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A Prediction Model for Electric Vehicle Sales Using Machine Learning Approaches

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ABSTRACT

The electric vehicle (EV) market is booming, but EV market trends vary by region. This study draws on the environmental, economic, and human development factors of 31 countries to predict sales of EVs. Based on machine learning (ML) algorithms and the PLS method, the authors constructed an EV sales performance prediction model and carried out the experiments. The experimental results demonstrate that ML algorithms can effectively achieve the desired accuracy and predictive performance levels. At the same time, this study investigates the relationship between quality training indicators and EV sales. CO2 emissions, PM2.5, consumer price index (CPI), renewable energy, and life expectancy are found to be significantly positive related to EV sales. The proposed model can be used globally by governments as a decision support tool to impose policies encouraging the adoption of EVs and develop sustainable strategies.

KEYWORDS:

Machine Learning, Electric Vehicles, Sustainability, Human Development Index, HDI

INTRODUCTION

In recent decades, global population growth and the rapid expansion of motorization have resulted in a significant escalation of greenhouse gas emissions from traffic, presenting substantial challenges to environmental sustainability. The transportation sector is a principal contributor to worldwide carbon dioxide emissions while simultaneously being a major source of air pollution (Sperling & Gordon, 2010). A discernible paradigm shift has occurred in response to the escalating environmental concerns and the mounting emphasis on sustainability and carbon emission reduction, with a growing focus on transitioning from conventional internal combustion engine vehicles to electric vehicles (EVs). This shift toward EVs has emerged as a global trend to reduce humanity's ecological footprint. EVs have been increasingly recognized as a practical and environmentally friendly alternative (Hanschke et al., 2013). Scholars have extensively highlighted the advantages of EVs in reducing air pollution, greenhouse gas emissions, and associated health risks, positioning them as a more sustainable

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transportation model (Requia et al., 2018). The global EV market has experienced remarkable growth, driven predominantly by key markets in China, Europe, and the United States.

In the current era of heightened environmental protection efforts, consumers are more responsible for safeguarding the environment. Consequently, there is a growing demand for eco-friendly products as consumers become more conscious of the environmental impact of their consumption behaviors. Previous research has shown that consumers' concern for the environment and their inclination toward eco-friendly behavior significantly influence their overall green purchasing behavior, including their intention to choose green products (Kaufmann et al., 2012). This shift in consumer behavior has led to new environmental ethics, increased personal awareness, and transformed purchasing habits (Jang et al., 2011). Moreover, a consistent relationship exists between income and green consumption behavior, with higher income groups demonstrating a greater inclination toward environmental and green consumption (Junaedi, 2012; Al Mamun et al., 2018; Zhang et al., 2019). This economic factor also plays a significant role in adopting EVs, as most electric car owners belong to higher income groups. However, despite the growing interest in eco-friendly behavior, affordability remains a significant barrier for many consumers when considering green products and technologies.

Human development, as measured by the Human Development Index (HDI), provides a comprehensive measure of human development, encompassing various indicators that assess the impact of economic growth on the quality of life, covering both economic and noneconomic dimensions (Elistia & Syahzuni, 2018). The level of environmental consciousness within a country has been found to be linked to its level on the HDI. Past studies suggest that higher levels of national wealth and positive economic growth trends are associated with an increased willingness among the general public to make financial sacrifices for environmental causes and endorse post-materialist values (Gelissen, 2007; Milfont & Markowitz, 2016). Furthermore, extensive education on environmental protection has been found to impact individuals' acceptance of environmental concepts positively and to significantly influence their environmentally friendly behaviors (Zhang et al., 2021).

Numerous studies have explored the motivations for EV adoption, primarily focusing on specific countries or regions. Yang et al. (2023) investigated the impact of socioeconomic drivers and climatic conditions on EV adoption in Norway. Paradies et al. (2023) identified routine purchasing behavior and social factors as barriers to widespread EV adoption in the Netherlands. However, these studies have predominantly focused on predicting EV sales within a single country or region. To address this research gap, in this study, we aim to develop a model to predict EV sales across multiple countries, considering the heterogeneity within the EV market. By adopting a broader perspective, this study challenges the assumption that the factors influencing EV sales are universally consistent across countries. It seeks to understand the broader dynamics and variations in EV sales at a country level.

By exploring EV sales at a country level, the study highlights the role of the HDI in shaping EV sales. Including the HDI in the analysis helps mitigate biases arising from an exclusive emphasis on economic factors. The study widens its perspective to consider overall human well-being and quality of life as essential factors influencing EV sales. Furthermore, the research avoids the bias of solely focusing on affordability as the primary driver of EV sales. It brings attention to the crucial role of environmental factors in shaping consumer behavior and government policies. High levels of air pollution can trigger heightened public awareness and concern regarding the adverse impacts of pollution on health and the environment. Consequently, environmental factors can be regarded as a potent driving force behind the growing demand for cleaner transportation alternatives like EVs. The study aims to comprehensively examine the factors influencing the sales of electric vehicles at the country level encompassing socioeconomic, environmental, and HDI aspects. We used two research questions for this investigation to explore the fundamental drivers of EV sales and their broader implications:

- RQ1: What factors contribute to the country's sales of electric vehicles?
- RQ2: How do these factors impact the country's sales of electric vehicles?

The data-driven model's improved performance and ease of deployment have garnered significant attention in recent years (Bourdeau et al., 2019). In previous studies, traditional statistical techniques, such as multiple linear and logistic regression, were commonly employed to analyze the relationship between input and output variables. However, ML methods have gained widespread use in many fields for prediction owing to their high accuracy, making them a frequently used model in data-driven methods (Ding et al., 2017). Compared with linear models adopted in previous studies, the ML model possesses certain advantages (Cheng et al., 2021). On the other hand, some researchers argue that traditional statistical techniques are still valuable and helpful in many situations. Bzdok and Ioannidis (2019) suggested that traditional statistical methods are still helpful in identifying the most critical predictors or testing a specific hypothesis. For this study we employed three ML algorithms to create a predictive model for EV sales at the country level, while using traditional statistical methods to identify relevant variables. By combining ML and traditional statistical approaches, we leveraged the strengths of ML models, while recognizing significant variables through traditional statistical analysis.

This study empirically identifies a more valid set of variables closely related to country EV sales. It provides valuable insights for policymakers in designing effective policies to promote EV deployment. Additionally, the predictive models developed in this study serve as a valuable reference for EV manufacturers in developing targeted green marketing strategies and for policymakers in formulating sustainable policies to support EV market growth.

In the remaining sections of this paper, we present the review of literature, based on which conceptual framework for predicting EV sales is developed; discuss our research methods; present our experimental procedures and the results; and finally, share our discussion, conclusions, and directions of future research.

LITERATURE REVIEW

Research on EV Purchase

Systematic review methodology is applied to collect and critically evaluate existing literature (Tranfield et al., 2003) using the ScienceDirect databases. The key search term that we chose for extracting the research papers is "EV purchase," ScienceDirect identified 508 EV purchase research studies from 2013 to 2022. We screened the extracted research papers based on the title and keywords to remove the inappropriate papers. Our selection criterion was whether the study aimed to identify factors for EV sales. A total of 98 "EV purchase" research papers were published in ScienceDirect from 2013 to 2017, and 410 studies, from 2018 to 2022. EV purchase studies are increasing rapidly; in ScienceDirect, 74 EV purchase studies were published from 2013 to 2017, and 356 EV purchase studies published in the 2018–2022 period focus on adoption. Seventy-nine EV purchase studies in the 2013–2017 period and 335 studies in the 2018–2022 period tried to relate the purchase of an EV and environmental factors. Three- hundred twenty studies conducted in the past decade have assessed income factors influential in purchasing EVs. After removing the irrelevant and duplicate articles, we selected 33 closely matched full-text articles for review.

From a theoretical perspective, most EV purchase studies are from the perspective of consumer purchase intentions. The emphasis of published studies on EV purchase has been on various aspects of adoption and non-adoption. The most applicable theory of EV purchase determinants is the Theory of Planned Behavior (TPB) (Zhang et al., 2018; Huang & Ge, 2019; Li et al.,2021). Huang & Ge (2019) pointed out that attitude, perceived behavioral control, cognitive status, product perception, monetary incentive policy measures, and charging facilities impact consumers' willingness to buy EVs in Beijing. Some scholars also used TPB to analyze the use of EVs by small and medium-sized enterprises in Austria, Denmark, Germany, and other EU countries and to establish a predictive model for whether enterprises intend to adopt EVs (Kaplan et al., 2016). Rational choice theory declares benefits and utility maximization as the basis of human behavior. In addition to TPB theory, some

EV purchase researchers showed positive and negative perceptions with rational behavior framework (He et al., 2018; Brase, 2019; Ling et al., 2021).

EV purchase researchers have also investigated socio-demographic variables in predicting consumer decisions (Sierzchula et al., 2014; Sovacool et al., 2018; Westin et al., 2018; Chen, 2020; De Souza Mendonça et al., 2020; Haidar & Rojas, 2022; Yilmaz et al., 2022). For example, one study determined that younger individuals are likely to show more interest in EVs (Chen et al., 2020). Sovacool et al. (2018) suggested that men with higher education levels and below middle age are likelier to buy low-carbon mobility. Research literature has also showed that age and education are the main factors that affect EV adoption and has observed that individuals with higher incomes are more inclined to purchase EVs and seek solutions for the cost of traveling long distances. Additionally, people living in urban areas are more likely to have higher incomes (Ivanova & Moreira, 2023).

Consumers adopt new products depending on their purchasing decision-making process and diverse internal and external influences (Sohaib et al., 2019). From a geographical perspective, a few EV purchase drivers refer to the country context, including government policy (Li et al., 2019; Azarafshar et al., 2020; Srivastava et al., 2022), infrastructure provision (Harrison & Thiel, 2017; Heidrich et al., 2017) and GDP variables. Affordability is a significant issue. Thus, income is one of the critical factors for EV adoption (Martins et al., 2021; Ruoso & Ribeiro, 2022). Bloom and Sevilla (2004) argued that countries with low per capita income are unwilling to pay higher expenses for green products. Meanwhile, consumers' EV preferences need to be more generalizable to any location. EV purchase intentions in Hong Kong are highly value-driven with the integration to social expectations; this pattern differs from that of the European countries where the adoption is built on assessing the usage difficulty (Sun et al., 2022).

Research on Environmental Factors

Past studies have gradually focused on the considerable impacts of the environment. Environmental problems can be regarded as collective social problems. The development of productive activities will both directly and indirectly produce greenhouse gases (Gössling & Peeters, 2015). With the progress of industrial development, populations grow and urbanize, leading to poor air quality. The adverse impact of air pollution on health and the consequent incidence of illness, high death rates, and economic losses make this the world's most extensive environmental health threat. The literature on pollution and public health (Lelieveld et al., 2015) points out that pollution is the most significant environmental cause of illness. Increasing urban populations will only accelerate the degree of air pollution in urban areas. Eze et al. (2014) noted that the long-term effects of air pollution create a variety of hazards to human health and life, even potentially causing death. Wang et al. (2014) argued that road traffic is one of the primary sources of PM2.5 emissions, especially in high-density urban areas. Energy and environmental problems are closely related.

Environmental concerns have become a pivotal factor influencing consumer behavior, especially regarding EV purchases. Extensive literature suggests a strong positive correlation between environmental consciousness and the intention to buy EVs (Jin & Cui, 2019; Chen et al., 2020; Dinh et al., 2021; He et al., 2021; Moon, 2021; Shalender & Sharma, 2021). Furthermore, in another study, researchers argued that individuals are more willing to pay a premium for EVs owing to their environmental considerations (Lim et al., 2019). As pollution levels increase, people become more aware of the environmental impact of their actions and are more likely to consider purchasing energy-saving products. Countries with higher CO2 emissions tend to prioritize the adoption of EVs as a means to reduce their carbon footprint and combat climate change. The perception of EVs as a more environmentally friendly transportation option strengthens the positive correlation between CO2 emissions and country-level EV sales. In light of this, we propose the following hypothesis:

Hypothesis1a: CO_2 emissions are positively related to country EV sales.

Given the potential health hazards of PM2.5 pollution, individuals and governments become increasingly aware of the need to address air pollution and its impact on public health. The detrimental effects of PM2.5 pollution on human health drive individuals and countries to prioritize cleaner transportation options such as EVs, leading to increased adoption and sales of EVs in regions with higher PM2.5 pollution levels. Therefore, we propose this hypothesis:

Hypothesis1b: PM2.5 is positively related to country EV sales.

The research findings from Axsen and Kurani (2012) and Sierzchula et al. (2014) support the view that urban residents, driven by their environmental awareness, are more inclined to consider EVs. These results suggest a positive correlation between urban populations and EV sales, as urban environments foster a sustainability-oriented atmosphere and encourage the adoption of cleaner transportation options such as EVs. Therefore, we propose the following hypothesis:

Hypothesis1c: Urban population is positively related to country EV sales.

Renewable energy, derived from natural sources, is crucial in promoting environmental sustainability, emphasizing the manufacturing and consumption of eco-friendly products (Liobikienė et al., 2017). Several studies have explored the connection between renewable energy consumption and environmental quality (Nasreen et al., 2017; Zafar et al., 2021). As the awareness of reducing carbon footprints grows with the increasing use of renewable energy, individuals are more inclined to consider EVs as an alternative to conventional gasoline-powered cars. Consequently, we propose this hypothesis:

Hypothesis 1d: Renewable energy consumption is positively related to country EV sales.

Research on Economic Factors

Gross national income (GNI) is a comprehensive indicator that combines gross domestic product (GDP) with net receipts from abroad of compensation of employees, property income, net taxes, and fewer subsidies on production (OECD, 2022). It provides a broader measure of income, including domestic and international sources, and is considered a better indicator of living standards than GDP (Duan et al., 2021; WHO, 2022). Levin and Tatsuzaki (2002), Schaefer et al. (2012), and Thi et al. (2015) extensively discussed the country's income data using the GNI index as a reliable measure of economic performance and living standards. Junaedi (2012) and Zhang et al. (2019) suggested that higher income levels positively influence green consumption behavior, emphasizing the connection between economic prosperity and environmentally conscious choices. Higher levels of GNI can lead to increased consumer purchasing power and a greater willingness to invest in environmentally sustainable transportation options. Individuals with higher disposable income are more likely to consider EVs a viable option, considering their potential long-term cost savings and positive environmental impact. The relationship between the Consumer Price Index (CPI) and EV sales underscores the role of higher disposable incomes in driving the country's EV sales. We propose the following hypothesis based on this understanding:

Hypothesis 2a: GNI is positively related to country EV sales.

Economic development is a crucial indicator for assessing a country's economic status and citizens' purchasing power. In economic analysis, price measurement plays a vital role, and the CPI is a significant macroeconomic indicator that reflects a country's consumption price level power (Barkan et al., 2022). The CPI represents the weighted average of the price level of goods and services paid by urban consumers, providing insights into the purchasing habits of most of the population. Moreover, the CPI is often used to adjust nominal measures to real wages, making it a critical tool in economic research (Moulton, 1996). CPI reflects the price level of goods and services. An increase in CPI signifies higher affordability of products, including EVs. Consumers with greater purchasing power are more likely to consider EVs a viable option, especially given their potential long-term cost savings and positive environmental impact. Considering the potential impact of the CPI on country-level EV sales, we propose the following hypothesis:

Hypothesis 2b: CPI is positively related to country EV sales.

Research on HDI

Consumers in different countries have differing perceptions, preferences, and values influencing their intention to adopt an innovation (Truong, 2013). On the other hand, consumption values bring different meanings in different countries and have different impacts on purchase intention (De Silva et al., 2021). National values and norms strongly determine motivation and behavior (Markus & Kitayama, 1991; Yeniyurt & Townsend, 2003). HDI is an indicator of social standards comprising life expectancy, access to education and literacy, and living conditions and income. Adult literacy and combined enrollment ratios are commonly employed when assessing the education dimension. Life expectancy at birth is typically used to gauge a population's health (Sagar & Najam, 1998). Environmental quality positively correlates with life expectancy across countries (Mariani et al., 2010). A healthier population may be more environmentally aware and willing to invest in sustainable transportation options. Countries with higher life expectancy, indicative of a healthier population, are expected to exhibit a stronger demand for EVs. Therefore, we propose the following hypothesis:

Hypothesis 3a: Life expectancy is positively related to country EV sales.

Education plays a significant role in influencing the attitudes and behaviors of individuals concerning diverse facets of the environment and sustainable development. Previous research has indicated that individuals who have attained higher levels of education possess a greater understanding of the impact of their actions on the environment. They are also more likely to prioritize environmental concerns over their own needs and recognize the significance of the environment for their well-being when making decisions or taking actions (Cheung & To, 2019; Witek & Kuźniar, 2020). Another study found that strong, highly educated respondents demonstrated a more robust association between health and environmental concerns (Cavaliere et al., 2014). Countries with higher levels of educational attainment are expected to exhibit a stronger demand for EVs owing to the increased environmental awareness, understanding of sustainable transportation benefits, and environmentally responsible attitudes among individuals with higher education. Therefore, we propose the following hypothesis:

Hypothesis 3b: Expected years of schooling are positively related to country EV sales.

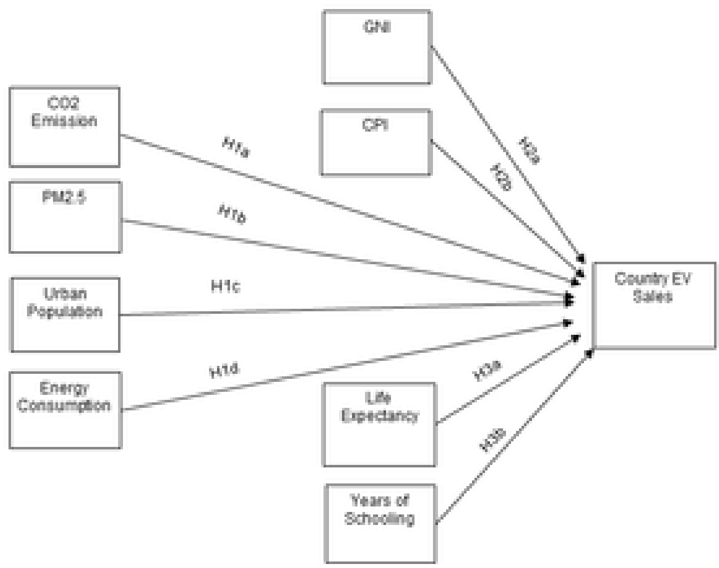
Figure 1 represents the conceptual model used in this study, illustrating the relationships and variables being investigated.

RESEARCH METHODOLOGY

Sample Selection and Data Collection

We carefully determined the sample selection of countries for studying country EV sales based on empirical considerations, including countries from Europe, North America, Asia, and Oceania,

Figure 1. Conceptual model



ensuring a comprehensive representation of different regions. We chose countries with larger automobile markets to capture significant global EV sales, facilitating a broader understanding of adoption trends and patterns, and considered economic diversity by including nations at various stages of development, encompassing both highly developed economies and emerging markets. Furthermore, the sample encompasses countries at different stages of EV market maturity and adoption rates; these countries range from those with considerable market share to those in the early stages of adoption. Lastly, data availability was crucial, ensuring robust empirical analysis by selecting countries with reliable and comprehensive data on EV sales and related factors.

We collected data from secondary sources (the World Bank, Human Development Data Center, Health Effects Institute, IMF) for 31 countries. These countries are listed in Table 1. Data in the datasets was the most recent available. Target variables, EV yearly sales for 2016 through 2020, were found in car sales statistics on the official websites of government agencies. For this study, we collected the predictor features from 2015 to 2019 by incorporating variables. Data in the datasets was the most recent available. Based on the studies cited in the "Literature Review" section, this study focused on features from three major indices: environment, economics, and HDI. We used four indicators of environmental quality: (1) greenhouse gas emissions (CO_2 emission), (2) renewable use as research variables, (3) PM2.5, and (4) urban population. Additionally, we included two economic indicators, the CPI and GNI per capita, along with two HDI indicators. These features are listed in Table 2, along with their descriptions.

Table 1. Sample countries

Sample country	Austria, Belgium, Canada, China, Czechia, Denmark, Estonia, Finland, France, Germany, Greece, Hungary, Ireland, Italy, Latvia, Lithuania, Malta, Netherlands, New Zealand, Norway, Poland, Portugal, Romania, Slovakia, Slovenia, Spain, Sweden, Switzerland, Thailand, United Kingdom, United States

Table 2. Descriptions of features

Factors	Data	Sources
CO_2 emissions	Metric tons per capita	The World Bank
PM2.5	Average Annual Population—Weighted PM2.5	Health Effects Institute
Consumer Price Index (CPI)	Measure changes in the prices of goods and services purchased or otherwise acquired by households	IMF Data
Expected years of schooling	Measured by expected years of schooling of children at school-entry age	HDI
GNI	Gross national income (GNI) per capita	HDI
Life expectancy at birth	Assessed by life expectancy at birth	HDI
Renewable energy	Percentage of total final energy consumption	The World Bank
Urban population	Percentage of the total population	The World Bank

ML

ML is the science of computer algorithms to recognize and acquire information from the real world and improve the execution of assignments based on new information (Portugal et al., 2018). By leveraging previous experiences, ML enables computers to construct models that effectively anticipate future events (Dogan & Birant, 2021). This study included three ML methods: neural networks, Bayesian linear regression, and light gradient boosting machine (LightGBM). We selected these methods because they have proven their performance in the field.

The Bayesian method, as highlighted by Baldwin and Larson (2017), offers valuable capabilities in prediction, model fit, data visualization, and handling uncertainty. Kokol et al. (2022) emphasized that more complex ML approaches are now being used to address the challenge of small data samples. Bayesian linear regression, in particular, is well suited for handling cases with insufficient or unevenly distributed data. Shen et al. (2022) employed a Bayesian approach to investigate the severity of COVID-19 symptoms in patients and identify associated characteristics.

Boosting involves combining a series of weak base learners to create a strong learner. The process of boosting entails fitting additive base learners that minimize the provided loss function, which evaluates the model's fit to the current data. Boosting continues until the reduction in the loss function becomes limited. LightGBM employs a gradient boosting-based algorithm to enhance model accuracy and address overfitting issues (Ke et al., 2017).

In contrast, neural networks are well known for their application in ML and their ability to model complex problems effectively. Marquez et al. (1991) pointed out several advantages of neural networks over traditional regression models, such as their capacity to learn from datasets without requiring a complete specification of the decision model.

Model Development

Database normalization involves structuring data into a consistent and comparable format (Han et al., 2011). In this study, the Z score was utilized as the data normalization technique.

Cross-validation is a practical approach to improve the model's fitting capability. For this study, we employed a k-fold cross-validation method to achieve optimal estimation. The dataset was divided into k sub-samples, with one sample for testing and the remaining k-1 samples for training. Employing the k-fold cross-validation enables biased estimates stemming from the skewed dataset distribution to be mitigated (Kumar et al., 2018). Recent research indicates that k-fold cross-validation can reduce uncertainties in dataset partitioning and effectively address overfitting concerns (Moore, 2001; Vu et al., 2022).

For this study, we used a train/test split cross-validation approach for model training and validation during modeling. We created training and test datasets and split the data into training and test sets in two patterns of data splitting. The first pattern was 70% for training and 30% for test sets. The second one was 80% for training and 20% for test sets.

Evaluation Metrics

We employed five commonly used measures in regression analysis: the mean absolute error (MAE), the root mean squared error (RMSE), the relative absolute error (RAE), the relative squared error (RSE), and the coefficient of determination. The MAE calculates the average absolute differences between the predicted and actual observations, providing a straightforward and intuitive measure of the model's accuracy (Ayala, 2021). The RMSE assesses the average magnitude of the errors, with outliers having a more significant impact on this measure (Ayala, 2021). The RAE compares the mean error of the model to the errors produced by a trivial or naive model. The RSE evaluates the model's performance relative to a simple predictor, typically the average of the actual values. It normalizes the total squared error by dividing it by the total squared error of the simple predictor, enabling a relative assessment of the model's predictive accuracy. The coefficient of determination (R^2) summarizes the explanatory power of the regression model by quantifying the proportion of the dependent variable's variance that the model can explain. R^2 values range from 0 to 1, where higher values indicate a stronger relationship or a better fit between the factors being studied. A value close to 1 indicates less error variance and a more accurate relationship representation (Krause et al., 2005).

Research Hypotheses Testing

For this study, we conducted the path model analysis using SmartPLS 3.0, a widely recognized software tool for partial least squares structural equation modeling (PLS-SEM). PLS-SEM possesses several advantageous characteristics. PLS-SEM is proficient in effectively exploring novel relationships and adeptly predicting outcomes in a flexible, adaptive manner. Moreover, PLS-SEM exhibits considerable flexibility when dealing with non-normal data distributions and situations involving small sample sizes, further enhancing its utility in such scenarios (Munerah et al., 2021).

RESULTS

Data Statistics

The fast growth in EV sales has been from 2016 to 2020. The mean of EV sales is 58404. The means of CO_2 and PM2.5 are 661.30 and 13.51. Note that China was the biggest market for EVs in the world. China also was the world's largest emitter of CO_2 during the research period of five years from 2015 to 2019. In 31 sample countries, Spain ($28,620) emerged as the country with the lowest average EV price, ahead of Portugal ($29,702) and Poland ($30,680). On the other hand, Thailand ($64,675) was the country with the most expensive average EV cost, more than Finland ($42,211). Sweden ($41,288) was the third most expensive in 2020 (Compare the Market, 2020).

Cross-Validation

Cross-validation is a resampling process often used to evaluate ML models on a limited data sample. For this study, we applied a 10-fold cross-validation approach to minimize over-fittings for multiple ML algorithms, including Bayesian linear, LightGBM, and neural networks. We evaluated the predictive performance based on training data to ensure the predictive error was in an appropriate range. We also evaluated the performance of the three models based on MAE and RMSE. Lower values of MAE and RMSE signified that the model was making more precise and accurate predictions. The Bayesian linear model exhibited the best performance, with an MAE of 0.260 and an RMSE of 0.511. In contrast, the neural network model had the highest error, with an MAE of 0.548 and an

RMSE of 0.608. Based on K-fold cross-validation results, we developed the prediction models using Bayesian linear regression.

Performances of Different Models

The development of the model consisted of two stages. We assessed the proposed technique for effectiveness in the first stage by comparing it with a benchmark model incorporating all features. We divided the data into 70% for training and 30% for the test pattern in this stage and allocated the training and test sets in an 80% to 20% ratio in the second stage. We applied Bayesian linear regression in two stages. The results obtained by the predictive models were evaluated using metrics. The metrics evaluated the model's performance when comparing the simulated values made during the training and testing and the actual observed values. For this study, we evaluated the model's performance using MAE, RMSE, RAE, RSE, and R^2 metrics. We used these metrics to compare the simulated values generated during the training and testing process with the actual observed values. The ultimate goal was to determine the predictive model's accuracy and identify which model performed the best.

Table 3 presents the predictive model's performance developed in the first stage of the study. The results show that the Bayesian linear regression model achieved an R^2 value of 0.837, indicating a strong correlation between the predicted and observed values. The RMSE value for the Bayesian linear regression model was 0.254, suggesting that the model predictions are relatively close to the actual values.

In Table 4, the R^2 value indicates the proportion of the variance in the observed values that the model predictions can explain. In this case, the Bayesian linear regression model achieved an R^2 value of 0.848, which suggests that the model can explain a significant portion of the variance in the data.

MAE measures the average absolute difference between the predicted and actual values, while RMSE measures the root mean squared difference between the predicted and actual values. A lower MAE indicates that the model is making more accurate predictions. However, the MAE does not consider the direction of the errors, so it can be helpful also to consider the RAE, which measures the ratio of the MAE to the mean of the actual values. This study's Bayesian linear regression model produced an MAE of 0.199, an RAE of 0.505, and an RMSE of 0.297. The MAE value of 0.199 suggests that the model can make relatively accurate predictions with an average error that is a manageable size. The RMSE value of 0.297 indicates that the Bayesian linear regression model can make reasonably accurate predictions. A reasonable model will result in a ratio of RAE less than one (Hill, 2012). The RAE value of 0.505 demonstrates that the model is effective in making predictions.

Discriminant Validity

We assessed discriminant validity using the Heterotrait-Monotrait (HTMT) ratio, employing the PLS algorithm. Table 5 represents discriminant validity using the HTMT ratio.

Table 3. Model results of 70% for training and 30% for test pattern

	MAE	RMSE	RAE	RSE	R^2
Bayesian linear	0.166	0.254	0.569	0.163	0.837

Table 4. Model results of 80% for training and 20% for test pattern

	MAE	RMSE	RAE	RSE	R^2
Bayesian linear	0.199	0.297	0.505	0.152	0.848

Table 5. Heterotrait-Monotrait ratio (HTMT)

	CPI	CO2	GNI	PM2.5	Sales	LE	RE	SY
CO_2	0.149							
GNI	0.024	0.205						
PM2.5	0.020	0.686	0.616					
EV sales	0.187	0.899	0.207	0.675				
Life expectance	0.165	0.270	0.625	0.479	0.193			
Renewable energy	0.094	0.136	0.495	0.388	0.045	0.427		
School year	0.065	0.356	0.589	0.577	0.300	0.567	0.346	
Urban pollution	0.059	0.146	0.481	0.509	0.123	0.562	0.224	0.647

Table 5 shows that all constructs achieved the recommended threshold values of less than 0.90. The acceptable levels of discriminant validity (< 0.90) are as suggested by Henseler et al. (2015). Thus, discriminant validity was achieved using the HTMT ratio.

Hypotheses Testing

Empirical evidence from the analysis supports five out of the eight hypotheses, as shown in Table 6. The regression coefficients align with the expected direction and are statistically significant, except for the relationships between three environmental factors (CO2, PM2.5, and renewable energy) and country EV sales. Specifically, hypotheses H1a, H1b, and H1d were supported, indicating the positive impact of certain environmental factors on country EV sales. However, hypothesis H1c, which proposed a significant influence of urban pollution on country EV sales, did not receive support. Urban pollution may not have a substantial impact on the sales of EVs at the country level.

Regarding economic factors, the CPI was found to have a significant effect on country EV sales, whereas GNI did not exhibit a significant influence. Furthermore, as anticipated, life expectancy was found to positively and significantly impact country EV sales. However, hypothesis H3b was not supported, indicating that countries with higher expected years of schooling do not necessarily have higher country EV sales.

Table 6. Hypotheses testing

Hypothesized Path	Path Coefficient	Standard Deviation	P-Value	Result
CO_2 -> sales	0.775	0.073	0.000	Supported
PM2.5 -> sales	0.232	0.106	0.028	Supported
Urban pollution -> sales	0.033	0.036	0.362	Unsupported
Renewable energy -> sales	0.114	0.046	0.013	Supported
GNI -> sales	-0.055	0.064	0.390	Unsupported
CPI -> sales	0.073	0.028	0.009	Supported
Life expectancy -> sales	0.085	0.030	0.004	Supported
School year -> sales	0.037	0.041	0.363	Unsupported

DISCUSSION AND CONCLUSION

Environmental issues have garnered significant attention globally. This study indicated that CO2 emissions, PM2.5 pollution, and renewable energy positively influence EV sales. Specifically, the results highlighted that CO2 emissions play a critical role in driving the sales of EVs at the country level. This finding supports the findings of Zhang et al. (2019), indicating a direct positive relationship between consumers' perception of haze and their inclination toward green consumption. Since 2009, the Chinese government has implemented various policies, such as a consumer subsidy program to promote the adoption of EVs. These policies have contributed to China becoming the world's largest buyer of EVs in 2020. Similarly, the U.S. federal government has initiated tax credits for EVs, further promoting their adoption. These government incentives, coupled with increasing awareness of climate change, have led to the rising trend of EV sales.

At the country level, research findings indicate that higher levels of PM2.5 pollution significantly drive the demand for EVs. It is attributed to individuals' pursuit of improved air quality and reduced exposure to harmful pollutants. These research findings are consistent with the study conducted by Guo et al. (2020), which reveals a positive correlation between awareness of PM2.5 pollution and the volume of EV sales. Additionally, the study suggests that greater utilization and availability of renewable energy sources positively impact EV sales. It supports the view that the increase in renewables would lead to an increase in EV demands (Li et al., 2017). This increase aligns with the consumer values of sustainability and contributes to the growing adoption of EVs.

The study's emphasis on CO2 emissions and PM2.5 pollution as influential factors in EV sales align with the global movement toward reducing carbon footprints and improving air quality. These findings underline the significance of addressing environmental challenges through the widespread adoption of EVs.

Moreover, the study recognizes the role of government incentives in promoting EV sales. This recognition contributes to the existing body of literature by highlighting the importance of policy support in accelerating country EV sales.

It is interesting finding that CPI is significantly related to country-level EV sales. However, GNI did not demonstrate a substantial influence on EV sales. The CPI indicates changes in the cost of living over time and is commonly used to adjust consumers' income payments. EVs usually have higher purchase prices. Sales of EVs are correlated to a country's real wage. Furthermore, this study highlights the vital role of expected life years in influencing the demand for EVs in the market. The significance of life expectancy goes beyond its impact on EV sales; it also serves as a key indicator of a population's overall well-being and development status for nations (Alam et al., 2016). Countries with higher life expectancies tend to demonstrate better health and prosperity, while those with lower life expectancies often face economic challenges and remain underprivileged. A positive correlation exists between economic growth and life expectancy (Wang et al., 2022). These findings emphasize the importance of considering demographic factors and health indicators when formulating policies to promote EV sales. By considering demographic factors, we highlight the need for tailored approaches to target specific consumer segments.

Most EV studies are from the perspective of consumer purchase intention (Huang et al., 2019; Lim et al., 2019). This study proposed ML methods for predicting country EV sales and analyzed the effectiveness of the proposed technique at different selected feature models. The ML model was trained and tested using five major indices: environment, economic, education, health, and demography dataset from 2015 to 2019 to predict EV sales from 2016 to 2020. Meanwhile, we applied a k-fold cross-validation algorithm to the training process. The performance and accuracy of different predictive models were compared at different error metrics. The results show that the proposed model has a good prediction effect. The Bayesian linear regression has the best overall performance in terms of prediction performance and model stability. The results support that Bayesian linear regression is a powerful tool for dealing with limited data scenarios and achieving superior predictive capabilities and model reliability (McNeish, 2016).

Including diverse countries in the sample enhances the study's generalizability. The countries selected for analysis represent a range of socioeconomic conditions. The study provides insights into how factors influencing EV sales may differ across different socioeconomic contexts by including countries with diverse characteristics, such as economic development, environmental policies, and HDI scores. It enables researchers to gain a more comprehensive understanding of the drivers of EV sales in various settings.

Theoretical Contributions

This study holds significant theoretical implications because it deviates from the conventional approach used in most EV purchase studies that rely on the Theory of Planned Behavior to gauge consumer perceptions and purchase intentions. Instead, this study draws from distinct research streams associated with three dimensions—environment, economics, and HDI— thereby providing a more comprehensive understanding of the factors influencing EV sales at the country level.

One contribution of this study is its empirical evidence supporting the stronger influence of CO2 emissions and PM2.5 on country-level EV sales. These findings highlight the critical role of environmental factors in shaping consumer behavior and emphasize the urgency of addressing climate change and air pollution by adopting EVs. Moreover, the study argues that CPI, life expectancy at birth, and renewable energy are crucial determinants of green purchases and EV adoption. The study emphasizes the multidimensional nature of consumer decision-making by considering economic indicators and quality-of-life measures. This holistic approach helps to broaden our understanding of the complex interplay between economic, environmental, and social factors in driving green purchasing behavior.

Furthermore, the study addresses a research gap in the current literature that predominantly focuses on green consumption behavior in Western developed countries. This study expands the scope and relevance of EV purchase research by using cross-country data and including developing countries in the analysis. It recognizes the global nature of the EV market and contributes to a more comprehensive understanding of EV adoption patterns worldwide.

Empirical Contributions

Given the insignificant numbers of EVs in most countries, the EU's goal of becoming climate-neutral by 2050 necessitates a well-designed strategy. Making EVs more affordable and convenient is crucial for achieving sustainable advantages. Governments can initiate consumer subsidy programs and reduce costs to enhance the affordability of EVs for motorists. Environmental quality positively correlates with life expectancy across countries, while carbon emissions are considered the primary factor in environmental deterioration and have detrimental effects on health. Aligning government policies and regulatory frameworks with a low-carbon economy is imperative. National long-term EV strategies can be devised to reduce greenhouse gas emissions and increase the adoption of renewable energy. The findings of this study provide valuable insights for EV suppliers in identifying critical determinants to improve their business strategies in the EV market.

Research Limitations and Future Works

This study has drawn some conclusions about the effects of the HDI, environment, and economics on EV sales. However, further investigation is warranted in several areas. First, the study's sample size was limited, consisting of only 31 countries. Therefore, future research should broaden the sample by including a more extensive and diverse range of countries, resulting in a larger dataset. This expansion would enhance the generalizability of the findings. Second, complementing the panel data research with individual economy time-series estimations would be beneficial. This approach would provide a more detailed understanding of the relationship between EV sales and the factors mentioned above at a country-specific level, enabling more nuanced insights. Finally,, future studies could consider incorporating additional variables to gain deeper insights into the connection between EV sales and the influencing factors. Variables such as policy measures, infrastructure development, and consumer preferences can be included to comprehensively understand the drivers behind EV sales. Including these variables would provide a more comprehensive analysis of the factors impacting EV sales. It will improve the generalizability of the findings and provide more detailed country-specific insights and a comprehensive analysis of the influencing factors. It will ultimately contribute to a more robust understanding of the dynamics between EV sales and the factors explored in this study, fostering the development of effective strategies and policies in the context of sustainable transportation.

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