Journal of Business Research and Reports

Review Article

Open Access

Comparing the Performance of Classification Algorithms for Predicting Electric Vehicle Adoption

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ABSTRACT

In this study, the Electric Vehicle (EV) purchase decisions of European consumers are predicted using supervised machine learning (ML), specifically classification. Following the replacement (imputing) of missing data values through predicted values and continuizing of all predictor features, the predictor features are ranked according to the Information Gain Ratio and the Gini coefficient. The results suggest that suiting daily driving needs (Q17), belief that society must reward electric cars instead of petrol and diesel cars (Q14), and opinion change regarding electric cars during the past year (Q21) ranked the highest with respect to the Gini coefficient metric. The same predictor features rank the highest with respect to the Information Gain Ratio metric, yet in a different rank (Q17, Q21, and Q14). For predictive analytics, a multitude of classification algorithms are applied to predict the decision of EV purchase, and the performance of the applied algorithms is compared. The results suggest that gradient boosting performed best in predicting EV adoption decisions, followed by the logistic regression and random forest algorithms.

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Received: February 25, 2025; **Accepted:** March 05, 2025; **Published:** March 12, 2025

Keywords: Electric Vehicles, Market Adoption, Sustainable Development Goals (SDG), Machine Learning, Feature Ranking, Classification Algorithms

Introduction

Electric vehicles (EVs) have emerged as a viable solution to the growing global need for environmentally sustainable transportation. However, a thorough understanding of the many features affecting EV performance and market acceptance is necessary before EVs can be widely adopted across the globe [1].

The key is to develop an advanced evaluation model that can yield precise and informative predictions regarding the future course of electric vehicle market adoption. This study tackles this problem by analyzing a peer-reviewed and published survey dataset using machine learning, specifically through classification analysis [2].

The main objectives of this study are to identify the classification algorithm(s) that may perform best with respect to prediction and the critical features (factors) that significantly influence EV market acceptance and adoption [3,4]. These objectives require a thorough investigation using a range of classification algorithms and the application of ranking analysis. The goal is not only to achieve accuracy in EV performance classification; we also aim to produce knowledge that may inform consumers, lead regulatory decision-making, and provide stakeholders in the automotive sector with strategic guidance that can spur further market penetration. Through the integration of data-driven classification algorithms and a comprehensive understanding of the automotive industry, EV industry stakeholders can enhance market forecasts and take data-driven decisions and actions towards the disruptive transformation that EVs are likely to bring. The results of this research are aimed at contributing to initiatives to move transportation toward a more environmentally friendly and sustainable future.

The present research contributes to the understanding of consumers and the features that determine EV adoption using a machine learning technique for classification analysis. Therefore, it is necessary to summarize the literature on this line of research.

Multiple benchmark studies have compared the performance of various supervised machine-learning algorithms in diverse domains, ranging from the classification of textual data to credit risk management, cancer detection, and wind turbine accidents. However, these benchmark studies did not focus on the specific context of EV purchase intentions [5-8].

On the other hand, multiple studies have applied machine learning to predict EV adoption behavior, however these are studies conducted with earlier and dated data. Furthermore, compared to the plethora of studies that use various mathematical modeling techniques to analyze EV adoption, the literature that applies machine learning approaches is rather limited. In the rapidly changing EV landscape and world, it is valuable to work with a more recent dataset that passed peer-review and is coming from a data journal (as will be detailed later) and to apply machine learning for analysis. Owing to space limitations, a full literature review is provided in the Supplement [9-13].

Motivated by the significance of EVs on the economic, environmental, legal, and social dimensions, and by earlier work in the field to understand the influencing factors, the present study applies machine learning, in particular classification and ranking analyses, to uncover more insights and develop an enhanced understanding of EV adoption.

Methodology

Model

Figure 1 illustrates the data analytics model developed using

Orange data analytics software for conducting machine learning (ML) methods of ranking and classification analysis. Orange, as a visual no-code analytics modeling software, provides a user-friendly visual interface that streamlines the process of loading, processing, and analyzing datasets. The model includes various widgets (nodes with icons) representing different steps in the analysis, such as data preprocessing, model training, and evaluation. This visual representation enhances transparency and allows for a clear understanding of the workflow employed in classification analysis [14].

Logistic Regression, k-nearest neighbor (kNN), Tree, Random Forest, Gradient Boosting, Support Vector Machine (SVM), Naïve Bayes, AdaBoost, and Stochastic Gradient Descent (SDG) algorithms were included as classification algorithms to predict EV adoption. While the Neural Network (NN) algorithm was also considered, it was later excluded owing to excessive training time. The predictive performance of the models was then compared and benchmarked through stratified 5-fold cross-validation experimentation, resulting in a comparison table and ROC. Finally, a confusion matrix was used to better understand and interpret the performance of the best-performing classification algorithm, which was a gradient boost, in this study.

Ranking analysis was conducted by computing the Gain Ratio and Gini Coefficient, and sorting in decreasing order of the Gini Coefficient values. In machine learning, ranking refers to ordering a set of items, typically a set of predictor attributes, based on a score or other metric. In this case, higher values of the Gain Ratio and Gini Coefficient indicate a higher influence of a given feature on the predictions. Definitions of these two-ranking metrics, as well as others, can be found in the orange documentation [15,16].

The developed and applied orange model can be found in Supplement as an *. ows file.

Model Evaluation and Comparison

The evaluation and comparison of the employed machine learning algorithms are important components of the analysis. A rigorous scrutiny of each classification algorithm's performance metrics, including AUC, Classification Accuracy (CA), F1 Score, Precision, Recall, and Matthews Correlation Coefficient (MCC), reveals the effectiveness of the predictive algorithms in reflecting the inherent patterns within the dataset. Definitions of these metrics can be found in the orange documentation [17].

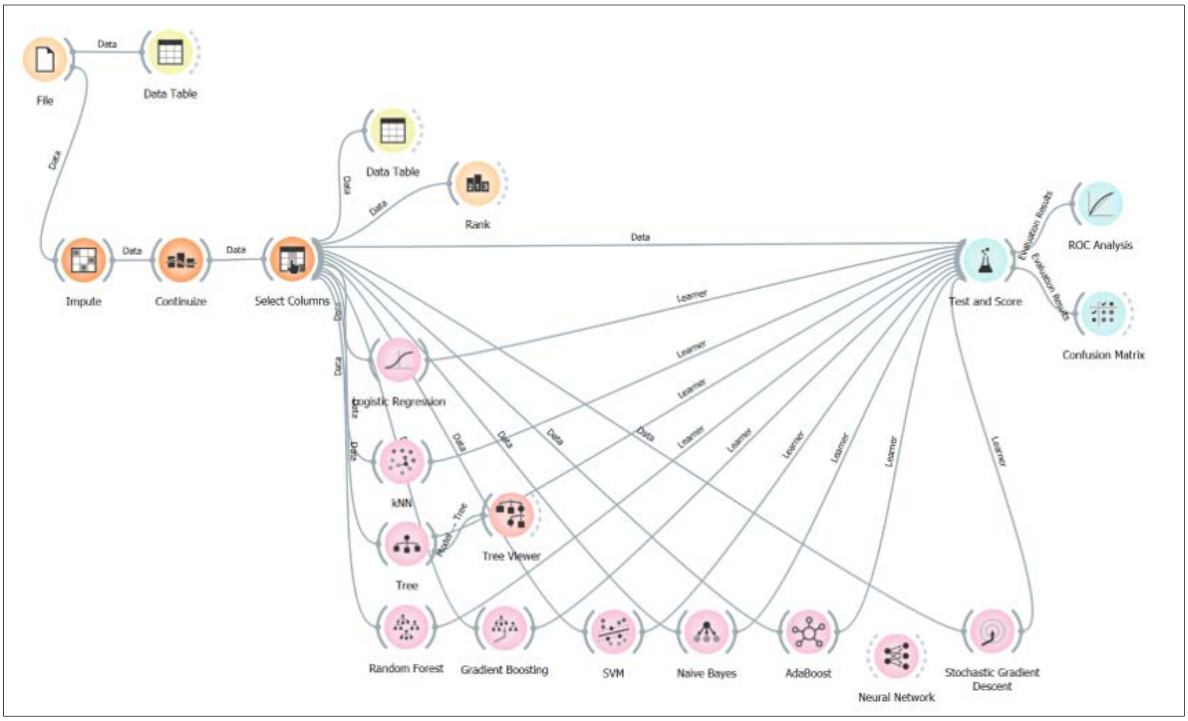


Figure 1: The Data Analytics Model in the Orange Software for Ranking and Classification Analysis

Analysis and Results

Data

The data used in the presented research were obtained from, published in "Data in Brief" journal, which was accompanied by the full research dataset shared under. This journal is a data journal, meaning that the journal specifically mandates that the source data for any published research in the journal should also be shared as public data. The rise of data journals is part of open data and open research trends [18-20].

The original dataset, as described in, is rich in multiple data tables and features that can potentially be analyzed in multiple research studies. For the research presented in this study, only a subset of the data was selected and used. The selected dataset consists of 69 binary predictor features, available as binary vectors, representing the Yes/No answers to survey question choices, as well as one target feature (response variable), namely Q16, which is the answer to the question "Which of the following statements about electric car suits you the best?". The original responses to Q16 were "If I had an EV, it would be my only car" (A), "If I had an EV, it would be a supplement to a petrol or diesel car" (B), "I would never buy an EV" (C) and "I do not know" (D).

For transparency and a comprehensive understanding of the features used in this analytical study, an exhaustive list of data features, along with their descriptions, is provided in Supplement [13]. However, as mentioned earlier, the source data and metadata for the study are taken directly from.

The benefit of using a dataset published in a data journal is that the data has readily passed through peer review and its validity and verification have been confirmed by the journal's reviewers before acceptance and publishing.

Data Preparation

For a focused analysis, for question Q16, which is the target feature, answers A and B have been merged into the single class label AB, which represents purchase intention and adoption, and answers C and D have been merged into the single class label CD, which represents no purchase intention (No Adoption). By reducing the number of values for the target feature Q16 from four to two, a binary classification model with a higher predictive power was obtained, which was subsequently run and analyzed. By designating Question 16 as the target feature, the classification algorithms focused on understanding the factors influencing the merged responses to this specific question. This step is pivotal in framing the analysis towards the business objective of predicting or understanding the factors contributing to electric vehicle adoption, based on the given survey.

There were multiple missing values in the original dataset. Addressing missing data is a critical pre-processing step that ensures the quality of the model, analysis, and results. To impute and fill in the missing values systematically, a model-based imputer that uses a single decision tree was used in the Orange software. As the next step, it was necessary to continue all the predictor features because most machine learning algorithms operate better when the predictor features take continuous numerical values. This step was conducted using the widget in orange software [21,22].

Results of Classification Analysis

The classification performance analysis in Table 1 reveals notable insights into the effectiveness of various algorithms for predicting electric vehicle adoption based on the selected and prepared datasets. Gradient Boosting emerged as the top-performing algorithm, exhibiting the highest values across all chosen metrics, namely AUC, Classification Accuracy (CA), F1 score, precision, recall, and Matthews Correlation Coefficient (MCC). This signifies its exceptional ability to distinguish between the two classes (AB vs. CD; i.e., adoption vs. No Adoption), leading to an overall accurate prediction of electric vehicle adoption.

Random Forest closely follows gradient boosting by demonstrating robust performance across multiple metrics. Random Forest, Logistic Regression, and Naïve Bayes also showed commendable results with respect to both CA and AUC, demonstrating their reliability in the classification task. kNN and Naïve Bayes performed well with respect to AUC, but not with respect to CA. SDG performed well with respect to CA, but not with respect to AUC.

While logistic regression did not have the top performance, it may be performed due to very fast running time and its ability to generate the parameters of a closed form logistic regression equation that can be used for very fast classification. Similarly, random forest did not have the top performance, yet may be preferred under certain settings, as it generates a multitude of trees, which can be browsed through as a collection through Pythagorean tree visualizations and each tree individually through decision tree visualization.

Table 1: Classification Performance Analysis Based on Multiple Metrics.

Algorithm	AUC	CA	F1	Prec	Recall	MCC
Logistic Regression	0.870	0.826	0.821	0.820	0.826	0.548
kNN	0.827	0.746	0.757	0.790	0.746	0.459
Tree	0.726	0.811	0.810	0.809	0.811	0.525
Random Forest	0.872	0.839	0.831	0.834	0.839	0.575
Gradient Boosting	0.901	0.854	0.849	0.850	0.854	0.621
SVM	0.662	0.707	0.718	0.740	0.707	0.345
Naïve Bayes	0.864	0.799	0.805	0.817	0.799	0.539
AdaBoost	0.732	0.779	0.780	0.782	0.779	0.458
SDG	0.749	0.818	0.813	0.812	0.818	0.572

On the other hand, SVM exhibited the worst performance across all metrics, suggesting its limitations in accurately discriminating between classes in this specific context and data. This was despite the fact that SVM was run with the RBF kernel as the default selected kernel, rather than the less robus linear kernel. These findings offer valuable guidance for selecting an appropriate algorithm, with gradient boosting and Random Forest standing out as strong candidates for predicting electric vehicle adoption with high precision and reliability.

The Area Under the Curve (AUC) values in Table 1 associated with each algorithm served as quantitative measures of their respective Receiver Operating Characteristic (ROC) curves, which are displayed in Fig. 2. Notably, Gradient Boosting led to a remarkable AUC of 0.901, indicative of an ROC curve closest to the top-left corner in Fig. 2, showcasing its superior discriminatory power. Random Forest closely follows an AUC of 0.872, reinforcing its robustness in distinguishing between the two classes (adoption vs. No Adoption). Logistic Regression and Naïve Bayes exhibited commendable AUC values (0.870 and 0.864, respectively), underlining their competency in predicting electric vehicle adoption. Conversely, the SVM trials had a lower AUC of 0.662, suggesting a comparatively weaker ROC curve. The AUC values provide a concise summary of each algorithm's ability to balance true-positive and false-positive rates, aiding in the selection of the most suitable model for accurate predictions in the context of electric vehicle adoption.

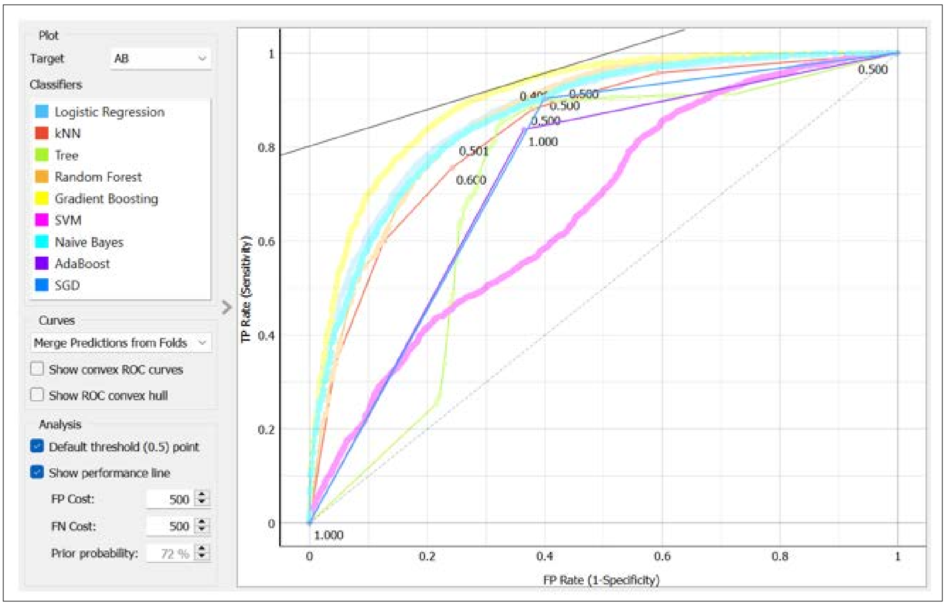
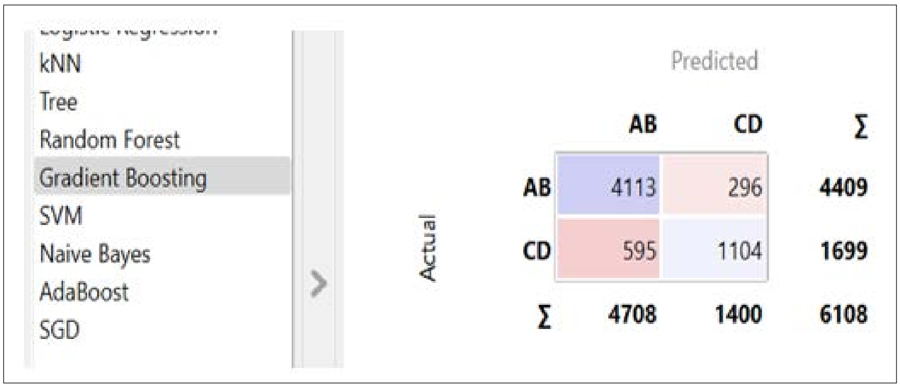


Figure 2: ROC Curves for the Applied Classification Algorithms

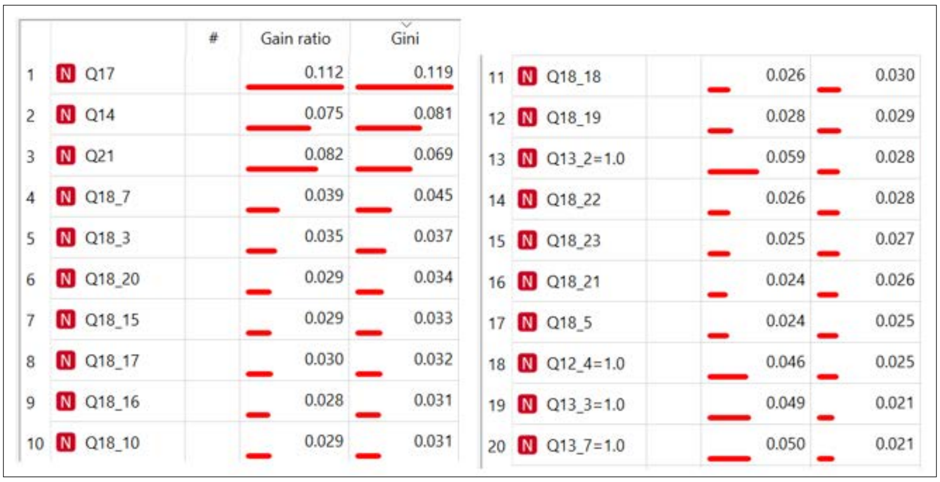
Fig. 3 displays the confusion matrix for the Gradient Boosting algorithm and offers a detailed perspective on the classification performance of the model. Among the 6,108 instances in the dataset, the algorithm correctly predicted 4,113 cases of adoption (AB) and 1,104 cases of No Adoption (CD). However, 595 No Adoption (CD) instances were incorrectly classified as Adoption (AB) and 296 Adoption (AB) instances were misclassified as no option (CD).

The confusion matrix enabled a nuanced evaluation of the model's strengths and areas for improvement. The high number of true positives and true negatives signifies the model's effectiveness and inaccurate predictions, whereas the occurrences of false positives and false negatives pinpoint specific instances where the model may need refinement.



	AB	CD	Σ
AB	4113	296	4409
CD	595	1104	1699
Σ	4708	1400	6108

Figure 3: Confusion Matrix for Gradient Boosting, Which Has the Highest CA (Classification Accuracy) Value



		#	Gain ratio	Gini
1	N Q17		0.112	0.119
2	N Q14		0.075	0.081
3	N Q21		0.082	0.069
4	N Q18_7		0.039	0.045
5	N Q18_3		0.035	0.037
6	N Q18_20		0.029	0.034
7	N Q18_15		0.029	0.033
8	N Q18_17		0.030	0.032
9	N Q18_16		0.028	0.031
10	N Q18_10		0.029	0.031
11	N Q18_18		0.026	0.030
12	N Q18_19		0.028	0.029
13	N Q13_2=1.0		0.059	0.028
14	N Q18_22		0.026	0.028
15	N Q18_23		0.025	0.027
16	N Q18_21		0.024	0.026
17	N Q18_5		0.024	0.025
18	N Q12_4=1.0		0.046	0.025
19	N Q13_3=1.0		0.049	0.021
20	N Q13_7=1.0		0.050	0.021

Figure 4: Feature Rankings for EV Adoption

Results of Ranking Analysis

The feature rankings in Fig. 4, based on the decreasing values of the Gini coefficients, reveal crucial insights into the factors that influence the prediction of electric vehicle adoption (Q16). The results suggest that suiting daily driving needs (Q17), belief that society must reward electric cars instead of petrol and diesel cars (Q14), and opinion change regarding electric cars during the past year (Q21) ranked the highest with respect to the Gini coefficient metric. The same predictor attributes rank highest with respect to the Information Gain Ratio metric, yet in a different rank (Q17, Q21, and Q14).

Further analysis reveals features such as Q12_4, Q13_2, Q13_3, and Q13_7, which consistently rank high in the Gain Ratio, but not in the Gini coefficient. The features are as follows:

- Q12_4: Purchase price
- Q13_2: Positive effect on global climate
- Q13_3: Less noise
- Q13_7: Positive effect on the local environment

Discussion

In this study, an investigation of the factors possibly affecting electric vehicle (EV) adoption was conducted to discern their impact on consumer purchase intention and societal adoption of electric vehicles (EVs) in EU countries. The investigation, through ranking analysis, also aimed to identify the most influential features affecting classification performance. Focusing on a binary categorical target feature, the study analyzed the prediction performance. The values of metrics, such as AUC, CA, F1-score, recall, and precision, were compared across the algorithms, leading to the identification of models exhibiting superior classification performance, thus delivering more accurate predictions of EV adoption. The relevance of features within the models was evaluated to comprehend the unique contribution of each feature to the classification. Receiver Operating Characteristic (ROC) curves were plotted to assess the performance of the classification models.

In the classification performance comparison, gradient boosting was consistently ranked as the best algorithm, followed by random forest and logistic regression. This insight, as well as the results for the other algorithms, has notable ramifications with regard to the selection of classification algorithms for carrying out predictions for the dataset at hand. Most notably, any classification benchmark study on a dataset with a similar structure or scope should consider gradient boosting, logistic regression, random forest, and naïve Bayes in the benchmark.

Despite the actionable insights obtained, there are three potential shortcomings in the conclusions and the presented research. These shortcomings and their discussions are as follows.

First, the dataset may not be representative of all European consumers. In other words, the data may not be representative of the population. However, this risk can be readily reduced by selecting a dataset from a data journal, where peer reviewers evaluate the theoretical and practical validity of the research and source data.

Second, only a few of the numerous classification algorithms in the literature were included in the study, according to their availability in the chosen orange data analytics software. There may be other algorithms, not here by included, that might outperform gradient boosting. This represents an avenue for future research.

The third is the selection of the hyperparameters that govern how the classification models are trained, including control over the model parameters. While parameters learn from data during training, hyperparameters do not learn their values from data; instead, they need to be specified before model training is initiated. In the conducted study, 5–fold stratified cross-validation was applied to conduct multiple experiments and obtain multiple results to help alleviate any bias problems with regard to parameter selection and optimization. However, the classification algorithms in the study were always run with their default hyperparameters rather than applying an experimental design, exhaustive evaluation, or hyperparameter optimization. Therefore, different and possibly optimized parameter values for the selected algorithms could potentially change the results and draw conclusions. More specifically, at least in theory, it is possible that there could be certain sets of parameter values for the lagging algorithms at which those lagging algorithms may outperform gradient boosting or other leading algorithms. An ideal future research, therefore, would be to conduct a much more comprehensive study, with proper experimental design and hyperparameter optimization for each algorithm, followed by a posterior comparison, which in itself may be a data analytics study. Ideally, multiple different sets of parameter values should be applied and evaluated systematically. Having mentioned this shortcoming, the present study is valuable as a preliminary study, as most analytics projects in industry also use default parameter settings and values readily set in the software that they are using. Therefore, the presented research in that aspect approximates a typical study that would be conducted in the industry [23].

Conclusions

In conclusion, our study presents a comprehensive analysis of electric vehicle adoption by utilizing some well-known supervised machine learning algorithms for classification. The identification of key features through rankings, focusing on experiences, satisfaction, and societal attitudes, offers actionable insights for stakeholders in the electric vehicle industry.

As the automotive landscape continues to evolve, our findings contribute to the collective understanding of the factors influencing EV adoption, paving the way for informed decision-making and strategic planning in the pursuit of sustainable and eco-friendly transportation solutions. Building on the insights gained from this analysis, recommendations for stakeholders in the electric vehicle industry could include improving the most significant factors that affect EV purchase intention and adoption, devising targeted marketing strategies, enhancing customer journeys and user experiences, and encouraging and supporting policies and regulations that can address consumer preferences and societal attitudes.

Future work can focus on extending the scope of the analysis to incorporate other classification algorithms, hyperparameter optimization, and explainable AI (XAI). Future work can also focus on exploring temporal trends, incorporating additional data sources such as demographics and charging network infrastructure, and refining the analysis to adapt to evolving consumer preferences and industry development [24,25].

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Supplement to "Comparing the Performance of Classification Algorithms for Predicting Electric Vehicle Adoption"

Literature Review

Sustainability

Electric Vehicles (EVs) can support four of the 17 Sustainable Development Goals (SDGs) set forth by the United Nations. These possibly supported SDGs are SDG3 (good health and well-being), SDG 7 (clean energy), SDG11 (sustainable cities and societies), SDG 12 (sustainable production and consumption), and SDG13 (climate). With respect to SDG7, EVs can use electricity produced through renewable energy sources, primarily wind and solar energy, reducing the use of polluting fossil fuels in transportation. With respect to SDG12, compared to gasoline cars, EVs have only a few moving components and a more durable engine, contributing to a longer lifecycle. However, eco-efficiency can differ significantly across regions, countries, and states, and EV adoption may even work holistically against the SDGs if electricity is produced through coal [1-5].

The transport sector is the fastest growing sector in terms of greenhouse gas (GHG) emissions. Therefore, international organizations have set emission targets for transport, such as those set forth by the European Commission. To this end, leading companies in the automation sector are developing and implementing strategies to achieve SDGs. Furthermore, the transition to electric mobility is supported by the UN and governments around the world [9], such as a tax credit of up to $7,500 in the US for new vehicle purchases in or after 2023 [6-10].

Market Adoption

The encouragement of consumers to adopt EVs has been sustained by various initiatives at the country level. In this regard, a considerable body of research has been conducted on the impact of government policies on the promotion of EV usage. Government incentives include EV car purchase subsidies in the US and China, tax exoneration in various European countries, and parking benefits in Sweden. Despite this positive institutional environment, the initial impact of these policies on consumers' EV adoption is low. However, EV markets have experienced significant sales growth during the last few years. The share of EVs in total sales tripled over three years, jumping from 4% in 2020 to 14% in 2022 [11-16].

Market Adoption Factors

"The safety, reliability, and economic feasibility of EVs are critical for mass adoption". Understanding the main factors influencing consumers' decisions regarding EV adoption is highly valuable. The outcomes of this line of research can help improve the decision making of consumers, designers, and manufacturers in selecting, designing, and producing EVs. As milestone research, presented a systematic literature review on the key determinants of EV adoption by integrating various frameworks and sets of factors. The authors reveal that there is no convergence of the various frameworks in the literature and that environmental factors are less important to consumers than expected [17,18].

Multiple studies have been conducted in various countries and regions, and For US owners of electric cars, identified technology innovation, driving satisfaction and pleasure, and reduction of maintenance costs as the main factors explaining the decision to acquire an EV. Adopting the perspective of Maslow's human needs on consumers' purchase decision-making processes, conducted a study in China. The authors concluded that conscientiousness about environment preservation, followed by price awareness, social influence, and self-esteem, are the key determinants of EV buying motivation. conducted a bibliometric analysis of the literature on electric vehicle consumers, with a focus on consumers in Türkiye. conducted a pioneering study on the effects of consumption motives to strengthen consumers' EV purchase intentions in the South Asian region. Having analyzed the 411 survey responses, the researchers found that hedonic motives had the strongest influence, followed by gain and normative motives. identified the social factors that slow down EV adoption in India, revealing that consumers with high vehicle performance expectations prefer EVs less. In a recent study, collected Delphi technique questionnaires from 11 experts in the state of Maharashtra in India and analyzed the data using the DEMATEL method. The objective was to identify the causal effect of the criteria for EV adoption. In conclusion, battery charging time, driving range, and price were identified as the determinants of EV purchase. concluded that in India, the willingness to adopt greener vehicles, such as EVs, is positively impacted by performance expectancy. In Malaysia, a survey of drivers demonstrated that the three top factors explaining EV acceptance are social influences, performance features, and monetary benefits. Finally, in the most extensive systematic literature review study we encountered, analyzed 1875 journal articles on the topic, revealing that psychological, social, and performance attributes are consistently appearing features in the literature. Furthermore, this study found infrastructure availability to be the most significant decision factor [19-27].

This study analyzes consumer attitudes, specifically in Europe. Therefore, it is crucial to review the literature on EV market adoption, which focuses specifically on Europe. As a milestone research focusing on the European continent, carried out a systematic literature review of 44 research publications, revealing the role of EVs as symbols of social status and innovativeness. applying conditional autoregressive models, analyzed the effects of socioeconomic and climatic factors on EV adoption in Norway, especially highlighting the effects of climatic factors. analyzed EV purchase intentions in Greece using discrete choice models, revealing financial incentives as significant and suggesting policy measures for increased EV adoption. A study conducted in Germany found that performance improvement in charging speed increased the usefulness perception of the technology and, subsequently, the usefulness of EVs. Similarly, other researchers, considering the case of Italy, found that the time spent charging electric cars has a negative impact on potential consumers' utility. On the other hand, free parking in city centers is perceived as a positive factor in the usage of EVs [28-32].

Machine Learning for Analyzing Ev Markets

Machine learning algorithms have also been applied, including the prediction of the evolution of EV market share. To investigate consumer sentiments toward EVs, applied deep learning algorithms and convolutional neural networks. As an example of another notable research stream, employed social network modeling to examine the market adoption of electrical cars when considering nudge policies [33-35].

The current study contributes to the understanding of consumers and the features that determine EV adoption using a machine learning technique for classification analysis. Therefore, it is necessary to summarize the literature on this line of research.

Multiple benchmark studies have compared the performance of various supervised machine learning algorithms in diverse domains, ranging from the classification of textual data to credit risk management, cancer detection, and wind turbine accidents. However, these benchmark studies do not focus on the specific context of EV purchase intentions [36-39].

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Motivated by the significance of EVs in the economic, environmental, legal, and social dimensions, and by earlier work in the field to understand the influencing factors, the present study applies machine learning, in particular classification and ranking analyses, to uncover more insights and develop an enhanced understanding of EV adoption.

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