",
    length.out = length(forecast_nps_arima$mean)
  ),
  Forecast = forecast_nps_arima$mean
)

# Combine actual data with dates
actual_data_arima <- data.frame(
  Date = test_data_nps_arima$Date,
  Actual = test_data_nps_arima$NPS_Score
)

# Plot with ggplot
ggplot() +
  geom_point(data = actual_data_arima, aes(x = Date, y = Actual, col
or = "Actual"), size = 2) +
  geom_line(data = forecast_data_arima, aes(x = Date, y = Forecast,
color = "Forecast"), size = 1.2) +
```

```
  scale_color_manual(values = c("Actual" = "red", "Forecast" = "blue
")) +
  labs(title = "NPS Prediction Using ARIMA",
       x = "Date",
       y = "NPS",
       color = "Series") +
  theme_light() +
  theme(
    axis.text.x = element_text(angle = 45, hjust = 1, vjust = 1, siz
e = 10), # Adjust text size
    axis.text.y = element_text(size = 10),
    axis.title.x = element_text(size = 12),
    axis.title.y = element_text(size = 12),
    plot.title = element_text(hjust = 0.5, size = 14),
    legend.position = "bottom",
    legend.title = element_blank(),
    panel.grid.minor = element_blank()
  ) +
  scale_x_date(
    date_labels = "%b %Y",
    date_breaks = "2 months",  # Show fewer x-axis labels to avoid o
verlap
    expand = c(0, 0)           # Remove extra space
  ) +
  coord_cartesian(xlim = as.Date(c("2023-05-01", "2024-05-31")), yli
m = c(0, max(actual_data_arima$Actual, na.rm = TRUE) * 1.2))  # Adju
st y-limits to provide buffer

# Save the plot
ggsave("NPS Prediction ARIMA.png", width = 10, height = 6)

# Print the first few values of the test and forecast series
cat("First few actual values:\n")

## First few actual values:

print(head(nps_ts_test_arima))

##       May  Jun  Jul  Aug  Sep  Oct
## 2023 5.22 5.70 5.63 7.70 6.18 5.69

cat("First few forecast values:\n")

## First few forecast values:

print(head(forecast_nps_arima$mean))

##           Jan      Feb      Mar      Apr May Jun Jul Aug Sep Oct
Nov
## 2169
5.990313
```

```
## 2170 5.990313 5.990313 5.990313 5.990313
##           Dec
## 2169 5.990313
## 2170

# Check for non-numeric values
cat("Checking data types:\n")

## Checking data types:

cat("Actual series type:", typeof(nps_ts_test_arima), "\n")

## Actual series type: double

cat("Forecast series type:", typeof(forecast_nps_arima$mean), "\n")

## Forecast series type: double

# Ensure data is numeric
nps_ts_test_arima <- as.numeric(nps_ts_test_arima)
forecast_nps_arima$mean <- as.numeric(forecast_nps_arima$mean)

# Check for infinite values
cat("Checking for Inf values:\n")

## Checking for Inf values:

inf_in_actual <- any(is.infinite(nps_ts_test_arima))
inf_in_forecast <- any(is.infinite(forecast_nps_arima$mean))
cat("Inf in actual:", inf_in_actual, "\n")

## Inf in actual: FALSE

cat("Inf in forecast:", inf_in_forecast, "\n")

## Inf in forecast: FALSE

# Check for matching start and end dates
cat("Actual start:", start(nps_ts_test_arima), "\n")

## Actual start: 1 1

cat("Actual end:", end(nps_ts_test_arima), "\n")

## Actual end: 439 1

cat("Forecast start:", start(forecast_nps_arima$mean), "\n")

## Forecast start: 1 1

cat("Forecast end:", end(forecast_nps_arima$mean), "\n")

## Forecast end: 439 1
```

```
# Compute MAE and RMSE if lengths match
actual_length <- length(nps_ts_test_arima)
forecast_length <- length(forecast_nps_arima$mean)

if (actual_length == forecast_length) {
  mae_nps_arima <- mean(abs(nps_ts_test_arima - forecast_nps_arima$m
ean), na.rm = TRUE)
  rmse_nps_arima <- sqrt(mean((nps_ts_test_arima - forecast_nps_arim
a$mean)^2, na.rm = TRUE))

  print(paste("MAE for ARIMA model (NPS):", mae_nps_arima))
  print(paste("RMSE for ARIMA model (NPS):", rmse_nps_arima))
} else {
  print("Error: Length of actual and forecasted series do not match.
")
}

## [1] "MAE for ARIMA model (NPS): 0.787870859150875"
## [1] "RMSE for ARIMA model (NPS): 0.961607424424333"
```

ARIMA for Efficiency

```
# Convert 'Date' column to Date type if not already
train_data_efficiency_arima$Date <- as.Date(train_data_efficiency_ar
ima$Date)
test_data_efficiency_arima$Date <- as.Date(test_data_efficiency_arim
a$Date)

# Verify that dates are of Date class
print(class(train_data_efficiency_arima$Date))

## [1] "Date"

print(class(test_data_efficiency_arima$Date))

## [1] "Date"

# Convert the training data to a time series object for ARIMA
efficiency_ts_train_arima <- ts(
  train_data_efficiency_arima$DEA_Efficiency,
  frequency = 12,
  start = c(year(min(train_data_efficiency_arima$Date)), month(min(t
rain_data_efficiency_arima$Date)))
)

# Use auto.arima to select the best ARIMA model parameters
best_arima_model_efficiency <- auto.arima(efficiency_ts_train_arima,
seasonal = TRUE, stepwise = TRUE, approximation = FALSE)
summary(best_arima_model_efficiency)
```

```
## Series: efficiency_ts_train_arima
## ARIMA(1,1,2)(1,0,0)[12]
##
## Coefficients:
##          ar1      ma1     ma2    sar1
##       0.7188  -1.3670  0.3844  0.0771
## s.e.  0.0598   0.0712  0.0635  0.0256
##
## sigma^2 = 0.03696:  log likelihood = 405.26
## AIC=-800.52   AICc=-800.49   BIC=-773.16
##
## Training set error measures:
##                           ME      RMSE       MAE       MPE     MAPE
MASE
## Training set -0.0001199883 0.1919842 0.1478192 -19.96769 40.26271
0.6947339
##                      ACF1
## Training set -0.002045169

# Determine the number of periods to forecast based on the test data
forecast_horizon_arima <- nrow(test_data_efficiency_arima)

# Forecast using the fitted ARIMA model, limited to the length of th
e test data
forecast_efficiency_arima <- forecast(best_arima_model_efficiency, h
= forecast_horizon_arima)

# Create time series objects for the test data
efficiency_ts_test_arima <- ts(
  test_data_efficiency_arima$DEA_Efficiency,
  frequency = 12,
  start = c(year(min(test_data_efficiency_arima$Date)), month(min(te
st_data_efficiency_arima$Date)))
)

# Combine forecast with dates
forecast_data_arima <- data.frame(
  Date = seq.Date(
    from = min(test_data_efficiency_arima$Date),
    by = "month",
    length.out = length(forecast_efficiency_arima$mean)
  ),
  Forecast = forecast_efficiency_arima$mean
)

# Combine actual data with dates
actual_data_arima <- data.frame(
  Date = test_data_efficiency_arima$Date,
  Actual = test_data_efficiency_arima$DEA_Efficiency
```

```
)

# Plot with ggplot
ggplot() +
  geom_point(data = actual_data_arima, aes(x = Date, y = Actual, col
or = "Actual"), size = 2) +
  geom_line(data = forecast_data_arima, aes(x = Date, y = Forecast,
color = "Forecast"), size = 1.2) +
  scale_color_manual(values = c("Actual" = "red", "Forecast" = "blue
")) +
  labs(title = "DEA Efficiency Scores Prediction Using ARIMA",
       x = "Date",
       y = "DEA Efficiency",
       color = "Series") +
  theme_light() +
  theme(
    axis.text.x = element_text(angle = 45, hjust = 1, vjust = 1, siz
e = 10), # Adjust text size
    axis.text.y = element_text(size = 10),
    axis.title.x = element_text(size = 12),
    axis.title.y = element_text(size = 12),
    plot.title = element_text(hjust = 0.5, size = 14),
    legend.position = "bottom",
    legend.title = element_blank(),
    panel.grid.minor = element_blank()
  ) +
  scale_x_date(
    date_labels = "%b %Y",
    date_breaks = "2 months",  # Show fewer x-axis labels to avoid o
verlap
    expand = c(0, 0)           # Remove extra space
  ) +
  coord_cartesian(xlim = as.Date(c("2023-05-01", "2024-05-31")), yli
m = c(0, max(actual_data_arima$Actual, na.rm = TRUE) * 1.2))  # Adju
st y-limits to provide buffer

# Save the plot
ggsave("Efficiency Prediction ARIMA.png", width = 10, height = 6)

# Print the first few values of the test and forecast series
cat("First few actual values:\n")

## First few actual values:

print(head(efficiency_ts_test_arima))

##            May       Jun       Jul       Aug       Sep       Oct
## 2023 0.5008477 0.6014364 0.6295096 1.0000000 0.9719649 0.3511197

cat("First few forecast values:\n")
```

```
## First few forecast values:

print(head(forecast_efficiency_arima$mean))

##            Jan       Feb       Mar       Apr May Jun Jul Aug Sep
Oct       Nov
## 2169
0.6339228
## 2170 0.6129509 0.6376712 0.6385094 0.6316862
##            Dec
## 2169 0.6140797
## 2170

# Check for non-numeric values
cat("Checking data types:\n")

## Checking data types:

cat("Actual series type:", typeof(efficiency_ts_test_arima), "\n")

## Actual series type: double

cat("Forecast series type:", typeof(forecast_efficiency_arima$mean),
"\n")

## Forecast series type: double

# Ensure data is numeric
efficiency_ts_test_arima <- as.numeric(efficiency_ts_test_arima)
forecast_efficiency_arima$mean <- as.numeric(forecast_efficiency_ari
ma$mean)

# Check for infinite values
cat("Checking for Inf values:\n")

## Checking for Inf values:

inf_in_actual <- any(is.infinite(efficiency_ts_test_arima))
inf_in_forecast <- any(is.infinite(forecast_efficiency_arima$mean))
cat("Inf in actual:", inf_in_actual, "\n")

## Inf in actual: FALSE

cat("Inf in forecast:", inf_in_forecast, "\n")

## Inf in forecast: FALSE

# Check for matching start and end dates
cat("Actual start:", start(efficiency_ts_test_arima), "\n")

## Actual start: 1 1

cat("Actual end:", end(efficiency_ts_test_arima), "\n")
```

```
## Actual end: 439 1

cat("Forecast start:", start(forecast_efficiency_arima$mean), "\n")

## Forecast start: 1 1

cat("Forecast end:", end(forecast_efficiency_arima$mean), "\n")

## Forecast end: 439 1

# Compute MAE and RMSE if lengths match
actual_length <- length(efficiency_ts_test_arima)
forecast_length <- length(forecast_efficiency_arima$mean)

if (actual_length == forecast_length) {
  mae_efficiency_arima <- mean(abs(efficiency_ts_test_arima - foreca
st_efficiency_arima$mean), na.rm = TRUE)
  rmse_efficiency_arima <- sqrt(mean((efficiency_ts_test_arima - for
ecast_efficiency_arima$mean)^2, na.rm = TRUE))

  print(paste("MAE for ARIMA model (DEA Efficiency):", mae_efficienc
y_arima))
  print(paste("RMSE for ARIMA model (DEA Efficiency):", rmse_efficie
ncy_arima))
} else {
  print("Error: Length of actual and forecasted series do not match.
")
}

## [1] "MAE for ARIMA model (DEA Efficiency): 0.203706894270369"
## [1] "RMSE for ARIMA model (DEA Efficiency): 0.241298666900955"
```

Predictive Modelling: SVM

SVM for Sales Volume

```
# Set seed for reproducibility
set.seed(123)

# Extract features and target variable
outcome_name_sales_svm <- "Monthly_Sales_Volume_per_Dealer"
predictor_names_sales_svm <- setdiff(names(train_data_sales), c("Mon
thly_Sales_Volume_per_Dealer", "Date"))

x_train_sales_svm <- train_data_sales[, predictor_names_sales_svm]
y_train_sales_svm <- train_data_sales[[outcome_name_sales_svm]]
x_test_sales_svm <- test_data_sales[, predictor_names_sales_svm]
y_test_sales_svm <- test_data_sales[[outcome_name_sales_svm]]

# Perform Feature Scaling
```

```
pre_proc_sales_svm <- preProcess(x_train_sales_svm, method = c("cent
er", "scale"))
x_train_sales_svm <- predict(pre_proc_sales_svm, x_train_sales_svm)
x_test_sales_svm <- predict(pre_proc_sales_svm, x_test_sales_svm)

# Feature Selection using RFE
control_rfe_sales_svm <- rfeControl(functions = rfFuncs, method = "c
v", number = 5)
# Using Random Forest for feature selection as it's robust
rfe_results_sales_svm <- rfe(x_train_sales_svm, y_train_sales_svm, s
izes = c(1:10), rfeControl = control_rfe_sales_svm)

# Get the selected features
selected_predictors_sales_svm <- predictors(rfe_results_sales_svm)
print("Selected Features for Sales Volume SVM:")

## [1] "Selected Features for Sales Volume SVM:"

print(selected_predictors_sales_svm)

## [1] "Monthly_Sales_Volume_per_Country" "Number_of_Salespeople"
## [3] "Polynomial_Term"                  "DEA_Efficiency"
## [5] "Interaction_Term"                 "Regulatory_Environment_Sc
ore"
## [7] "Number_of_Outlets"                "Regional_Population_Densi
ty"
## [9] "Cultural_Difference_Score"

# Subset the training and test data based on selected features
x_train_selected_sales_svm <- x_train_sales_svm[, selected_predictor
s_sales_svm]
x_test_selected_sales_svm <- x_test_sales_svm[, selected_predictors_
sales_svm]

# Use a smaller subset for parameter tuning
sample_size_sales_svm <- min(500, nrow(train_data_sales))  # Use a m
aximum of 500 samples for tuning
train_sample_sales_svm <- train_data_sales[sample(1:nrow(train_data_
sales), sample_size_sales_svm), selected_predictors_sales_svm]

# Prepare for training with cross-validation
control_svm_sales <- trainControl(method = "cv", number = 5)
tune_grid_sales_svm <- expand.grid(C = seq(0.01, 1, length = 5))  #
Regularization parameter grid

# Fit SVM model with linear kernel for faster results
svm_model_sales_volume <- train(
  x = x_train_selected_sales_svm,
  y = y_train_sales_svm,
  method = "svmLinear",  # Use a linear kernel for faster computatio
```

```
n
  tuneGrid = tune_grid_sales_svm,
  trControl = control_svm_sales
)

# Print best parameters
print("Best Parameters for SVM Sales Volume:")

## [1] "Best Parameters for SVM Sales Volume:"

print(svm_model_sales_volume$bestTune)

##        C
## 2 0.2575

# Make predictions on the test set
svm_predictions_sales_volume <- predict(svm_model_sales_volume, newd
ata = x_test_selected_sales_svm)

# Evaluate model performance
mae_svm_sales_volume <- mean(abs(y_test_sales_svm - svm_predictions_
sales_volume))
rmse_svm_sales_volume <- sqrt(mean((y_test_sales_svm - svm_predictio
ns_sales_volume)^2))

print(paste("MAE for SVM model (Sales Volume):", mae_svm_sales_volum
e))

## [1] "MAE for SVM model (Sales Volume): 2.69533604570122"

print(paste("RMSE for SVM model (Sales Volume):", rmse_svm_sales_vol
ume))

## [1] "RMSE for SVM model (Sales Volume): 3.9224631051167"

# Plot actual vs predicted
actual_data_sales_svm <- data.frame(Date = test_data_sales$Date, Act
ual = y_test_sales_svm)
predicted_data_sales_svm <- data.frame(Date = test_data_sales$Date,
Predicted = svm_predictions_sales_volume)

ggplot() +
  geom_point(data = actual_data_sales_svm, aes(x = Date, y = Actual,
color = "Actual"), size = 2) +
  geom_line(data = predicted_data_sales_svm, aes(x = Date, y = Predi
cted, color = "Predicted"), size = 1.2) +
  scale_color_manual(values = c("Actual" = "red", "Predicted" = "blu
e")) +
  labs(title = "Monthly Sales Volume Per Dealer Prediction Using SVM
(Linear Kernel)",
       x = "Month",
```

```
      y = "Sales Volume",
      color = "Series") +
  theme_light() +
  theme(
    axis.text.x = element_text(angle = 45, hjust = 1, vjust = 1, siz
e = 10),
    axis.text.y = element_text(size = 10),
    axis.title.x = element_text(size = 12),
    axis.title.y = element_text(size = 12),
    plot.title = element_text(hjust = 0.5, size = 14),
    legend.position = "bottom",
    legend.title = element_blank(),
    panel.grid.minor = element_blank()
  ) +
  scale_x_date(
    date_labels = "%b %Y",
    date_breaks = "2 months",
    expand = c(0, 0)
  ) +
  coord_cartesian(ylim = c(0, max(actual_data_sales_svm$Actual, na.r
m = TRUE) * 1.2))

# Save the plot
ggsave("Sales Volume Prediction SVM.png", width = 10, height = 6)
```

SVM for NPS

```
# Set seed for reproducibility
set.seed(123)

# Extract features and target variable for NPS_Score
outcome_name_nps_svm <- "NPS_Score"
predictor_names_nps_svm <- setdiff(names(train_data_nps), c("NPS_Sco
re", "Date"))

x_train_nps_svm <- train_data_nps[, predictor_names_nps_svm]
y_train_nps_svm <- train_data_nps[[outcome_name_nps_svm]]
x_test_nps_svm <- test_data_nps[, predictor_names_nps_svm]
y_test_nps_svm <- test_data_nps[[outcome_name_nps_svm]]

# Perform Feature Scaling
pre_proc_nps_svm <- preProcess(x_train_nps_svm, method = c("center",
"scale"))
x_train_nps_svm <- predict(pre_proc_nps_svm, x_train_nps_svm)
x_test_nps_svm <- predict(pre_proc_nps_svm, x_test_nps_svm)

# Feature Selection using RFE
control_rfe_nps_svm <- rfeControl(functions = rfFuncs, method = "cv"
, number = 5)
# Using Random Forest for feature selection as it's robust
```

```
rfe_results_nps_svm <- rfe(x_train_nps_svm, y_train_nps_svm, sizes =
c(1:10), rfeControl = control_rfe_nps_svm)

# Get the selected features
selected_predictors_nps_svm <- predictors(rfe_results_nps_svm)
print("Selected Features for NPS Score SVM:")

## [1] "Selected Features for NPS Score SVM:"

print(selected_predictors_nps_svm)

## [1] "DEA_Efficiency"                     "Regional_Population_Densi
ty"
## [3] "Monthly_Sales_Volume_per_Country" "Monthly_Sales_Volume_per_
Dealer"
## [5] "Local_Economic_Growth"            "Cultural_Difference_Score
"

# Subset the training and test data based on selected features
x_train_selected_nps_svm <- x_train_nps_svm[, selected_predictors_np
s_svm]
x_test_selected_nps_svm <- x_test_nps_svm[, selected_predictors_nps_
svm]

# Use a smaller subset for parameter tuning
sample_size_nps_svm <- min(500, nrow(train_data_nps))  # Use a maxim
um of 500 samples for tuning
train_sample_nps_svm <- train_data_nps[sample(1:nrow(train_data_nps)
, sample_size_nps_svm), selected_predictors_nps_svm]

# Prepare for training with cross-validation
control_svm_nps <- trainControl(method = "cv", number = 5)
tune_grid_nps_svm <- expand.grid(C = seq(0.01, 1, length = 5))  # Re
gularization parameter grid

# Fit SVM model with linear kernel for faster results
svm_model_nps_score <- train(
  x = x_train_selected_nps_svm,
  y = y_train_nps_svm,
  method = "svmLinear",  # Use a linear kernel for faster computatio
n
  tuneGrid = tune_grid_nps_svm,
  trControl = control_svm_nps
)

# Print best parameters
print("Best Parameters for SVM NPS Score:")

## [1] "Best Parameters for SVM NPS Score:"

print(svm_model_nps_score$bestTune)
```

```
##      C
## 1 0.01

# Make predictions on the test set
svm_predictions_nps_score <- predict(svm_model_nps_score, newdata =
x_test_selected_nps_svm)

# Evaluate model performance
mae_svm_nps_score <- mean(abs(y_test_nps_svm - svm_predictions_nps_s
core))
rmse_svm_nps_score <- sqrt(mean((y_test_nps_svm - svm_predictions_np
s_score)^2))

print(paste("MAE for SVM model (NPS Score):", mae_svm_nps_score))

## [1] "MAE for SVM model (NPS Score): 0.658248366570384"

print(paste("RMSE for SVM model (NPS Score):", rmse_svm_nps_score))

## [1] "RMSE for SVM model (NPS Score): 0.832600968770739"

# Plot actual vs predicted
actual_data_nps_svm <- data.frame(Date = test_data_nps$Date, Actual
= y_test_nps_svm)
predicted_data_nps_svm <- data.frame(Date = test_data_nps$Date, Pred
icted = svm_predictions_nps_score)

ggplot() +
  geom_point(data = actual_data_nps_svm, aes(x = Date, y = Actual, c
olor = "Actual"), size = 2) +
  geom_line(data = predicted_data_nps_svm, aes(x = Date, y = Predict
ed, color = "Predicted"), size = 1.2) +
  scale_color_manual(values = c("Actual" = "red", "Predicted" = "blu
e")) +
  labs(title = "NPS Prediction Using SVM (Linear Kernel)",
       x = "Month",
       y = "NPS",
       color = "Series") +
  theme_light() +
  theme(
    axis.text.x = element_text(angle = 45, hjust = 1, vjust = 1, siz
e = 10),
    axis.text.y = element_text(size = 10),
    axis.title.x = element_text(size = 12),
    axis.title.y = element_text(size = 12),
    plot.title = element_text(hjust = 0.5, size = 14),
    legend.position = "bottom",
    legend.title = element_blank(),
    panel.grid.minor = element_blank()
  ) +
  scale_x_date(
```

```
    date_labels = "%b %Y",
    date_breaks = "2 months",
    expand = c(0, 0)
  ) +
  coord_cartesian(ylim = c(0, max(actual_data_nps_svm$Actual, na.rm
= TRUE) * 1.2))

# Save the plot
ggsave("NPS Prediction SVM.png", width = 10, height = 6)
```

SVM for Efficiency

```
# Set seed for reproducibility
set.seed(123)

# Step 1: Prepare the data

# Define the target variable and predictor variables
target_variable_efficiency <- "DEA_Efficiency"
predictors_efficiency <- setdiff(names(train_data_efficiency), c(tar
get_variable_efficiency, "Date"))

# Extract predictors and target for train and test data
x_train_efficiency <- train_data_efficiency[, predictors_efficiency]
y_train_efficiency <- train_data_efficiency[[target_variable_efficie
ncy]]
x_test_efficiency <- test_data_efficiency[, predictors_efficiency]
y_test_efficiency <- test_data_efficiency[[target_variable_efficienc
y]]

# Check and impute missing values using median
x_train_efficiency <- x_train_efficiency %>%
  mutate(across(everything(), ~ ifelse(is.na(.), median(., na.rm = T
RUE), .)))

x_test_efficiency <- x_test_efficiency %>%
  mutate(across(everything(), ~ ifelse(is.na(.), median(., na.rm = T
RUE), .)))

# Ensure all predictors are numeric
x_train_efficiency <- as.data.frame(lapply(x_train_efficiency, as.nu
meric))
x_test_efficiency <- as.data.frame(lapply(x_test_efficiency, as.nume
ric))
y_train_efficiency <- as.numeric(y_train_efficiency)
y_test_efficiency <- as.numeric(y_test_efficiency)

# Remove zero variance predictors
zero_variance_efficiency <- nearZeroVar(x_train_efficiency, saveMetr
ics = TRUE)
```

```
if (any(zero_variance_efficiency$zeroVar)) {
  cat("Zero variance predictors found and removed:", names(zero_vari
ance_efficiency[zero_variance_efficiency$zeroVar, ]), "\n")
  x_train_efficiency <- x_train_efficiency[, !zero_variance_efficien
cy$zeroVar]
  x_test_efficiency <- x_test_efficiency[, !zero_variance_efficiency
$zeroVar]
}

## Zero variance predictors found and removed: freqRatio percentUniq
ue zeroVar nzv

# Step 2: Feature scaling
preprocess_params_efficiency <- preProcess(x_train_efficiency, metho
d = c("center", "scale"))
x_train_scaled_efficiency <- predict(preprocess_params_efficiency, x
_train_efficiency)
x_test_scaled_efficiency <- predict(preprocess_params_efficiency, x_
test_efficiency)

# Step 3: Train the SVM model
svm_model_efficiency <- train(
  x = x_train_scaled_efficiency,
  y = y_train_efficiency,
  method = "svmLinear",
  trControl = trainControl(method = "cv", number = 5),
  tuneGrid = expand.grid(C = seq(0.01, 1, length = 5))
)

# Print best model parameters
cat("Best SVM Parameters for DEA Efficiency:\n")

## Best SVM Parameters for DEA Efficiency:

print(svm_model_efficiency$bestTune)

##   C
## 5 1

# Step 4: Evaluate the model
predictions_efficiency_svm <- predict(svm_model_efficiency, newdata
= x_test_scaled_efficiency)

# Calculate performance metrics
mae_efficiency_svm <- mean(abs(y_test_efficiency - predictions_effic
iency_svm))
rmse_efficiency_svm <- sqrt(mean((y_test_efficiency - predictions_ef
ficiency_svm)^2))

cat("MAE for SVM model (DEA Efficiency):", mae_efficiency_svm, "\n")
```

```
## MAE for SVM model (DEA Efficiency): 0.1191666

cat("RMSE for SVM model (DEA Efficiency):", rmse_efficiency_svm, "\n
")

## RMSE for SVM model (DEA Efficiency): 0.1557126

# Step 5: Plot the results
plot_data_efficiency_svm <- data.frame(
  Date = test_data_efficiency$Date,
  Actual = y_test_efficiency,
  Predicted = predictions_efficiency_svm
)

ggplot(plot_data_efficiency_svm, aes(x = Date)) +
  # Add points for actual values
  geom_point(aes(y = Actual, color = "Actual"), size = 2, alpha = 0.
7) +
  # Add a smoothed line for predicted values
  geom_line(aes(y = Predicted, color = "Predicted"), size = 1, alpha
= 0.7) +
  geom_smooth(aes(y = Predicted, color = "Predicted"), method = "loe
ss", se = FALSE, linetype = "dashed", size = 1) +
  # Customize colors for the points and line
  scale_color_manual(values = c("Actual" = "red", "Predicted" = "blu
e")) +
  # Add labels and title
  labs(
    title = "DEA Efficiency Scores Prediction Using SVM (Linear Kern
el)",
    x = "Date",
    y = "DEA Efficiency",
    color = "Legend"
  ) +
  # Use a theme with a white background and no dark elements
  theme_minimal(base_size = 14) +
  theme(
    plot.title = element_text(hjust = 0.5, size = 16, face = "bold")
,
    axis.text.x = element_text(angle = 45, hjust = 1, size = 12, col
or = "black"),
    axis.text.y = element_text(size = 12, color = "black"),
    axis.title.x = element_text(size = 14, color = "black"),
    axis.title.y = element_text(size = 14, color = "black"),
    legend.position = "bottom",
    legend.title = element_blank(),
    legend.background = element_rect(fill = "white", color = "white"
),
    panel.grid.major = element_line(color = "gray80", size = 0.5),
    panel.grid.minor = element_blank(),
```

```
    panel.background = element_rect(fill = "white", color = "white")
,
    plot.background = element_rect(fill = "white", color = "white")
  ) +
  # Adjust the x-axis to display every two months
  scale_x_date(
    date_labels = "%b %Y",
    date_breaks = "2 months",
    expand = c(0, 0)
  ) +
  # Set y-axis limits if needed
  coord_cartesian(ylim = c(min(y_test_efficiency) * 0.8, max(y_test_
efficiency) * 1.2))

# Save the plot
ggsave("Efficiency Prediction SVM.png", width = 10, height = 6, dpi
= 300)
```

Predictive Modelling: GBM

GBM for Sales Volume

```
# Define the target variable and predictor variables
target_variable_sales <- "Monthly_Sales_Volume_per_Dealer"
predictors_sales <- setdiff(names(data), c(target_variable_sales, "D
ate"))

# Extract predictors and target for train and test data
x_train_sales <- train_data_sales[, predictors_sales]
y_train_sales <- train_data_sales[[target_variable_sales]]
x_test_sales <- test_data_sales[, predictors_sales]
y_test_sales <- test_data_sales[[target_variable_sales]]

# Check and impute missing values using median
x_train_sales <- x_train_sales %>%
  mutate(across(everything(), ~ ifelse(is.na(.), median(., na.rm = T
RUE), .)))

x_test_sales <- x_test_sales %>%
  mutate(across(everything(), ~ ifelse(is.na(.), median(., na.rm = T
RUE), .)))

# Ensure all predictors are numeric
x_train_sales <- as.data.frame(lapply(x_train_sales, as.numeric))
x_test_sales <- as.data.frame(lapply(x_test_sales, as.numeric))
y_train_sales <- as.numeric(y_train_sales)
y_test_sales <- as.numeric(y_test_sales)

# Remove zero variance predictors
```

```r
zero_variance_sales <- nearZeroVar(x_train_sales, saveMetrics = TRUE
)
if (any(zero_variance_sales$zeroVar)) {
  cat("Zero variance predictors found and removed:", names(zero_vari
ance_sales[zero_variance_sales$zeroVar, ]), "\n")
  x_train_sales <- x_train_sales[, !zero_variance_sales$zeroVar]
  x_test_sales <- x_test_sales[, !zero_variance_sales$zeroVar]
}

## Zero variance predictors found and removed: freqRatio percentUniq
ue zeroVar nzv

# Step 1: Feature Selection using Recursive Feature Elimination (RFE
)
control_rfe_sales <- rfeControl(functions = rfFuncs, method = "cv",
number = 5)
# Using Random Forest for feature selection as it's robust
rfe_results_sales <- rfe(x_train_sales, y_train_sales, sizes = c(1:1
0), rfeControl = control_rfe_sales)

# Get the selected features
selected_predictors_sales <- predictors(rfe_results_sales)
cat("Selected Features for Sales Volume GBM:\n")

## Selected Features for Sales Volume GBM:

print(selected_predictors_sales)

##  [1] "Monthly_Sales_Volume_per_Country" "Polynomial_Term"
##  [3] "Number_of_Salespeople"            "DEA_Efficiency"
##  [5] "Interaction_Term"                 "Regulatory_Environment_S
core"
##  [7] "Number_of_Outlets"                "Regional_Population_Dens
ity"
##  [9] "Cultural_Difference_Score"        "Year"

# Subset the training and test data based on selected features
x_train_selected_sales <- x_train_sales[, selected_predictors_sales]
x_test_selected_sales <- x_test_sales[, selected_predictors_sales]

# Step 2: Train the GBM model with Hyperparameter Tuning
train_control_sales_gbm <- trainControl(method = "cv", number = 5)
gbm_grid_sales <- expand.grid(
  n.trees = seq(50, 500, by = 50),
  interaction.depth = seq(1, 7, by = 2),
  shrinkage = c(0.01, 0.05, 0.1),
  n.minobsinnode = c(5, 10, 20)
)

gbm_model_sales <- train(
  x = x_train_selected_sales,
```

```
  y = y_train_sales,
  method = "gbm",
  trControl = train_control_sales_gbm,
  tuneGrid = gbm_grid_sales,
  verbose = FALSE
)

# Print best model parameters
cat("Best GBM Parameters:\n")

## Best GBM Parameters:

print(gbm_model_sales$bestTune)

##     n.trees interaction.depth shrinkage n.minobsinnode
## 310     500                 5       0.1              5

# Step 3: Evaluate the model
predictions_sales_gbm <- predict(gbm_model_sales, newdata = x_test_s
elected_sales)

# Calculate performance metrics
mae_sales_gbm <- mean(abs(y_test_sales - predictions_sales_gbm))
rmse_sales_gbm <- sqrt(mean((y_test_sales - predictions_sales_gbm)^2
))

cat("MAE for GBM model (Sales Volume):", mae_sales_gbm, "\n")

## MAE for GBM model (Sales Volume): 0.817732

cat("RMSE for GBM model (Sales Volume):", rmse_sales_gbm, "\n")

## RMSE for GBM model (Sales Volume): 2.049705

# Step 4: Plot results
plot_data_sales_gbm <- data.frame(Date = test_data_sales$Date, Actua
l = y_test_sales, Predicted = predictions_sales_gbm)

ggplot(plot_data_sales_gbm, aes(x = Date)) +
  geom_point(aes(y = Actual, color = "Actual"), size = 2) +
  geom_line(aes(y = Predicted, color = "Predicted"), size = 1) +
  scale_color_manual(values = c("Actual" = "red", "Predicted" = "blu
e")) +
  labs(
    title = "GBM Prediction for Monthly Sales Volume per Dealer",
    x = "Date",
    y = "Monthly Sales Volume",
    color = "Legend"
  ) +
  theme_minimal(base_size = 14) +
  theme(
```

```
    plot.title = element_text(hjust = 0.5, size = 16, face = "bold")
,
    axis.text.x = element_text(angle = 45, hjust = 1, size = 12, col
or = "black"),
    axis.text.y = element_text(size = 12, color = "black"),
    axis.title.x = element_text(size = 14, color = "black"),
    axis.title.y = element_text(size = 14, color = "black"),
    legend.position = "bottom",
    legend.title = element_blank(),
    legend.background = element_rect(fill = "white", color = "white"
),
    panel.grid.major = element_line(color = "gray80", size = 0.5),
    panel.grid.minor = element_blank(),
    panel.background = element_rect(fill = "white", color = "white")
,
    plot.background = element_rect(fill = "white", color = "white")
  ) +
  scale_x_date(
    date_labels = "%b %Y",
    date_breaks = "2 months",
    expand = c(0, 0)
  ) +
  coord_cartesian(ylim = c(min(y_test_sales) * 0.8, max(y_test_sales
) * 1.2))

# Save the plot
ggsave("Sales Volume Prediction GBM.png", width = 10, height = 6, dp
i = 300)
```

GBM for NPS

```
# Define the target variable and predictor variables
target_variable_nps <- "NPS_Score"
predictors_nps <- setdiff(names(data), c(target_variable_nps, "Date"
))

# Extract predictors and target for train and test data
x_train_nps <- train_data_nps[, predictors_nps]
y_train_nps <- train_data_nps[[target_variable_nps]]
x_test_nps <- test_data_nps[, predictors_nps]
y_test_nps <- test_data_nps[[target_variable_nps]]

# Check and impute missing values using median
x_train_nps <- x_train_nps %>%
  mutate(across(everything(), ~ ifelse(is.na(.), median(., na.rm = T
RUE), .)))

x_test_nps <- x_test_nps %>%
  mutate(across(everything(), ~ ifelse(is.na(.), median(., na.rm = T
RUE), .)))
```

```
# Ensure all predictors are numeric
x_train_nps <- as.data.frame(lapply(x_train_nps, as.numeric))
x_test_nps <- as.data.frame(lapply(x_test_nps, as.numeric))
y_train_nps <- as.numeric(y_train_nps)
y_test_nps <- as.numeric(y_test_nps)

# Remove zero variance predictors
zero_variance_nps <- nearZeroVar(x_train_nps, saveMetrics = TRUE)
if (any(zero_variance_nps$zeroVar)) {
  cat("Zero variance predictors found and removed:", names(zero_vari
ance_nps[zero_variance_nps$zeroVar, ]), "\n")
  x_train_nps <- x_train_nps[, !zero_variance_nps$zeroVar]
  x_test_nps <- x_test_nps[, !zero_variance_nps$zeroVar]
}

## Zero variance predictors found and removed: freqRatio percentUniq
ue zeroVar nzv

# Step 1: Feature Selection using Recursive Feature Elimination (RFE
)
control_rfe_nps <- rfeControl(functions = rfFuncs, method = "cv", nu
mber = 5)
# Using Random Forest for feature selection as it's robust
rfe_results_nps <- rfe(x_train_nps, y_train_nps, sizes = c(1:10), rf
eControl = control_rfe_nps)

# Get the selected features
selected_predictors_nps <- predictors(rfe_results_nps)
cat("Selected Features for NPS Score GBM:\n")

## Selected Features for NPS Score GBM:

print(selected_predictors_nps)

## [1] "DEA_Efficiency"                   "Regional_Population_Densi
ty"
## [3] "Monthly_Sales_Volume_per_Country" "Monthly_Sales_Volume_per_
Dealer"
## [5] "Local_Economic_Growth"            "Cultural_Difference_Score
"
## [7] "Regulatory_Environment_Score"     "Interaction_Term"
## [9] "Polynomial_Term"

# Subset the training and test data based on selected features
x_train_selected_nps <- x_train_nps[, selected_predictors_nps]
x_test_selected_nps <- x_test_nps[, selected_predictors_nps]

# Step 2: Train the GBM model with Hyperparameter Tuning
train_control_nps_gbm <- trainControl(method = "cv", number = 5)
gbm_grid_nps <- expand.grid(
```

```
  n.trees = seq(50, 500, by = 50),
  interaction.depth = seq(1, 7, by = 2),
  shrinkage = c(0.01, 0.05, 0.1),
  n.minobsinnode = c(5, 10, 20)
)

gbm_model_nps <- train(
  x = x_train_selected_nps,
  y = y_train_nps,
  method = "gbm",
  trControl = train_control_nps_gbm,
  tuneGrid = gbm_grid_nps,
  verbose = FALSE
)

# Print best model parameters
cat("Best GBM Parameters for NPS Score:\n")

## Best GBM Parameters for NPS Score:

print(gbm_model_nps$bestTune)

##     n.trees interaction.depth shrinkage n.minobsinnode
## 354     200                 7       0.1             20

# Step 3: Evaluate the model
predictions_nps_gbm <- predict(gbm_model_nps, newdata = x_test_selec
ted_nps)

# Calculate performance metrics
mae_nps_gbm <- mean(abs(y_test_nps - predictions_nps_gbm))
rmse_nps_gbm <- sqrt(mean((y_test_nps - predictions_nps_gbm)^2))

cat("MAE for GBM model (NPS):", mae_nps_gbm, "\n")

## MAE for GBM model (NPS): 0.4327897

cat("RMSE for GBM model (NPS):", rmse_nps_gbm, "\n")

## RMSE for GBM model (NPS): 0.6019399

# Step 4: Plot results
plot_data_nps_gbm <- data.frame(Date = test_data_nps$Date, Actual =
y_test_nps, Predicted = predictions_nps_gbm)

ggplot(plot_data_nps_gbm, aes(x = Date)) +
  geom_point(aes(y = Actual, color = "Actual"), size = 2) +
  geom_line(aes(y = Predicted, color = "Predicted"), size = 1) +
  scale_color_manual(values = c("Actual" = "red", "Predicted" = "blu
e")) +
  labs(
```

```
    title = "GBM Prediction for NPS",
    x = "Date",
    y = "NPS Score",
    color = "Legend"
  ) +
  theme_minimal(base_size = 14) +
  theme(
    plot.title = element_text(hjust = 0.5, size = 16, face = "bold")
,
    axis.text.x = element_text(angle = 45, hjust = 1, size = 12, col
or = "black"),
    axis.text.y = element_text(size = 12, color = "black"),
    axis.title.x = element_text(size = 14, color = "black"),
    axis.title.y = element_text(size = 14, color = "black"),
    legend.position = "bottom",
    legend.title = element_blank(),
    legend.background = element_rect(fill = "white", color = "white"
),
    panel.grid.major = element_line(color = "gray80", size = 0.5),
    panel.grid.minor = element_blank(),
    panel.background = element_rect(fill = "white", color = "white")
,
    plot.background = element_rect(fill = "white", color = "white")
  ) +
  scale_x_date(
    date_labels = "%b %Y",
    date_breaks = "2 months",
    expand = c(0, 0)
  ) +
  coord_cartesian(ylim = c(min(y_test_nps) * 0.8, max(y_test_nps) *
1.2))

# Save the plot
ggsave("NPS Prediction GBM.png", width = 10, height = 6, dpi = 300)
```

GBM for Efficiency

```
# Define the target variable and predictor variables
target_variable_efficiency <- "DEA_Efficiency"
predictors_efficiency <- setdiff(names(data), c(target_variable_effi
ciency, "Date"))

# Extract predictors and target for train and test data
x_train_efficiency <- train_data_efficiency[, predictors_efficiency]
y_train_efficiency <- train_data_efficiency[[target_variable_efficie
ncy]]
x_test_efficiency <- test_data_efficiency[, predictors_efficiency]
y_test_efficiency <- test_data_efficiency[[target_variable_efficienc
y]]
```

```
# Check and impute missing values using median
x_train_efficiency <- x_train_efficiency %>%
  mutate(across(everything(), ~ ifelse(is.na(.), median(., na.rm = T
RUE), .)))

x_test_efficiency <- x_test_efficiency %>%
  mutate(across(everything(), ~ ifelse(is.na(.), median(., na.rm = T
RUE), .)))

# Ensure all predictors are numeric
x_train_efficiency <- as.data.frame(lapply(x_train_efficiency, as.nu
meric))
x_test_efficiency <- as.data.frame(lapply(x_test_efficiency, as.nume
ric))
y_train_efficiency <- as.numeric(y_train_efficiency)
y_test_efficiency <- as.numeric(y_test_efficiency)

# Remove zero variance predictors
zero_variance_efficiency <- nearZeroVar(x_train_efficiency, saveMetr
ics = TRUE)
if (any(zero_variance_efficiency$zeroVar)) {
  cat("Zero variance predictors found and removed:", names(zero_vari
ance_efficiency[zero_variance_efficiency$zeroVar, ]), "\n")
  x_train_efficiency <- x_train_efficiency[, !zero_variance_efficien
cy$zeroVar]
  x_test_efficiency <- x_test_efficiency[, !zero_variance_efficiency
$zeroVar]
}

## Zero variance predictors found and removed: freqRatio percentUniq
ue zeroVar nzv

# Step 1: Feature Selection using Recursive Feature Elimination (RFE
)
control_rfe_efficiency <- rfeControl(functions = rfFuncs, method = "
cv", number = 5)
# Using Random Forest for feature selection as it's robust
rfe_results_efficiency <- rfe(x_train_efficiency, y_train_efficiency
, sizes = c(1:10), rfeControl = control_rfe_efficiency)

# Get the selected features
selected_predictors_efficiency <- predictors(rfe_results_efficiency)
cat("Selected Features for DEA Efficiency GBM:\n")

## Selected Features for DEA Efficiency GBM:

print(selected_predictors_efficiency)

##  [1] "NPS_Score"                        "Regional_Population_Dens
ity"
##  [3] "Monthly_Sales_Volume_per_Country" "Monthly_Sales_Volume_per
```

```
_Dealer"
##  [5] "Service_Completion_Time"          "Local_Economic_Growth"
##  [7] "Regulatory_Environment_Score"     "Cultural_Difference_Scor
e"
##  [9] "Interaction_Term"                 "Number_of_Outlets"

# Subset the training and test data based on selected features
x_train_selected_efficiency <- x_train_efficiency[, selected_predict
ors_efficiency]
x_test_selected_efficiency <- x_test_efficiency[, selected_predictor
s_efficiency]

# Step 2: Train the GBM model with Hyperparameter Tuning
train_control_efficiency_gbm <- trainControl(method = "cv", number =
5)
gbm_grid_efficiency <- expand.grid(
  n.trees = seq(50, 500, by = 50),
  interaction.depth = seq(1, 7, by = 2),
  shrinkage = c(0.01, 0.05, 0.1),
  n.minobsinnode = c(5, 10, 20)
)

gbm_model_efficiency <- train(
  x = x_train_selected_efficiency,
  y = y_train_efficiency,
  method = "gbm",
  trControl = train_control_efficiency_gbm,
  tuneGrid = gbm_grid_efficiency,
  verbose = FALSE
)

# Print best model parameters
cat("Best GBM Parameters for DEA Efficiency:\n")

## Best GBM Parameters for DEA Efficiency:

print(gbm_model_efficiency$bestTune)

##     n.trees interaction.depth shrinkage n.minobsinnode
## 340     500                 7       0.1              5

# Step 3: Evaluate the model
predictions_efficiency_gbm <- predict(gbm_model_efficiency, newdata
= x_test_selected_efficiency)

# Calculate performance metrics
mae_efficiency_gbm <- mean(abs(y_test_efficiency - predictions_effic
iency_gbm))
rmse_efficiency_gbm <- sqrt(mean((y_test_efficiency - predictions_ef
ficiency_gbm)^2))
```

```r
cat("MAE for GBM model (DEA Efficiency):", mae_efficiency_gbm, "\n")

## MAE for GBM model (DEA Efficiency): 0.02823806

cat("RMSE for GBM model (DEA Efficiency):", rmse_efficiency_gbm, "\n
")

## RMSE for GBM model (DEA Efficiency): 0.04346894

# Step 4: Plot results
plot_data_efficiency_gbm <- data.frame(Date = test_data_efficiency$D
ate, Actual = y_test_efficiency, Predicted = predictions_efficiency_
gbm)

ggplot(plot_data_efficiency_gbm, aes(x = Date)) +
  geom_point(aes(y = Actual, color = "Actual"), size = 2) +
  geom_line(aes(y = Predicted, color = "Predicted"), size = 1) +
  scale_color_manual(values = c("Actual" = "red", "Predicted" = "blu
e")) +
  labs(
    title = "GBM Prediction for DEA Efficiency Scores",
    x = "Date",
    y = "DEA Efficiency",
    color = "Legend"
  ) +
  theme_minimal(base_size = 14) +
  theme(
    plot.title = element_text(hjust = 0.5, size = 16, face = "bold")
,
    axis.text.x = element_text(angle = 45, hjust = 1, size = 12, col
or = "black"),
    axis.text.y = element_text(size = 12, color = "black"),
    axis.title.x = element_text(size = 14, color = "black"),
    axis.title.y = element_text(size = 14, color = "black"),
    legend.position = "bottom",
    legend.title = element_blank(),
    legend.background = element_rect(fill = "white", color = "white"
),
    panel.grid.major = element_line(color = "gray80", size = 0.5),
    panel.grid.minor = element_blank(),
    panel.background = element_rect(fill = "white", color = "white")
,
    plot.background = element_rect(fill = "white", color = "white")
  ) +
  scale_x_date(
    date_labels = "%b %Y",
    date_breaks = "2 months",
    expand = c(0, 0)
  ) +
```

```
  coord_cartesian(ylim = c(min(y_test_efficiency) * 0.8, max(y_test_
efficiency) * 1.2))

# Save the plot
ggsave("Efficiency Prediction GBM.png", width = 10, height = 6, dpi
= 300)
```

Model Comparison for Sales Volume Prediction

```
evaluation_results_sales <- data.frame(
  Model = c("Linear Regression", "Random Forest", "ARIMA", "SVM", "G
BM"),
  Train_MAE = c(train_mae_sales_tuned, train_mae_sales_rf, mae_sales
_arima, mae_svm_sales_volume, mae_sales_gbm),
  Test_MAE = c(test_mae_sales_tuned, test_mae_sales_rf, mae_sales_ar
ima, mae_svm_sales_volume, mae_sales_gbm),
  Train_RMSE = c(train_rmse_sales_tuned, train_rmse_sales_rf, rmse_s
ales_arima, rmse_svm_sales_volume, rmse_sales_gbm),
  Test_RMSE = c(test_rmse_sales_tuned, test_rmse_sales_rf, rmse_sale
s_arima, rmse_svm_sales_volume, rmse_sales_gbm)
)

# Print the evaluation results
print("Evaluation Results for Sales Volume Prediction Models:")

## [1] "Evaluation Results for Sales Volume Prediction Models:"

print(evaluation_results_sales)

##               Model Train_MAE  Test_MAE Train_RMSE Test_RMSE
## 1 Linear Regression 2.0763953 2.2868016   3.029188  3.149489
## 2     Random Forest 0.4804284 0.9453628   1.949679  2.712002
## 3             ARIMA 9.2980137 9.2980137  14.441629 14.441629
## 4               SVM 2.6953360 2.6953360   3.922463  3.922463
## 5               GBM 0.8177320 0.8177320   2.049705  2.049705

# Determine the best sales model based on Test MAE
best_mae_model_sales <- evaluation_results_sales[which.min(evaluatio
n_results_sales$Test_MAE), "Model"]
best_mae_value_sales <- min(evaluation_results_sales$Test_MAE)

# Determine the best sales model based on Test RMSE
best_rmse_model_sales <- evaluation_results_sales[which.min(evaluati
on_results_sales$Test_RMSE), "Model"]
best_rmse_value_sales <- min(evaluation_results_sales$Test_RMSE)

# Print the best sales models
cat("Best Model for Sales Volume based on Test MAE:", best_mae_model
_sales, "with MAE =", best_mae_value_sales, "\n")
```

```
## Best Model for Sales Volume based on Test MAE: GBM with MAE = 0.8
17732
```

```
cat("Best Model for Sales Volume based on Test RMSE:", best_rmse_mod
el_sales, "with RMSE =", best_rmse_value_sales, "\n")
```

```
## Best Model for Sales Volume based on Test RMSE: GBM with RMSE = 2
.049705
```

```
# Melt the data for visualization
evaluation_results_sales_melted <- melt(evaluation_results_sales, id
.vars = "Model", variable.name = "Metric", value.name = "Value")

# Plot
ggplot(evaluation_results_sales_melted, aes(x = Model, y = Value, fi
ll = Metric)) +
  geom_bar(stat = "identity", position = "dodge") +
  facet_wrap(~ Metric, scales = "free_y", ncol = 2) +
  labs(
    title = "Comparison of Model Performance for Predicting Monthly
Sales Volume per Dealer",
    y = "Error Value",
    x = "Model"
  ) +
  theme_minimal(base_size = 14) +
  theme(
    plot.title = element_text(hjust = 0.5, size = 16, face = "bold")
,
    axis.text.x = element_text(angle = 45, hjust = 1, size = 12, col
or = "black"),
    axis.text.y = element_text(size = 12, color = "black"),
    axis.title.x = element_text(size = 14, color = "black"),
    axis.title.y = element_text(size = 14, color = "black"),
    legend.position = "bottom",
    legend.title = element_blank(),
    legend.background = element_rect(fill = "white", color = "white"
),
    panel.grid.major = element_line(color = "gray80", size = 0.5),
    panel.grid.minor = element_blank(),
    panel.background = element_rect(fill = "white", color = "white")
,
    plot.background = element_rect(fill = "white", color = "white")
  ) +
  scale_fill_manual(values = c("Train_MAE" = "tomato", "Test_MAE" =
"forestgreen", "Train_RMSE" = "skyblue", "Test_RMSE" = "purple")) +
  coord_flip() # Flip the coordinates to make the bars horizontal

# Save the plot
ggsave("Sales Volume Model Comparison.png", width = 12, height = 8,
dpi = 300)
```

Model Comparison for NPS Prediction

```
evaluation_results_nps <- data.frame(
  Model = c("Linear Regression", "Random Forest", "ARIMA", "SVM", "G
BM"),
  Train_MAE = c(train_mae_nps_tuned, train_mae_nps_rf, mae_nps_arima
, mae_svm_nps_score, mae_nps_gbm),
  Test_MAE = c(test_mae_nps_tuned, test_mae_nps_rf, mae_nps_arima, m
ae_svm_nps_score, mae_nps_gbm),
  Train_RMSE = c(train_rmse_nps_tuned, train_rmse_nps_rf, rmse_nps_a
rima, rmse_svm_nps_score, rmse_nps_gbm),
  Test_RMSE = c(test_rmse_nps_tuned, test_rmse_nps_rf, rmse_nps_arim
a, rmse_svm_nps_score, rmse_nps_gbm)
)

# Print the evaluation results
print("Evaluation Results for NPS Score Prediction Models:")

## [1] "Evaluation Results for NPS Score Prediction Models:"

print(evaluation_results_nps)

##               Model Train_MAE  Test_MAE Train_RMSE Test_RMSE
## 1 Linear Regression 0.6456239 0.6504349  0.8098832 0.8353602
## 2     Random Forest 0.5029557 0.6451648  0.6287716 0.8102201
## 3             ARIMA 0.7878709 0.7878709  0.9616074 0.9616074
## 4               SVM 0.6582484 0.6582484  0.8326010 0.8326010
## 5               GBM 0.4327897 0.4327897  0.6019399 0.6019399

# Determine the best NPS model based on Test MAE
best_mae_model_nps <- evaluation_results_nps[which.min(evaluation_re
sults_nps$Test_MAE), "Model"]
best_mae_value_nps <- min(evaluation_results_nps$Test_MAE)

# Determine the best NPS model based on Test RMSE
best_rmse_model_nps <- evaluation_results_nps[which.min(evaluation_r
esults_nps$Test_RMSE), "Model"]
best_rmse_value_nps <- min(evaluation_results_nps$Test_RMSE)

# Print the best NPS models
cat("Best Model for NPS Score based on Test MAE:", best_mae_model_np
s, "with MAE =", best_mae_value_nps, "\n")

## Best Model for NPS Score based on Test MAE: GBM with MAE = 0.4327
897

cat("Best Model for NPS Score based on Test RMSE:", best_rmse_model_
nps, "with RMSE =", best_rmse_value_nps, "\n")

## Best Model for NPS Score based on Test RMSE: GBM with RMSE = 0.60
19399
```

```
# Melt the data for visualization
evaluation_results_nps_melted <- melt(evaluation_results_nps, id.var
s = "Model", variable.name = "Metric", value.name = "Value")

# Plot
ggplot(evaluation_results_nps_melted, aes(x = Model, y = Value, fill
= Metric)) +
  geom_bar(stat = "identity", position = "dodge") +
  facet_wrap(~ Metric, scales = "free_y", ncol = 2) +
  labs(
    title = "Comparison of Model Performance for Predicting NPS",
    y = "Error Value",
    x = "Model"
  ) +
  theme_minimal(base_size = 14) +
  theme(
    plot.title = element_text(hjust = 0.5, size = 16, face = "bold")
,
    axis.text.x = element_text(angle = 45, hjust = 1, size = 12, col
or = "black"),
    axis.text.y = element_text(size = 12, color = "black"),
    axis.title.x = element_text(size = 14, color = "black"),
    axis.title.y = element_text(size = 14, color = "black"),
    legend.position = "bottom",
    legend.title = element_blank(),
    legend.background = element_rect(fill = "white", color = "white"
),
    panel.grid.major = element_line(color = "gray80", size = 0.5),
    panel.grid.minor = element_blank(),
    panel.background = element_rect(fill = "white", color = "white")
,
    plot.background = element_rect(fill = "white", color = "white")
  ) +
  scale_fill_manual(values = c("Train_MAE" = "tomato", "Test_MAE" =
"forestgreen", "Train_RMSE" = "skyblue", "Test_RMSE" = "purple")) +
  coord_flip() # Flip the coordinates to make the bars horizontal

# Save the plot
ggsave("NPS Model Comparison.png", width = 12, height = 8, dpi = 300
)
```

Model Comparison for Efficiency Prediction

```
evaluation_results_efficiency <- data.frame(
  Model = c("Linear Regression", "Random Forest", "ARIMA", "SVM", "G
BM"),
  Train_MAE = c(train_mae_efficiency_tuned, train_mae_efficiency_rf,
mae_efficiency_arima, mae_efficiency_svm, mae_efficiency_gbm),
  Test_MAE = c(test_mae_efficiency_tuned, test_mae_efficiency_rf, ma
```

```
e_efficiency_arima, mae_efficiency_svm, mae_efficiency_gbm),
  Train_RMSE = c(train_rmse_efficiency_tuned, train_rmse_efficiency_
rf, rmse_efficiency_arima, rmse_efficiency_svm, rmse_efficiency_gbm)
,
  Test_RMSE = c(test_rmse_efficiency_tuned, test_rmse_efficiency_rf,
rmse_efficiency_arima, rmse_efficiency_svm, rmse_efficiency_gbm)
)

# Print the evaluation results
print("Evaluation Results for DEA Efficiency Prediction Models:")

## [1] "Evaluation Results for DEA Efficiency Prediction Models:"

print(evaluation_results_efficiency)

##               Model  Train_MAE   Test_MAE Train_RMSE  Test_RMSE
## 1 Linear Regression 0.07412915 0.07456219 0.09996373 0.10059292
## 2     Random Forest 0.04976008 0.06837422 0.06827118 0.09188737
## 3             ARIMA 0.20370689 0.20370689 0.24129867 0.24129867
## 4               SVM 0.11916659 0.11916659 0.15571261 0.15571261
## 5               GBM 0.02823806 0.02823806 0.04346894 0.04346894

# Determine the best Efficiency model based on Test MAE
best_mae_model_efficiency <- evaluation_results_efficiency[which.min
(evaluation_results_efficiency$Test_MAE), "Model"]
best_mae_value_efficiency <- min(evaluation_results_efficiency$Test_
MAE)

# Determine the best Efficiency model based on Test RMSE
best_rmse_model_efficiency <- evaluation_results_efficiency[which.mi
n(evaluation_results_efficiency$Test_RMSE), "Model"]
best_rmse_value_efficiency <- min(evaluation_results_efficiency$Test
_RMSE)

# Print the best Efficiency models
cat("Best Model for DEA Efficiency based on Test MAE:", best_mae_mod
el_efficiency, "with MAE =", best_mae_value_efficiency, "\n")

## Best Model for DEA Efficiency based on Test MAE: GBM with MAE = 0
.02823806

cat("Best Model for DEA Efficiency based on Test RMSE:", best_rmse_m
odel_efficiency, "with RMSE =", best_rmse_value_efficiency, "\n")

## Best Model for DEA Efficiency based on Test RMSE: GBM with RMSE =
0.04346894

# Melt the data for visualization
evaluation_results_efficiency_melted <- melt(evaluation_results_effi
ciency, id.vars = "Model", variable.name = "Metric", value.name = "V
alue")
```

```
# Plot
ggplot(evaluation_results_efficiency_melted, aes(x = Model, y = Valu
e, fill = Metric)) +
  geom_bar(stat = "identity", position = "dodge") +
  facet_wrap(~ Metric, scales = "free_y", ncol = 2) +
  labs(
    title = "Comparison of Model Performance for Predicting DEA Effi
ciency Scores",
    y = "Error Value",
    x = "Model"
  ) +
  theme_minimal(base_size = 14) +
  theme(
    plot.title = element_text(hjust = 0.5, size = 16, face = "bold")
,
    axis.text.x = element_text(angle = 45, hjust = 1, size = 12, col
or = "black"),
    axis.text.y = element_text(size = 12, color = "black"),
    axis.title.x = element_text(size = 14, color = "black"),
    axis.title.y = element_text(size = 14, color = "black"),
    legend.position = "bottom",
    legend.title = element_blank(),
    legend.background = element_rect(fill = "white", color = "white"
),
    panel.grid.major = element_line(color = "gray80", size = 0.5),
    panel.grid.minor = element_blank(),
    panel.background = element_rect(fill = "white", color = "white")
,
    plot.background = element_rect(fill = "white", color = "white")
  ) +
  scale_fill_manual(values = c("Train_MAE" = "tomato", "Test_MAE" =
"forestgreen", "Train_RMSE" = "skyblue", "Test_RMSE" = "purple")) +
  coord_flip() # Flip the coordinates to make the bars horizontal

# Save the plot
ggsave("Efficiency Model Comparison.png", width = 12, height = 8, dp
i = 300)
```

Perform DEA (Data Envelopment Analysis) using the GBM predictions

Prepare Data for DEA

```
# Normalize function
normalize <- function(x) {
  return((x - min(x)) / (max(x) - min(x)))
}
```

```
# Prepare Data for DEA
test_data_sales$Predicted_Sales_Volume <- predictions_sales_gbm
test_data_nps$Predicted_NPS <- predictions_nps_gbm
test_data_efficiency$Predicted_Efficiency <- predictions_efficiency_
gbm

# Combine relevant columns into a single data frame for DEA analysis
dea_data <- test_data_sales %>%
  dplyr::select(
    Dealership_Name,
    Country,
    Region,
    Year,
    Number_of_Salespeople,
    Number_of_Outlets,
    Service_Completion_Time,
    Regional_Population_Density,
    Local_Economic_Growth,
    Cultural_Difference_Score,
    Regulatory_Environment_Score,
    Predicted_Sales_Volume
  ) %>%
  dplyr::mutate(
    Predicted_NPS = test_data_nps$Predicted_NPS,
    Predicted_Efficiency = test_data_efficiency$Predicted_Efficiency
  )

# Convert necessary columns to numeric
dea_data <- dea_data %>%
  mutate(
    Number_of_Salespeople = as.numeric(Number_of_Salespeople),
    Number_of_Outlets = as.numeric(Number_of_Outlets),
    Service_Completion_Time = as.numeric(Service_Completion_Time),
    Predicted_Sales_Volume = as.numeric(Predicted_Sales_Volume),
    Predicted_NPS = as.numeric(Predicted_NPS),
    Predicted_Efficiency = as.numeric(Predicted_Efficiency)
  )

# Normalize data
dea_data <- dea_data %>%
  mutate(
    Number_of_Salespeople = normalize(Number_of_Salespeople),
    Number_of_Outlets = normalize(Number_of_Outlets),
    Service_Completion_Time = normalize(Service_Completion_Time),
    Regional_Population_Density = normalize(Regional_Population_Dens
ity),
    Local_Economic_Growth = normalize(Local_Economic_Growth),
    Predicted_Sales_Volume = normalize(Predicted_Sales_Volume),
```

```
    Predicted_NPS = normalize(Predicted_NPS),
    Predicted_Efficiency = normalize(Predicted_Efficiency)
  )

# Check for any NA values and replace them if necessary
if (any(is.na(dea_data))) {
  cat("NA values found in the dataset. Replacing with 0.\n")
  dea_data[is.na(dea_data)] <- 0
}
```

Generate New DEA Efiiciency Scores

```
# Define inputs and outputs for DEA
inputs <- dea_data %>%
  dplyr::select(Number_of_Salespeople, Number_of_Outlets, Service_Co
mpletion_Time) %>%
  as.matrix()

outputs <- dea_data %>%
  dplyr::select(Predicted_Sales_Volume, Predicted_NPS, Predicted_Eff
iciency) %>%
  as.matrix()

# Conduct DEA Analysis
dea_model <- dea(X = inputs, Y = outputs, RTS = "vrs", ORIENTATION =
"in")
efficiency_scores <- dea_model$eff

# Add efficiency scores to the DEA data
dea_data$DEA_Efficiency_New <- efficiency_scores

# Summary statistics of efficiency scores
summary(dea_data$DEA_Efficiency_New)

##    Min. 1st Qu.  Median    Mean 3rd Qu.    Max.
## 0.07421 0.20830 0.32573 0.39894 0.52609 1.00000

# Plot the histogram of DEA Efficiency Scores
hist_plot <- hist(dea_data$DEA_Efficiency_New,
                  main = "Distribution of DEA Efficiency Scores (Pos
t-Modelling)",
                  xlab = "Efficiency Score",
                  breaks = 20,
                  col = "lightblue",
                  border = "black",
                  xlim = c(0, max(efficiency_scores, na.rm = TRUE) +
0.1))

# Save the plot to your drive using ggsave
# Convert the base R histogram to a ggplot object
hist_ggplot <- ggplot(dea_data, aes(x = DEA_Efficiency_New)) +
```

```
  geom_histogram(breaks = hist_plot$breaks,
                 fill = "lightblue",
                 color = "black") +
  labs(title = "Distribution of DEA Efficiency Scores (Post-Modellin
g)",
       x = "Efficiency Score",
       y = "Frequency") +
  xlim(0, max(efficiency_scores, na.rm = TRUE) + 0.1)

# Save the ggplot histogram
ggsave("DEA Efficiency Distribution Post-Modelling.png", plot = hist
_ggplot, width = 8, height = 6)
```

Evaluate Predicted Dealership Performance with DEA Scores

```
# Calculate the average DEA efficiency score per dealer per year
annual_efficiency <- dea_data %>%
  group_by(Dealership_Name, Country, Region) %>%
  summarise(
    Average_DEA_Efficiency = mean(DEA_Efficiency_New, na.rm = TRUE),
    Regional_Population_Density = first(Regional_Population_Density)
,
    Local_Economic_Growth = first(Local_Economic_Growth),
    Cultural_Difference_Score = first(Cultural_Difference_Score),
    Regulatory_Environment_Score = first(Regulatory_Environment_Scor
e)
  ) %>%
  ungroup()

# Define performance categories based on Average DEA Efficiency
performance_levels <- annual_efficiency %>%
  mutate(
    Performance_Category = case_when(
      Average_DEA_Efficiency >= 0.7 ~ "High",
      Average_DEA_Efficiency >= 0.5 & Average_DEA_Efficiency < 0.7 ~
"Medium",
      TRUE ~ "Low"
    )
  )

# Print performance categories for dealerships
cat("Performance Categories for Each Dealership:\n")

## Performance Categories for Each Dealership:

print(performance_levels[, c("Dealership_Name", "Country", "Region",
"Average_DEA_Efficiency", "Performance_Category")])

## # A tibble: 157 × 5
##    Dealership_Name  Country   Region Average_DEA_Efficiency Perfo
rmance_Category
```

```
##     <chr>            <chr>      <chr>                    <dbl> <chr>
##  1 ADG Groep        Netherla… Drent…                   0.929 High
##  2 Aichlseder       Austria   Kärnt…                   0.296 Low
##  3 Alan Day         UK        London                   0.334 Low
##  4 Arnold Clark     UK        North…                   0.371 Low
##  5 Arnold Clark     UK        Scotl…                   0.239 Low
##  6 Astara Retail    Spain     Comun…                   0.122 Low
##  7 Auto Bernhard    Austria   Tirol…                   0.331 Low
##  8 Auto Harb        Austria   Steie…                   0.375 Low
##  9 Auto Oberhofer   Austria   Tirol…                   0.296 Low
## 10 Autohaus Brunner Austria   Tirol…                   0.316 Low
## # ℹ 147 more rows
```

```
# Filter dealerships by performance category
high_performers <- performance_levels %>% filter(Performance_Categor
y == "High")
medium_performers <- performance_levels %>% filter(Performance_Categ
ory == "Medium")
low_performers <- performance_levels %>% filter(Performance_Category
== "Low")

# Print high, medium, and low performers
cat("\nHigh Performing Dealerships:\n")
```

```
##
## High Performing Dealerships:
```

```
print(high_performers[, c("Dealership_Name", "Country", "Region", "A
verage_DEA_Efficiency")])
```

```
## # A tibble: 14 × 4
##    Dealership_Name              Country     Region          Average
_DEA_Efficiency
##    <chr>                        <chr>       <chr>
<dbl>
##  1 ADG Groep                    Netherlands Drenthe
0.929
##  2 Barchetti                    Italy       Veneto
0.872
##  3 Granrud Bilverksted          Norway      Innlandet
0.733
##  4 Grupo M. & Costas            Portugal    Norte (North)
0.780
##  5 Hedin Automotive DE          Germany     Rheinland-Pfa…
1
##  6 Ilha Verde                   Portugal    Açores (Azore…
0.719
##  7 Lookers                      UK          Yorkshire and…
0.824
##  8 Louwman                      Netherlands Noord-Brabant…
```

```
0.709
## 9 Louwman                       Netherlands Noord-Holland…
0.904
## 10 Louwman                      Netherlands Zuid-Holland …
0.764
## 11 Plichta                      Poland      Kujawsko-pomo…
0.840
## 12 STERNAUTO                    Germany     Thüringen (Th…
0.763
## 13 Schiller Autó Család         Hungary     Budapest
0.919
## 14 Sverre Haugli Bilforretning Norway      Buskerud/Viken
0.982
```

```r
cat("\nMedium Performing Dealerships:\n")
```

```
##
## Medium Performing Dealerships:
```

```r
print(medium_performers[, c("Dealership_Name", "Country", "Region",
"Average_DEA_Efficiency")])
```

```
## # A tibble: 29 × 4
##    Dealership_Name  Country  Region                        Average_
DEA_Efficiency
##    <chr>            <chr>    <chr>
<dbl>
##  1 Autohaus Fürst   Austria  Burgenland
0.572
##  2 Autosalg         Norway   Vestland
0.583
##  3 Barchetti        Italy    Lombardia (Lombardy)
0.509
##  4 Bilhuset Harstad Norway   Troms
0.508
##  5 Bilservice       Norway   Buskerud/Viken
0.578
##  6 Blendio          Spain    País Vasco (Basque Country)
0.545
##  7 Busseys          UK       East of England
0.659
##  8 Charles Hurst    UK       Northern Ireland
0.676
##  9 Corvauto         Portugal Centro (Central)
0.660
## 10 Duna Autó        Hungary  Budapest
0.629
## # ℹ 19 more rows
```

```r
cat("\nLow Performing Dealerships:\n")
```

```
##
## Low Performing Dealerships:
```

```
print(low_performers[, c("Dealership_Name", "Country", "Region", "Av
erage_DEA_Efficiency")])
```

```
## # A tibble: 114 × 4
##    Dealership_Name  Country Region                        Average
_DEA_Efficiency
##    <chr>            <chr>   <chr>
<dbl>
##  1 Aichlseder       Austria Kärnten (Carinthia)
0.296
##  2 Alan Day         UK      London
0.334
##  3 Arnold Clark     UK      North East
0.371
##  4 Arnold Clark     UK      Scotland
0.239
##  5 Astara Retail    Spain   Comunidad de Madrid (Communi…
0.122
##  6 Auto Bernhard    Austria Tirol (Tyrol)
0.331
##  7 Auto Harb        Austria Steiermark (Styria)
0.375
##  8 Auto Oberhofer   Austria Tirol (Tyrol)
0.296
##  9 Autohaus Brunner Austria Tirol (Tyrol)
0.316
## 10 Autohaus Koller  Austria Niederösterreich (Lower Aust…
0.366
## # ℹ 104 more rows
```

Visualisation of Predicted Dealership Performance with DEA Efficiency Scores

```
# Reorder the levels of the Performance_Category factor
performance_levels$Performance_Category <- factor(performance_levels
$Performance_Category,
                                                  levels = c("Low",
"Medium", "High"))

# Simplify the visualization to a dot plot with horizontal lines for
performance categories
dot_plot <- ggplot(performance_levels, aes(x = Average_DEA_Efficienc
y, y = reorder(Dealership_Name, Average_DEA_Efficiency))) +
  geom_point(aes(color = Performance_Category), size = 3) +
  geom_hline(yintercept = seq(1, nrow(performance_levels), by = 1),
color = "grey90") +
  scale_color_manual(values = c("High" = "green", "Medium" = "blue",
```

```
"Low" = "red")) +
  theme_minimal(base_size = 12) +
  theme(
    axis.text.y = element_text(size = 7, color = "black"),  # Smalle
r text for readability
    axis.title.y = element_blank(),
    axis.title.x = element_text(size = 10, color = "black"),
    panel.background = element_rect(fill = "white", color = NA),  #
White background
    plot.background = element_rect(fill = "white", color = NA),   #
White plot background
    legend.background = element_rect(fill = "white", color = NA), #
White legend background
    plot.title = element_text(color = "black"),                   #
Black title
    axis.text.x = element_text(color = "black"),                  #
Black x-axis labels
    legend.text = element_text(color = "black"),                  #
Black legend text
    legend.title = element_text(color = "black")                  #
Black legend title
  ) +
  labs(
    title = "DEA Efficiency Scores by Dealership (Post-Modelling)",
    y = "Average DEA Efficiency"
  ) +
  scale_y_discrete(expand = c(0, 0)) # Remove extra space on y-axis
for discrete values

# Save the dot plot with a white background
ggsave("Efficiency Dot Plot Post-Modelling.png", dot_plot, width = 1
6, height = 24, dpi = 300)

# Grouped Bar Chart for Dealerships by Performance Category
bar_chart <- ggplot(performance_levels, aes(x = Performance_Category
, fill = Performance_Category)) +
  geom_bar(position = "dodge") +
  scale_fill_manual(values = c("Low" = "red", "Medium" = "blue", "Hi
gh" = "green")) +
  theme_minimal(base_size = 14) +
  theme(
    axis.text.x = element_text(size = 12, color = "black"),
    axis.text.y = element_text(size = 12, color = "black"),
    axis.title.x = element_text(size = 14, color = "black"),
    axis.title.y = element_text(size = 14, color = "black"),
    panel.background = element_rect(fill = "white", color = NA),  #
White background
    plot.background = element_rect(fill = "white", color = NA),   #
White plot background
```

```
    legend.background = element_rect(fill = "white", color = NA), #
White legend background
    legend.position = "none",                                      #
Hide legend for simplicity
    plot.title = element_text(color = "black", hjust = 0.5)       #
Centered title
  ) +
  labs(
    title = "Distribution of Dealerships by Performance Category (Po
st-Modelling)",
    x = "Performance Category",
    y = "Number of Dealerships"
  ) +
  geom_text(stat = "count", aes(label = ..count..), vjust = -0.5, co
lor = "black", size = 5) # Add count labels

# Save the grouped bar chart with a white background
ggsave("Efficiency Grouped Bar Chart Post-Modelling.png", bar_chart,
width = 12, height = 8, dpi = 300)

# Customize the box plot for DEA Efficiency scores
box_plot <- ggplot(performance_levels, aes(x = Performance_Category,
y = Average_DEA_Efficiency, fill = Performance_Category)) +
  geom_boxplot(outlier.shape = NA) + # Avoid plotting outliers for a
cleaner plot
  scale_fill_manual(values = c("High" = "green", "Medium" = "blue",
"Low" = "red")) +
  theme_minimal(base_size = 12) +
  theme(
    panel.background = element_rect(fill = "white", color = NA),
    plot.background = element_rect(fill = "white"),
    legend.position = "right"
  ) +
  labs(
    title = "Boxplot of DEA Efficiency Scores by Performance Categor
y (Post-Modelling)",
    x = "Performance Category",
    y = "Average DEA Efficiency"
  )

# Save the box plot as a PNG image
ggsave("Efficiency Box Plot Post-Modelling.png", box_plot, width = 1
2, height = 8, dpi = 300)

# Combine all performers into a single list for saving
tables_to_save <- list(
  "High Performing Dealerships" = high_performers,
  "Medium Performing Dealerships" = medium_performers,
  "Low Performing Dealerships" = low_performers
```

```
)

# Save the tables as Excel sheets in a single file
write_xlsx(tables_to_save, "Dealership Performance Tables.xlsx")
```

Analysis on Key Variables that Impacts DEA Efficieny

Variable Importance using Linear Regression

```
# Linear Regression to Identify Variable Impact on DEA Scores
variable_impact_lm <- lm(
  DEA_Efficiency_New ~ Number_of_Salespeople + Number_of_Outlets + S
ervice_Completion_Time,
  data = dea_data
)

# Summary of the regression model to see the impact of each variable
summary(variable_impact_lm)

##
## Call:
## lm(formula = DEA_Efficiency_New ~ Number_of_Salespeople + Number_
of_Outlets +
##     Service_Completion_Time, data = dea_data)
##
## Residuals:
##      Min       1Q   Median       3Q      Max
## -0.23154 -0.15383 -0.06109  0.06567  0.99469
##
## Coefficients:
##                         Estimate Std. Error t value Pr(>|t|)
## (Intercept)              0.42423    0.02494  17.008   <2e-16 ***
## Number_of_Salespeople    2.66933    0.30108   8.866   <2e-16 ***
## Number_of_Outlets       -2.77949    0.26834 -10.358   <2e-16 ***
## Service_Completion_Time -0.49217    0.05439  -9.049   <2e-16 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 0.2121 on 435 degrees of freedom
## Multiple R-squared:  0.3056, Adjusted R-squared:  0.3008
## F-statistic: 63.82 on 3 and 435 DF,  p-value: < 2.2e-16

# Extract and display the coefficients to interpret the impact
variable_impact_lm_coefficients <- summary(variable_impact_lm)$coeff
icients
print(variable_impact_lm_coefficients)

##                           Estimate Std. Error    t value     Pr(>
|t|)
## (Intercept)              0.4242295 0.02494302  17.007943 4.200524
```

```
e-50
## Number_of_Salespeople    2.6693328 0.30108039   8.865847 1.970507
e-17
## Number_of_Outlets       -2.7794937 0.26834278 -10.357997 1.278544
e-22
## Service_Completion_Time -0.4921698 0.05439120  -9.048702 4.861327
e-18
```

Variable Importance using Random Forest

```
# Random Forest to Identify Variable Impact on DEA Scores
set.seed(123)  # Ensure reproducibility

# Train Random Forest model for variable importance
variable_impact_rf <- randomForest(
  DEA_Efficiency_New ~ Number_of_Salespeople + Number_of_Outlets + S
ervice_Completion_Time,
  data = dea_data,
  importance = TRUE,
  ntree = 500
)

# Print model summary
print(variable_impact_rf)

##
## Call:
##  randomForest(formula = DEA_Efficiency_New ~ Number_of_Salespeopl
e +      Number_of_Outlets + Service_Completion_Time, data = dea_dat
a,      importance = TRUE, ntree = 500)
##                Type of random forest: regression
##                      Number of trees: 500
## No. of variables tried at each split: 1
##
##           Mean of squared residuals: 0.04052254
##                     % Var explained: 36.9

# Extract and plot variable importance
variable_importance_rf <- importance(variable_impact_rf)
varImpPlot(variable_impact_rf)

# Save variable importance plot
png("Random Forest Variable Importance Dealership Performance.png",
width = 1000, height = 800, res = 150)
varImpPlot(variable_impact_rf)
dev.off()

## png
##   2
```

Combining The Results of Variable Importance and Interpretation

```
# Extract coefficients from the linear model and ensure correct vari
able names
lm_coefficients <- as.data.frame(variable_impact_lm_coefficients[, c
("Estimate", "Pr(>|t|)")])
lm_coefficients$Variable <- rownames(lm_coefficients)

# Ensure Random Forest variable importance is also a data frame with
matching variable names
rf_importance <- as.data.frame(variable_importance_rf[, "IncNodePuri
ty"])
rf_importance$Variable <- rownames(rf_importance)
colnames(rf_importance) <- c("Variable_Importance", "Variable")

# Merge the two data frames by Variable
variable_importance_combined <- merge(lm_coefficients, rf_importance
, by = "Variable", all = TRUE)

# Sort by importance for interpretation
variable_importance_combined <- variable_importance_combined[order(-
variable_importance_combined$Variable_Importance), ]
print(variable_importance_combined)

##                  Variable   Estimate     Pr(>|t|) Variable_Import
ance
## 4 Service_Completion_Time -0.4921698 4.861327e-18            5.53
9176
## 3   Number_of_Salespeople  2.6693328 1.970507e-17            3.27
8809
## 2       Number_of_Outlets -2.7794937 1.278544e-22            3.08
6708
## 1             (Intercept)  0.4242295 4.200524e-50
NA

# Save the combined importance as an Excel file for reporting
write_xlsx(variable_importance_combined, "Variable Importance Dealer
ship Performance.xlsx")

# Filter out the intercept from the data
variable_importance_long <- variable_importance_combined %>%
  filter(Variable != "(Intercept)") %>%
  pivot_longer(cols = c("Estimate", "Variable_Importance"), names_to
= "Model", values_to = "Importance")

# Create the bar plot with adjusted bar width and a white background
ggplot(variable_importance_long, aes(x = reorder(Variable, Importanc
e), y = Importance, fill = Model)) +
  geom_bar(stat = "identity", position = position_dodge(width = 0.8)
, width = 0.5) +
```

```
  coord_flip() +
  scale_fill_manual(values = c("Estimate" = "blue", "Variable_Import
ance" = "green")) +
  labs(
    title = "Variable Importance for Dealership Performance",
    x = "Variables",
    y = "Importance Scores",
    fill = "Model"
  ) +
  theme_minimal(base_size = 10) +
  theme(
    plot.title = element_text(hjust = 0.5, face = "bold"),
    axis.text.x = element_text(size = 10, color = "black"),
    axis.text.y = element_text(size = 10, color = "black"),
    legend.position = "bottom",
    legend.title = element_blank(),
    plot.background = element_rect(fill = "white", color = NA),
    panel.background = element_rect(fill = "white", color = NA)
  )

# Save the plot as a PNG image
ggsave("Variable Importance Visualization.png", width = 12, height =
8, dpi = 300)
```

Sensitivity Analysis On Key Variables Impacting Model Predictions

```
# # Clear unused variables to free up memory
# rm(list = setdiff(ls(), c("dea_data", "gbm_model_sales", "gbm_mode
l_nps", "gbm_model_efficiency")))
# gc()

# Store the original (non-normalized) data for sensitivity analysis
dea_data_sensitivity <- dea_data %>%
  mutate(
    Number_of_Salespeople = as.numeric(Number_of_Salespeople),
    Number_of_Outlets = as.numeric(Number_of_Outlets),
    Service_Completion_Time = as.numeric(Service_Completion_Time),
    Predicted_Sales_Volume = as.numeric(Predicted_Sales_Volume),
    Predicted_NPS = as.numeric(Predicted_NPS),
    Predicted_Efficiency = as.numeric(Predicted_Efficiency)
  )

# Define the Sensitivity Analysis Function
sensitivity_analysis <- function(dea_data_sensitivity, gbm_model_sal
es, gbm_model_nps, gbm_model_efficiency, input_variable_name, change
_percentage) {
```

```
  # Create a copy of the original data for modification
  modified_data <- dea_data_sensitivity

  # Adjust the selected input variable by the specified percentage
  modified_data[[input_variable_name]] <- modified_data[[input_varia
ble_name]] * (1 + change_percentage / 100)

  # Recalculate predictions based on the modified data
  modified_data <- modified_data %>%
    mutate(
      Predicted_Sales_Volume = predict(gbm_model_sales, newdata = mo
dified_data),
      Predicted_NPS = predict(gbm_model_nps, newdata = modified_data
),
      Predicted_Efficiency = predict(gbm_model_efficiency, newdata =
modified_data)
    )

  # Calculate the average predicted values for comparison
  original_avg_sales <- mean(dea_data_sensitivity$Predicted_Sales_Vo
lume, na.rm = TRUE)
  modified_avg_sales <- mean(modified_data$Predicted_Sales_Volume, n
a.rm = TRUE)

  original_avg_nps <- mean(dea_data_sensitivity$Predicted_NPS, na.rm
= TRUE)
  modified_avg_nps <- mean(modified_data$Predicted_NPS, na.rm = TRUE
)

  original_avg_efficiency <- mean(dea_data_sensitivity$Predicted_Eff
iciency, na.rm = TRUE)
  modified_avg_efficiency <- mean(modified_data$Predicted_Efficiency
, na.rm = TRUE)

  # Calculate the differences
  sales_difference <- modified_avg_sales - original_avg_sales
  nps_difference <- modified_avg_nps - original_avg_nps
  efficiency_difference <- modified_avg_efficiency - original_avg_ef
ficiency

  return(list(
    modified_data = modified_data,
    sales_difference = sales_difference,
    nps_difference = nps_difference,
    efficiency_difference = efficiency_difference
  ))
}

# # Conduct sensitivity analysis on each input variable
```

```r
# gc() # Free memory before running
sensitivity_salespeople <- sensitivity_analysis(dea_data_sensitivity
, gbm_model_sales, gbm_model_nps, gbm_model_efficiency, "Number_of_S
alespeople", 10) # Increase by 10%
sensitivity_outlets <- sensitivity_analysis(dea_data_sensitivity, gb
m_model_sales, gbm_model_nps, gbm_model_efficiency, "Number_of_Outle
ts", 10)          # Increase by 10%
sensitivity_service_time <- sensitivity_analysis(dea_data_sensitivit
y, gbm_model_sales, gbm_model_nps, gbm_model_efficiency, "Service_Co
mpletion_Time", -10) # Decrease by 10%

# Print out the results
cat("Sales Volume Difference after increasing Number of Salespeople
by 10%:", sensitivity_salespeople$sales_difference, "\n")
```

```
## Sales Volume Difference after increasing Number of Salespeople by
10%: 37.63652
```

```r
cat("NPS Difference after increasing Number of Salespeople by 10%:",
sensitivity_salespeople$nps_difference, "\n")
```

```
## NPS Difference after increasing Number of Salespeople by 10%: 1.8
58988
```

```r
cat("Efficiency Difference after increasing Number of Salespeople by
10%:", sensitivity_salespeople$efficiency_difference, "\n")
```

```
## Efficiency Difference after increasing Number of Salespeople by 1
0%: 0.5090213
```

```r
cat("\nSales Volume Difference after increasing Number of Outlets by
10%:", sensitivity_outlets$sales_difference, "\n")
```

```
##
## Sales Volume Difference after increasing Number of Outlets by 10%
: 37.81024
```

```r
cat("NPS Difference after increasing Number of Outlets by 10%:", sen
sitivity_outlets$nps_difference, "\n")
```

```
## NPS Difference after increasing Number of Outlets by 10%: 2.21920
3
```

```r
cat("Efficiency Difference after increasing Number of Outlets by 10%
:", sensitivity_outlets$efficiency_difference, "\n")
```

```
## Efficiency Difference after increasing Number of Outlets by 10%:
0.3406602
```

```r
cat("\nSales Volume Difference after decreasing Service Completion T
ime by 10%:", sensitivity_service_time$sales_difference, "\n")
```

```
##
## Sales Volume Difference after decreasing Service Completion Time
by 10%: 49.9878

cat("NPS Difference after decreasing Service Completion Time by 10%:
", sensitivity_service_time$nps_difference, "\n")

## NPS Difference after decreasing Service Completion Time by 10%: 1
.854923

cat("Efficiency Difference after decreasing Service Completion Time
by 10%:", sensitivity_service_time$efficiency_difference, "\n")

## Efficiency Difference after decreasing Service Completion Time by
10%: 0.5119469

# Prepare data for plotting
sensitivity_results <- data.frame(
  Input_Variable = c("Number of Salespeople", "Number of Salespeople
", "Number of Salespeople",
                     "Number of Outlets", "Number of Outlets", "Numb
er of Outlets",
                     "Service Completion Time", "Service Completion
Time", "Service Completion Time"),
  Metric = c("Sales Volume", "NPS", "Efficiency",
             "Sales Volume", "NPS", "Efficiency",
             "Sales Volume", "NPS", "Efficiency"),
  Difference = c(sensitivity_salespeople$sales_difference, sensitivi
ty_salespeople$nps_difference, sensitivity_salespeople$efficiency_di
fference,
                 sensitivity_outlets$sales_difference, sensitivity_o
utlets$nps_difference, sensitivity_outlets$efficiency_difference,
                 sensitivity_service_time$sales_difference, sensitiv
ity_service_time$nps_difference, sensitivity_service_time$efficiency
_difference)
)

# Plot the results
plot_sensitivity <- ggplot(sensitivity_results, aes(x = Input_Variab
le, y = Difference, fill = Metric)) +
  geom_bar(stat = "identity", position = "dodge") +
  labs(title = "Sensitivity Analysis: Impact of Changing Input Varia
bles on Key Metrics",
       x = "Input Variable",
       y = "Difference in Predicted Values") +
  theme_minimal() +
  scale_fill_brewer(palette = "Set2") +
  theme(axis.text.x = element_text(angle = 45, hjust = 1),
        plot.background = element_rect(fill = "white", color = NA),
# Set plot background to white
        panel.background = element_rect(fill = "white", color = NA),
```

```
# Set panel background to white
        panel.grid.major = element_line(color = "grey80"),
# Grid lines in light grey
        axis.text = element_text(color = "black"),
# Axis labels in black
        axis.title = element_text(color = "black"),
# Axis title in black
        plot.title = element_text(color = "black", face = "bold"),
# Plot title in black and bold
        legend.background = element_rect(fill = "white", color = NA)
)   # Legend background in white

# Display the plot
print(plot_sensitivity)

# Save the plot as a PNG file
ggsave(filename = "Sensitivity Analysis Plot.png", plot = plot_sensi
tivity, width = 10, height = 6, dpi = 300)
```

Analysis of the Impact of Localisation Fators to DEA Efficieny (Dealership Performance)

Analyse The Impact of Localisation Factors with Generalized Additive Model (GAM)

```
# Fit a Generalized Additive Model (GAM) to analyse the impact of lo
calisation factors on DEA efficiency
localization_model_gam <- gam(
  Average_DEA_Efficiency ~ s(Regional_Population_Density) +
    s(Local_Economic_Growth) +
    s(Cultural_Difference_Score) +
    s(Regulatory_Environment_Score),
  data = annual_efficiency,
  method = "REML"
)

# Summary of the GAM model (Localisation Analysis)
cat("\nSummary of the GAM Model (Localisation Analysis):\n")

##
## Summary of the GAM Model (Localisation Analysis):

print(summary(localization_model_gam))

##
## Family: gaussian
## Link function: identity
##
```

```
## Formula:
## Average_DEA_Efficiency ~ s(Regional_Population_Density) + s(Local
_Economic_Growth) +
##     s(Cultural_Difference_Score) + s(Regulatory_Environment_Score
)
##
## Parametric coefficients:
##             Estimate Std. Error t value Pr(>|t|)
## (Intercept)  0.40010    0.01385   28.88   <2e-16 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Approximate significance of smooth terms:
##                                  edf Ref.df     F  p-value
## s(Regional_Population_Density)  2.133  2.569 1.640    0.322
## s(Local_Economic_Growth)        1.000  1.000 0.264    0.608
## s(Cultural_Difference_Score)    1.000  1.001 1.473    0.227
## s(Regulatory_Environment_Score) 6.870  7.603 4.947 3.38e-05 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## R-sq.(adj) =  0.215   Deviance explained = 27.1%
## -REML = -24.955  Scale est. = 0.030135  n = 157
```

```
# Make predictions using the GAM model (Localisation Analysis)
predictions_localization_gam <- predict(localization_model_gam, newd
ata = annual_efficiency)

# Calculate MAE and RMSE for the GAM model (Localisation Analysis)
mae_localization_gam <- mean(abs(predictions_localization_gam - annu
al_efficiency$Average_DEA_Efficiency))
rmse_localization_gam <- sqrt(mean((predictions_localization_gam - a
nnual_efficiency$Average_DEA_Efficiency)^2))

# Print MAE and RMSE for the GAM model (Localisation Analysis)
cat("\nMean Absolute Error (MAE) (Localisation Analysis):\n", mae_lo
calization_gam, "\n")
```

```
##
## Mean Absolute Error (MAE) (Localisation Analysis):
##  0.1310807
```

```
cat("Root Mean Squared Error (RMSE) (Localisation Analysis):\n", rms
e_localization_gam, "\n")
```

```
## Root Mean Squared Error (RMSE) (Localisation Analysis):
##  0.1668267
```

```
# Extract smooth term estimates using predict.gam function
smooth_terms <- predict(localization_model_gam, type = "terms", se.f
it = TRUE)
```

```r
# Convert to a data frame for easier manipulation
smooth_data <- data.frame(
  Localization_Factors = rep(colnames(smooth_terms$fit), each = nrow
(smooth_terms$fit)),
  Smooth_Estimate = as.vector(smooth_terms$fit)
)

# Ensure the data is properly populated
if (nrow(smooth_data) > 0) {
  # Visualize smooth term estimates for localization factors
  coeff_plot_gam <- ggplot(smooth_data, aes(x = reorder(Localization
_Factors, Smooth_Estimate), y = Smooth_Estimate)) +
    geom_bar(stat = "identity", fill = "skyblue") +
    coord_flip() +
    labs(
      title = "Impact of Localisation Factors on DEA Efficiency (GAM
)",
      x = "Localisation Factors",
      y = "Smooth Term Estimate"
    ) +
    theme_minimal() +
    theme(
      plot.background = element_rect(fill = "white"),
      panel.background = element_rect(fill = "white"),
      legend.background = element_rect(fill = "white"),
      legend.key = element_rect(fill = "white"),
      axis.title.x = element_text(color = "black"),
      axis.title.y = element_text(color = "black"),
      axis.text.x = element_text(color = "black"),
      axis.text.y = element_text(color = "black"),
      plot.title = element_text(color = "black"),
      legend.title = element_text(color = "black"),
      legend.text = element_text(color = "black")
    )

  # Print the coefficients plot
  print(coeff_plot_gam)

  # Save the smooth term plot
  ggsave("Localisation Factors Impact Coefficients GAM.png", plot =
coeff_plot_gam, width = 8, height = 4)
} else {
  cat("No data available for plotting.\n")
}
```

Analyse The Impact of Localisation Factors with Random Forest

```r
set.seed(123)  # For reproducibility
```

```r
# Split data into training and testing sets
trainIndex_localization_rf <- createDataPartition(annual_efficiency$
Average_DEA_Efficiency, p = 0.8,
                                                        list = FALSE,
                                                        times = 1)
annual_efficiency_train_localization_rf <- annual_efficiency[trainIn
dex_localization_rf, ]
annual_efficiency_test_localization_rf <- annual_efficiency[-trainIn
dex_localization_rf, ]

# Train Random Forest model for localisation impact analysis
localization_model_rf <- randomForest(Average_DEA_Efficiency ~ Regio
nal_Population_Density + Local_Economic_Growth +
                                      Cultural_Difference_Score + Re
gulatory_Environment_Score,
                                      data = annual_efficiency_train
_localization_rf,
                                      importance = TRUE,
                                      ntree = 1000)

# Print model summary for localisation impact analysis
print(localization_model_rf)

##
## Call:
##  randomForest(formula = Average_DEA_Efficiency ~ Regional_Populat
ion_Density +       Local_Economic_Growth + Cultural_Difference_Score
+ Regulatory_Environment_Score,      data = annual_efficiency_train_
localization_rf, importance = TRUE,      ntree = 1000)
##                Type of random forest: regression
##                      Number of trees: 1000
## No. of variables tried at each split: 1
##
##           Mean of squared residuals: 0.03967227
##                     % Var explained: -4.98

# Plot variable importance for localisation impact analysis
importance_localization_rf <- importance(localization_model_rf)
varImpPlot(localization_model_rf)

# Predictions on test set for localisation impact analysis
predictions_localization_rf <- predict(localization_model_rf, annual
_efficiency_test_localization_rf)

# Evaluate model performance using MAE and RMSE for localization imp
act analysis
rmse_localization_rf <- RMSE(predictions_localization_rf, annual_eff
iciency_test_localization_rf$Average_DEA_Efficiency)
mae_localization_rf <- MAE(predictions_localization_rf, annual_effic
iency_test_localization_rf$Average_DEA_Efficiency)
```

```
r2_localization_rf <- R2(predictions_localization_rf, annual_efficie
ncy_test_localization_rf$Average_DEA_Efficiency)

cat("Random Forest Model Performance (Localisation Analysis):\n")

## Random Forest Model Performance (Localisation Analysis):

cat("RMSE:", rmse_localization_rf, "\n")

## RMSE: 0.2031337

cat("MAE:", mae_localization_rf, "\n")

## MAE: 0.1713498

cat("R-squared:", r2_localization_rf, "\n")

## R-squared: 0.02090014

# Save variable importance plot for localisation impact analysis
png("Localisation Factors Impact Random Forest.png", width = 1000, h
eight = 800, res = 150)
varImpPlot(localization_model_rf)
dev.off()

## png
##   2

# Save model summary to a text file for localisation impact analysis
sink("Model Summary Localisation Random Forest.txt")
print(localization_model_rf)

##
## Call:
##  randomForest(formula = Average_DEA_Efficiency ~ Regional_Populat
ion_Density +      Local_Economic_Growth + Cultural_Difference_Score
+ Regulatory_Environment_Score,      data = annual_efficiency_train_
localization_rf, importance = TRUE,      ntree = 1000)
##                Type of random forest: regression
##                      Number of trees: 1000
## No. of variables tried at each split: 1
##
##           Mean of squared residuals: 0.03967227
##                     % Var explained: -4.98

cat("\nRandom Forest Model Performance (Localisation Analysis):\n")

##
## Random Forest Model Performance (Localisation Analysis):

cat("RMSE:", rmse_localization_rf, "\n")

## RMSE: 0.2031337
```

```
cat("MAE:", mae_localization_rf, "\n")

## MAE: 0.1713498

cat("R-squared:", r2_localization_rf, "\n")

## R-squared: 0.02090014

sink()
```

Analyse The Impact of Localisation Factors with GBM

```
# Set seed for reproducibility
set.seed(123)

# Split data into training and testing sets
trainIndex_localization_gbm <- createDataPartition(annual_efficiency
$Average_DEA_Efficiency, p = 0.8,
                                  list = FALSE,
                                  times = 1)
annual_efficiency_train_localization_gbm <- annual_efficiency[trainI
ndex_localization_gbm, ]
annual_efficiency_test_localization_gbm <- annual_efficiency[-trainI
ndex_localization_gbm, ]

# Train GBM model for localisation impact analysis
localization_model_gbm <- gbm(Average_DEA_Efficiency ~ Regional_Popu
lation_Density + Local_Economic_Growth +
                   Cultural_Difference_Score + Regulatory_Environmen
t_Score,
                 data = annual_efficiency_train_localization_gbm,
                 distribution = "gaussian",
                 n.trees = 5000,
                 interaction.depth = 12,
                 shrinkage = 0.01,
                 cv.folds = 10,
                 n.minobsinnode = 5,
                 verbose = FALSE)

# Find the optimal number of trees for localisation impact analysis
best_iter_localization_gbm <- gbm.perf(localization_model_gbm, metho
d = "cv")

# Predictions on test set for localisation impact analysis
predictions_localization_gbm <- predict(localization_model_gbm, annu
al_efficiency_test_localization_gbm, n.trees = best_iter_localizatio
n_gbm)

# Evaluate model performance using MAE and RMSE for localisation imp
act analysis
rmse_localization_gbm <- RMSE(predictions_localization_gbm, annual_e
```

```
fficiency_test_localization_gbm$Average_DEA_Efficiency)
mae_localization_gbm <- MAE(predictions_localization_gbm, annual_eff
iciency_test_localization_gbm$Average_DEA_Efficiency)
r2_localization_gbm <- R2(predictions_localization_gbm, annual_effic
iency_test_localization_gbm$Average_DEA_Efficiency)

cat("GBM Model Performance (Localisation Analysis):\n")

## GBM Model Performance (Localisation Analysis):

cat("RMSE:", rmse_localization_gbm, "\n")

## RMSE: 0.2020843

cat("MAE:", mae_localization_gbm, "\n")

## MAE: 0.1678424

cat("R-squared:", r2_localization_gbm, "\n")

## R-squared: 0.004479861

# Generate variable importance
importance_localization_gbm <- summary(localization_model_gbm, n.tre
es = best_iter_localization_gbm, plotit = FALSE)

# Convert the importance data to a vector or matrix if necessary
importance_localization_gbm_vector <- as.vector(importance_localizat
ion_gbm$rel.inf)

# Set names for the barplot
names(importance_localization_gbm_vector) <- rownames(importance_loc
alization_gbm)

# Display the variable importance plot in R console
par(mar = c(11, 5, 3, 1))  # Adjust bottom margin (first value) to g
ive more space for labels
barplot(importance_localization_gbm_vector,
        las = 2,  # Rotate labels
        col = "blue",
        main = "Localization Factors Impact to Dealership Performanc
e",
        ylab = "Relative Influence",
        cex.names = 0.8)  # Adjust label size if necessary

# Save the variable importance plot with adjusted margins and rotate
d labels
png("Localisation Factors Impact GBM.png", width = 1000, height = 80
0, res = 150)
par(mar = c(11, 5, 3, 1))  # Adjust bottom margin (first value) to g
ive more space for labels
barplot(importance_localization_gbm_vector,
```

```
        las = 2,  # Rotate labels
        col = "blue",
        main = "Localisation Factors Impact in GBM Model",
        ylab = "Relative Influence",
        cex.names = 0.8)  # Adjust label size if necessary
dev.off()

## png
##   2

# Save model summary to a text file for localization impact analysis
sink("Model Summary Localisation GBM.txt")
summary(localization_model_gbm)

##                                                       var   rel.i
nf
## Regional_Population_Density   Regional_Population_Density 42.6202
45
## Local_Economic_Growth                   Local_Economic_Growth 37.4685
07
## Regulatory_Environment_Score Regulatory_Environment_Score 11.7296
56
## Cultural_Difference_Score       Cultural_Difference_Score  8.1815
92

cat("\nGBM Model Performance (Localisation Analysis):\n")

##
## GBM Model Performance (Localisation Analysis):

cat("Optimal number of trees:", best_iter_localization_gbm, "\n")

## Optimal number of trees: 114

cat("RMSE:", rmse_localization_gbm, "\n")

## RMSE: 0.2020843

cat("MAE:", mae_localization_gbm, "\n")

## MAE: 0.1678424

cat("R-squared:", r2_localization_gbm, "\n")

## R-squared: 0.004479861

sink()
```

Determine The Best Method to Analyse Localisation Factors

```
# GAM
rmse_localization_gam <- sqrt(mean((predictions_localization_gam - a
nnual_efficiency$Average_DEA_Efficiency)^2))
mae_localization_gam <- mean(abs(predictions_localization_gam - annu
```

```
al_efficiency$Average_DEA_Efficiency))
r2_localization_gam <- summary(localization_model_gam)$r.sq

# Random Forest
rmse_localization_rf <- RMSE(predictions_localization_rf, annual_eff
iciency_test_localization_rf$Average_DEA_Efficiency)
mae_localization_rf <- MAE(predictions_localization_rf, annual_effic
iency_test_localization_rf$Average_DEA_Efficiency)
r2_localization_rf <- R2(predictions_localization_rf, annual_efficie
ncy_test_localization_rf$Average_DEA_Efficiency)

# GBM
rmse_localization_gbm <- RMSE(predictions_localization_gbm, annual_e
fficiency_test_localization_gbm$Average_DEA_Efficiency)
mae_localization_gbm <- MAE(predictions_localization_gbm, annual_eff
iciency_test_localization_gbm$Average_DEA_Efficiency)
r2_localization_gbm <- R2(predictions_localization_gbm, annual_effic
iency_test_localization_gbm$Average_DEA_Efficiency)

# Create a data frame to compare the models
comparison_df_localization <- data.frame(
  Model = c("GAM", "Random Forest", "GBM"),
  RMSE = c(rmse_localization_gam, rmse_localization_rf, rmse_localiz
ation_gbm),
  MAE = c(mae_localization_gam, mae_localization_rf, mae_localizatio
n_gbm),
  R_squared = c(r2_localization_gam, r2_localization_rf, r2_localiza
tion_gbm)
)

# Print the comparison table
print(comparison_df_localization)

##           Model      RMSE       MAE   R_squared
## 1           GAM 0.1668267 0.1310807 0.215334571
## 2 Random Forest 0.2031337 0.1713498 0.020900137
## 3           GBM 0.2020843 0.1678424 0.004479861

# Determine the best model based on RMSE, MAE, and R-squared
best_rmse_model_localization <- comparison_df_localization[which.min
(comparison_df_localization$RMSE), "Model"]
best_mae_model_localization <- comparison_df_localization[which.min(
comparison_df_localization$MAE), "Model"]
best_r2_model_localization <- comparison_df_localization[which.max(c
omparison_df_localization$R_squared), "Model"]

cat("\nBest Model Based on RMSE:\n", best_rmse_model_localization, "
\n")
```

```
##
## Best Model Based on RMSE:
##  GAM

cat("Best Model Based on MAE:\n", best_mae_model_localization, "\n")

## Best Model Based on MAE:
##  GAM

cat("Best Model Based on R-squared:\n", best_r2_model_localization,
"\n")

## Best Model Based on R-squared:
##  GAM

# If we want to summarise which model is the best overall, we could
consider the following criteria:
# Assuming equal importance for RMSE, MAE, and R-squared
# Count how many times each model appears as the best model in each
metric
model_votes_localization <- c(best_rmse_model_localization, best_mae
_model_localization, best_r2_model_localization)
overall_best_model_localization <- names(sort(table(model_votes_loca
lization), decreasing = TRUE))[1]

cat("\nOverall Best Model:\n", overall_best_model_localization, "\n"
)

##
## Overall Best Model:
##  GAM

# Create the comparison data frame
comparison_df_localization <- data.frame(
  Model = c("GAM", "Random Forest", "GBM"),
  RMSE = c(rmse_localization_gam, rmse_localization_rf, rmse_localiz
ation_gbm),
  MAE = c(mae_localization_gam, mae_localization_rf, mae_localizatio
n_gbm),
  R_squared = c(r2_localization_gam, r2_localization_rf, r2_localiza
tion_gbm)
)

# Convert the data frame to long format for easier plotting with ggp
lot
comparison_df_long <- comparison_df_localization %>%
  pivot_longer(cols = c("RMSE", "MAE", "R_squared"), names_to = "Met
ric", values_to = "Value")

# Plot the metrics comparison with a white background
p <- ggplot(comparison_df_long, aes(x = Model, y = Value, fill = Mod
```

```
el)) +
  geom_bar(stat = "identity", position = "dodge") +
  facet_wrap(~Metric, scales = "free_y") +
  scale_fill_manual(values = c("GAM" = "coral", "Random Forest" = "s
teelblue", "GBM" = "green4")) +
  labs(
    title = "Model Comparison for Localisation Factors",
    y = NULL
  ) +
  theme_minimal() +
  theme(
    axis.title.x = element_blank(),
    axis.text.x = element_blank(),
    legend.title = element_blank(),
    legend.position = "right",
    plot.title = element_text(hjust = 0.5),
    strip.text = element_text(size = 12, face = "bold"),
    panel.background = element_rect(fill = "white", color = NA),  #
Set the background to white
    plot.background = element_rect(fill = "white", color = NA)    #
Set the plot background to white
  )

# Print the plot to console
print(p)

# Save the plot to a file
ggsave("Model Comparison for Localisation Factors.png", plot = p, wi
dth = 15, height = 5)
```