energies

MDPI

Article

Determinants of the Perception of Electromobility—Analysis of Dependencies and Barriers to the Development of the Electric Vehicle Market

Mariola Michałowska

Institute of Economics and Finance, University of Zielona Góra, Podgórna Street 50, 65-246 Zielona Góra, Poland; m.michalowska@wez.uz.zgora.pl

Abstract

Electromobility is a key direction in the development of sustainable transport. The aim of the study was to determine its level of development and to identify and assess factors associated with the perception of electromobility among residents of the Lubusz Voivodeship. Additionally, an attempt was made to identify user segments with differing perceptions of this phenomenon. The analysis covered the years 2010–June 2026, with a survey conducted at the turn of 2025/2026. The level of electromobility development was assessed based on quantitative indicators, while resident opinions were collected via a survey. Linear regression and cluster segmentation were used to analyze the data. Relationships between variables were examined, focusing on factors associated with the price acceptance of electric vehicles. The regression results indicated that, of the eight predictors included in the model, only four—infrastructure quality, charging time, vehicle range, and environmental awareness—exhibited statistically significant associations with price acceptance. Cluster analysis allowed for the identification of diverse user segments with different preferences, motivations, and barriers related to electromobility. The results can form the basis for designing public policies, marketing strategies, and investment activities in the area of sustainable transport.

Keywords: electromobility; battery electric vehicle; energy mix; sustainable transport; linear regression; cluster analysis; electromobility indicators; electric vehicle market; survey research; determinants; Lubuskie Voivodeship

1. Introduction

The development of civilization brings with it profound changes in the natural environment, including rising temperatures and environmental pollution. These changes determine and will continue to determine market behavior toward the development of new technologies, especially electromobility. Electromobility aligns with the concept of sustainable transport, which, as a key element of a country's socioeconomic development, should not only ensure efficient and safe access to mobility but also protect human health and the stability of ecosystems. Transport shapes not only the spatial structure of cities but also influences the living conditions of their inhabitants and the state of the natural environment [1]. Miller, De Barros, and Kattan [2] and Low [3] emphasize that one of the key approaches to assessing sustainable transport is to consider three interconnected areas: the environment, the economy and society. The environmental, social, and economic dimensions must be balanced for transport development to be considered truly sustainable.

Academic Editor: Petr Musilek

Received: 2 August 2026
Revised: 6 September 2026
Accepted: 14 September 2026
Published: 17 September 2026

A transport system based on the principles of sustainable development not only responds to the needs of current users but also considers the interests of future generations, minimizing negative environmental impacts, supporting economic stability, and strengthening social cohesion. From this perspective, electromobility is a tool for meeting the transport needs of the current generation without compromising the ability of future generations, as it reduces emissions, supports improved air quality, and promotes a more responsible use of natural resources.

According to Motowidlak, electromobility is a complex strategy encompassing many sectors of the economy, including [4]:

- Work on the use of bacteria in fuel cells;
- Improvement of construction materials to improve the properties of electric vehicles;
- Development of the Internet of Things and digital tools;
- Implementation of smart energy networks (smart grids);
- Creation of communication systems such as vehicle-to-grid (V2G), vehicle-to-vehicle (V2V), and vehicle-to-home (V2H);
- Design of advanced smart charging methods;
- Shaping of new mobility patterns;
- Development of innovative business models;
- Development of legal regulations and economic instruments to support the transformation.

As noted by Biresselioglu, Demirbag Kaplan, and Yilmaz [5], since the announcement of the EU energy transition plan in 2009, research on the possibilities of a transition to electromobility has been developing intensively, although translating its results into effective policy actions is still a challenge.

The article is structured as follows. Section 1 introduces electromobility as a key direction in the development of sustainable transport. Section 2 presents the determinants of electromobility development, including a literature review and an analysis of market and energy factors influencing the development of electromobility, with particular emphasis on consumer perception. Section 3 describes the research material and the research methods used, and Section 4 demonstrates the degree of electromobility development based on quantitative indicators. Section 5 presents the results of linear regression and cluster analysis. Section 6 includes a discussion of the results in the context of previous studies. Section 7 presents the most important conclusions of the study, its limitations, directions for further research, and practical implications.

2. Conditions for the Development of Electromobility

2.1. Literature Review

Issues related to electromobility are widely analyzed in the literature [6–17], both in studies based on secondary [6,7,11] mixed-method papers that integrate secondary source analysis with the collection of primary data [8–10,12–17]. One such study is based on a comprehensive review of European publications, the aim of which is to identify and organize the drivers and barriers to the development of electromobility at three decision-making levels: institutional, collective, and individual [5]. Another approach found in the literature combines environmental analysis (LCA method) with survey research, obtaining a more comprehensive picture of both the actual environmental impact of electric vehicles (BEVs) and the social determinants of their acceptance [17]. The LCA method allowed for the assessment of the environmental impact of electric vehicles during their use phase, comparing the energy mix of Poland and Italy. The results of this analysis formed the basis for the second stage, which involved conducting a survey among Polish respondents. This survey assessed the level of public knowledge about the environmental impacts of BEV use and identified factors influencing purchasing decisions, including concerns about charging infrastructure [17].

The literature also includes studies forecasting the development of electromobility, based on advanced forecasting methods such as artificial intelligence models, deterministic chaos theory models, and selected techniques for extrapolating trends in selected European countries [18]. These studies also propose models forecasting the sales volume and growth rate of electric vehicles globally and in China [19]. The analyses indicate the following:

(1) In countries with a currently low share of electric vehicles, such as Poland or the Czech Republic, even a moderate growth rate could trigger a rapid increase in infrastructure demand. This would necessitate the rapid expansion of charging networks, the strengthening of distribution systems, and the provision of stable regulatory incentives.
(2) In countries with a moderate level of electromobility market development, such as Germany, France, Spain, and the United Kingdom, it is crucial to synchronize the pace of electrification with the development of charging infrastructure, energy availability, and the maintenance of affordability. In the United Kingdom, an additional challenge is adapting to regulations governing the sale of zero-emission vehicles.
(3) In countries with a mature market, such as Norway, maintaining the smooth operation of the entire electromobility system becomes a priority. This includes improving charging reliability, integration with the electricity grid, and modifying the incentive system to support market stability rather than merely further sales growth [18].
(4) Globally, particularly dynamic development is being observed in China, where the growth rate of electric vehicle sales is higher than the global average, and EV market share is expected to exceed 50% by 2025. This means that China will remain a key driver of global transport electrification, setting the pace for other regions and influencing the development of technologies, infrastructure, and policies supporting electromobility [19].

As Bielski, Marks-Bielska, Wiśniewski, Kurowska and Sobieraj [15] emphasize, the development of the global electric vehicle market is determined primarily by three fundamental groups of factors: technical, economic (such as purchase cost, operating savings, and the availability of charging infrastructure), and environmental (including consumer environmental awareness and the potential for reducing emissions). According to Sobiech-Grabka, Stankowska and Jerzak [16], to increase consumer acceptance and willingness to purchase electric vehicles, it is necessary to strengthen public environmental awareness.

Regardless of the methodology adopted, whether it is k-means clustering or other non-hierarchical methods based on quantitative and spatial variables [20] or approaches using latent structure analysis [21], the research leads to a similar conclusion: consumer attitudes are shaped not by demographics but by coherent sets of evaluations and priorities [21], which is consistent with the results of this study.

In summary, in light of the results of this study, it is worth emphasizing that the development of electromobility is multidimensional and complex, deeply rooted in the broader concept of sustainable development. Although this concept is widely promoted by governments and international organizations, it remains ambiguous and difficult to define clearly, which is also reflected in the diverse consumer attitudes revealed by the segmentation conducted.

This study fills a research gap by combining two analytical approaches, linear regression and cluster segmentation, enabling the identification of factors associated with the price acceptance of electric vehicles and the identification of diverse user groups with distinct perceptions of electromobility. Furthermore, it integrates macroeconomic indicators with microeconomic consumer perceptions at the regional scale. Although electromobility has been widely analyzed at the national and European levels, there is a lack of research demonstrating how regional infrastructure development, local market maturity, and individual assessments of technical parameters jointly shape price acceptance and user segmentation in regions less advanced in electromobility, such as the Lubusz Voivodeship. This study fills this gap by integrating national and European indicators with regression and segmentation results based on survey data. The study was conducted using a survey method in the Lubusz Voivodeship. The findings can serve as a basis for designing public policies, marketing strategies, and investment initiatives in the area of sustainable transport, further justifying the need for research and highlighting its value. The research on the perception of electromobility aims to help better understand public opinion and expectations regarding the development of low-emission transport. Its goal is to identify factors associated with the acceptance of electric vehicles and to determine which factors may increase residents' willingness to use such solutions.

The remainder of the study focuses on the market and energy conditions for the development of electromobility, supplemented by an analysis of consumer perception of electric vehicles as a significant element of the social dimension of sustainable transport.

2.2. Market and Energy Conditions for the Development of Electromobility in the Context of Its Perception by Consumers

Interest in electric cars is currently growing, driven by rapid technological advances in batteries, the development of charging infrastructure, growing environmental awareness, and the desire to reduce pollutant and greenhouse gas emissions [22]. As Gis, Waśkiewicz and Pawlak [23] point out, the key reasons for popularizing the idea of developing electric cars stem from factors such as environmental protection, diversification of energy sources used in the automotive industry, and the improvement of road safety (Table 1).

Table 1. Key factors in the development of electric cars [23].

Category of Premises	Characteristics of the Category
Ecological	Using renewable energy to generate electricity and then charge electric vehicle batteries significantly reduces air pollutant emissions. This is particularly important in large urban areas, improving air quality.
Diversification of energy sources	The use of electricity as a power source in transport promotes greater economic and political autonomy in countries lacking their own oil reserves. In practice, switching to electric means of transport reduces their vulnerability to commodity price fluctuations and reduces dependence on major oil-exporting countries.
Improving road safety	Technical limitations related to the capacity of electric vehicle batteries mean that drivers often drive less dynamically, which may consequently contribute to improved road safety.

Electric cars are perceived as a zero-emission solution, but their actual environmental impact depends on a given country's energy mix [24]. Poland is characterized by a relatively low share of renewable energy sources and a high degree of dependence on fossil fuels, which means that most of the energy used to charge electric cars comes from fossil fuels [25,26]. It is worth noting, as the IEA report indicates, that renewable energy sources currently provide only 7% of global district heating, which contrasts with the rapid development of other clean energy technologies [27]. According to IEA data, in recent years, global photovoltaic capacity has more than quadrupled, wind capacity has almost doubled, and electric car sales are growing rapidly [27]. The noticeable growth of the electric car market may influence how consumers perceive electromobility, which in turn influences their purchasing decisions, particularly in the context of the environmental benefits associated with electric vehicles. As Kurytka points out, the enormous importance of electric cars in Polish conditions lies in their potential to radically improve air quality in cities where up to 60% of pollution comes from road transport [28].

2.3. Sustainable Transport: Assessment Methods and Perception of Electromobility

Implementing a sustainable transport concept requires systematic monitoring of progress and assessment of the effectiveness of the actions undertaken. This process should be based on sets of indicators reflecting three key areas of sustainable development: social, economic and environmental [29]. These areas are closely interconnected; therefore, transport assessment must consider their interplay. In practice, both hard indicators based on statistical data and measurements (such as BEV share and growth) and soft indicators analyzing perceptions of electromobility, derived from resident opinion surveys and their subjective assessments of the transport system's performance, are used. Indicator analysis is conducted both at the stage of formulating transport policy and selecting implementation instruments, as well as during implementation. These sets of indicators allow, on the one hand, determination of the current state of the transport system, and on the other hand, monitoring of the effects of the actions undertaken and assessment of whether they are bringing the city or region closer to achieving sustainable development goals. In the following section, the focus will be on the social dimension of sustainable transport, analyzing perceptions of electromobility based on surveys.

3. Materials and Methods

The main objective of the study was to determine the level of electromobility development and to identify and assess factors statistically associated with its perception among residents of the Lubusz Voivodeship. Additionally, the study aimed to identify user segments with differing perceptions of electromobility, providing a better understanding of the diverse attitudes and expectations regarding electric transport solutions in the region. The Lubusz Voivodeship was selected because the region is intensifying activities related to energy transition and the development of low-emission transport, allowing for the observation of the early stages of electromobility implementation.

To achieve the stated objectives, the following research problems were formulated:

Problem 1 (P1). *What is the level of electromobility development in the Lubusz Voivodeship, assessed in the context of national and European trends in BEV adoption and charging-infrastructure expansion?*

Problem 2 (P2). *What factors are statistically associated with the price acceptance of an electric vehicle among residents of the Lubusz Voivodeship?*

Problem 3 (P3). *Can user segments be distinguished among residents of the Lubusz Voivodeship that differ in their assessment of technical parameters, economic factors, environmental aspects, and price acceptance of an electric vehicle?*

Problem 4 (P4). *What are the characteristic profiles of attitudes toward electromobility in the identified user segments?*

Based on the stated objectives and the formulated research problems, two main hypotheses and a set of auxiliary hypotheses were developed. The main hypotheses are as follows:

H1. *The level of price acceptance of electric vehicles is statistically associated with the assessment of key user factors, such as the quality of charging infrastructure, charging time, vehicle range, availability of public chargers, home charging options, operating costs, environmental awareness, and the attractiveness of purchase incentives.*

H2. *The electromobility market is characterized by distinct user segments whose perceptions of electric vehicles are statistically associated with the importance assigned to technical parameters, economic factors, environmental aspects, and price acceptance.*

To verify Hypothesis 1 (H1), it was broken down into a set of specific hypotheses relating to the association of individual variables:

H1a. *A better assessment of charging infrastructure is statistically associated with higher price acceptance of an electric vehicle.*

H1b. *Longer charging times are statistically associated with lower price acceptance of an electric vehicle.*

H1c. *A longer vehicle range is statistically associated with higher price acceptance.*

H1d. *Higher environmental awareness is statistically associated with higher price acceptance of an electric vehicle.*

H1e. *Greater availability of public chargers is statistically associated with higher price acceptance.*

H1f. *The ability to charge a vehicle at home is statistically associated with higher price acceptance.*

H1g. *Lower operating costs are statistically associated with higher price acceptance.*

H1h. *Attractive purchase incentives are statistically associated with higher price acceptance of an electric vehicle.*

As a result, 510 correctly completed surveys were collected. The study included adult residents of the Lubusz Voivodeship, aged 18 and over, who hold or might hold a driving license. The sample structure indicates a diverse socioeconomic profile of the respondents (Table 2). The study involved 510 respondents, of whom over 40% were women and 59% were men, meaning men constituted a slightly larger proportion of the sample. In terms of place of residence, over 66% were urban residents, while approximately 34% came from rural areas. The educational structure of the respondents varied. The largest group was made up of respondents with secondary education (41%), followed by those with higher education (37%). A smaller portion of the sample consisted of those with vocational/technical education (approximately 15%), and the smallest group comprised respondents with primary education (6.9%). In terms of age, the largest group of respondents consisted of those aged 35–44, and the smallest group consisted of those over 65. Household income also varied, with the largest group being those with a net income per capita of PLN 5000–10,000.

Table 2. Socioeconomic structure of respondents.

Specification	Respondents	
	Number	Percent
Gender		
Woman	207	40.59
Man	303	59.41
Place of residence		
City	337	66.08
Countryside	173	33.92
Education		
Primary	35	6.86
Vocational/technical education	76	14.90
Secondary	210	41.18
Higher	189	37.06
Age range		
18–24 years	48	9.41
25–34 years	105	20.59
35–44 years	146	28.63
45–54 years	102	20.00
55–65 years	90	17.64
Over 65 years	19	3.73
Net income per person in the household		
Below 5000 PLN net	136	26.67
5000–10,000 PLN net	171	33.53
10,001–15,000 PLN net	115	22.55
15,001–20,000 PLN net	62	12.16
Above 20,000 PLN net	26	5.09

The survey was conducted using the CAWI (computer-aided web interview) method, providing respondents with a link to the online survey. The use of the CAWI method can lead to several sources of error. These include self-selection bias, limited access to technology in certain demographic groups, and overrepresentation of individuals more interested in electromobility. Online survey results may also be influenced by differences in digital literacy levels and uncontrolled response conditions. Consequently, the sample may not fully reflect the demographic structure of the region's population, which should be taken into account when interpreting the results. The survey was conducted at the turn of 2025/2026. The study used a five-point Likert scale, treated in the analyses as quasi-quantitative. All variables were measured using a five-point Likert scale, with 1 representing the lowest rating and 5 representing the highest (increasing coding direction). Higher values corresponded to more positive assessments of a given aspect of electromobility. The variables used in the regression and cluster segmentation models were as follows:

– Price—measured by a single item regarding the declared acceptability of the purchase price of an electric vehicle.

– Infrastructure—measured by an item assessing the general perception of the quality of charging infrastructure in the region (e.g., availability, technical condition, location).
– Charging time—subjective assessment of the acceptability of the time required to fully charge an electric vehicle.
– Range—measured by assessing satisfaction with the declared range of electric vehicles available on the market.
– Availability of chargers—assessment of the number and availability of public charging points in the respondent's immediate vicinity.
– Charging access at home—measured by assessing the ease or accessibility of charging a vehicle at home, e.g., one's own garage, a single-family home with access to the system, or a parking space with access to the system.
– Operating costs—measured as an assessment of the perceived costs of using an electric vehicle compared to combustion vehicles.
– Environmental awareness—the perception of the environmental impact of electric vehicles, the importance of emission reduction, and personal environmental motivation.
– Purchase incentives—the assessment of the importance and attractiveness of available financial incentives (e.g., subsidies, tax breaks) when deciding to purchase an electric vehicle.

Research [30,31] confirms that five-point Likert scales should be treated as quasi-interval data when the categories are symmetrical and equidistant. This approach is widely used in empirical research when the scale is symmetrical and contains at least five categories. The results of the study by Kaiser and Lepinteur [30] show that although responses on five-point Likert scales are not perfectly linear, deviations from linearity are small, and the direction of coefficients in linear models remains very stable even with a large number of replications. Ferrer-i-Carbonell and Frijters [31] showed that the coefficients obtained in ordered logit and ordered probit models are very similar to those estimated using ordinary least squares (OLS) regression, both in terms of the direction and significance of the effects. This indicates that linear regression provides stable and interpretable results even for variables measured on Likert scales. OLS and ordered logit/probit lead to the same conclusions regarding the direction and significance of effects; the differences mainly concern the interpretation of the scale, not the structure of the relationship itself [31]. Consequently, the use of linear regression in this study can be considered methodologically sound.

Although linear regression is widely used with Likert-type variables, it is important to acknowledge its limitations, such as the fact that predicted values may fall outside the response range, normality is not fully satisfied, and variability is non-constant across categories [32,33].

Cluster analysis was performed using the k-means algorithm, which groups observations by minimizing the sum of squared distances within clusters. The distance measure used was the classical Euclidean distance, consistent with the algorithm's implementation in Stata 17 software [34]. Although all items were rated on a five-point Likert scale, the variables differed in their empirical distributions and standard deviations. Therefore, before proceeding with the segmentation analysis, the variables were standardized using a z-score transformation to ensure comparability and prevent variables with higher variance from dominating. However, the regression analysis used raw data to facilitate direct interpretation of the model coefficients.

Before clustering, the data structure was analyzed using principal component analysis (PCA). The resulting PCA structure confirmed the validity of cluster analysis, as the data showed significant heterogeneity that justified segmenting respondents.

The optimal number of clusters was formally verified using a statistical validation procedure with the Calinski–Harabasz index (pseudo-F) [35] and the overall silhouette score [36]. The final choice of the three-cluster solution was justified by both its superior mathematical quality and the high interpretability of the resulting segments. The three-cluster model allowed for the identification of clear, consistent, and distinguishable respondent profiles. These segments differed both in the levels of individual variable ratings and in the overall nature of attitudes toward electromobility, confirming the validity of adopting three segments.

The study employed two complementary analytical procedures: cluster analysis and regression analysis, which utilized variables in different roles according to the purpose of each method. The price variable serves as the dependent variable in the regression analysis, as this stage of the study assessed factors statistically associated with the price acceptance of an electric vehicle. At the same time, price was used in the cluster analysis as one of the characteristics describing the respondents' attitude profile.

The analysis utilized statistical data from sources such as the IEA [27], Globenergia [37], UDT/EIPA [38], PSNM [39] and IBRM Samar [40]. Calculations from the survey were performed using STATA 17.0 software [34].

4. Indicators for Assessing the Development of Electromobility

According to Globenergia [37] data on the share of BEVs in new registrations in June 2026, the highest level of electromobility was recorded in Denmark, where fully electric vehicles accounted for 64.9% of all new registrations. High BEV shares were also recorded in Sweden (35.0%) and the Netherlands (34.5%). Considering the average values for Europe (25.6%) and the European Union (23.6%), it can be seen that approximately one in four new cars registered in the analyzed period was a fully electric vehicle (BEV). Poland, with a 5.2% share, and Croatia, with a 3.8% share, ranked last (Figure 1).

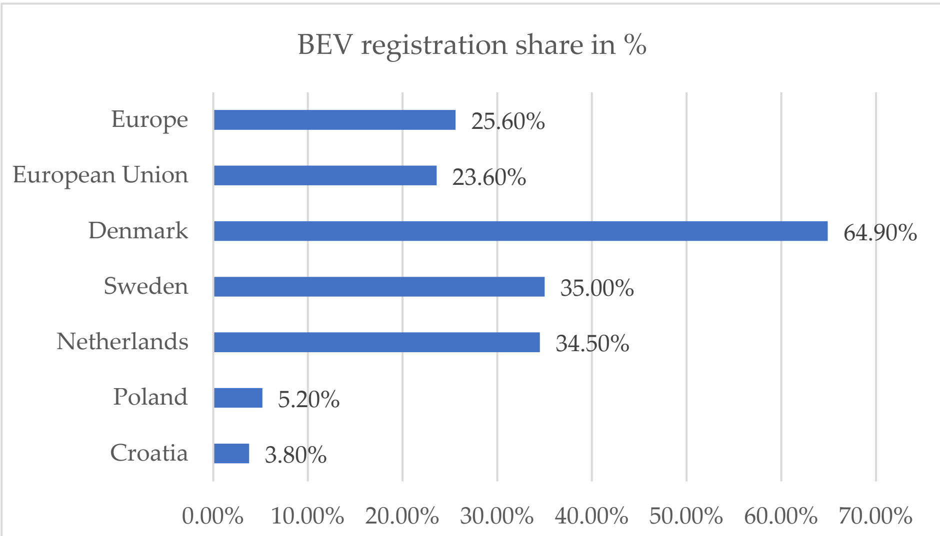

Figure 1. Share of BEV registrations in selected EU countries and in the EU and Europe overall (June 2026) [37].

In Poland, the number of BEVs increased from 11 to over 22,000 annually between 2010 and 2026, and in the record-breaking year of 2025, it exceeded 52,000 (Figure 2). In the first half of 2026, the number of all-electric vehicle (BEV) registrations reached 22,508 units. However, the BEV share of the electric vehicle market was lower compared to the previous year. In June 2026, it reached 39.4%, while in all of 2025, it reached 52.8%, indicating a significant weakening of the BEV segment's dynamics compared to the previous year [40].

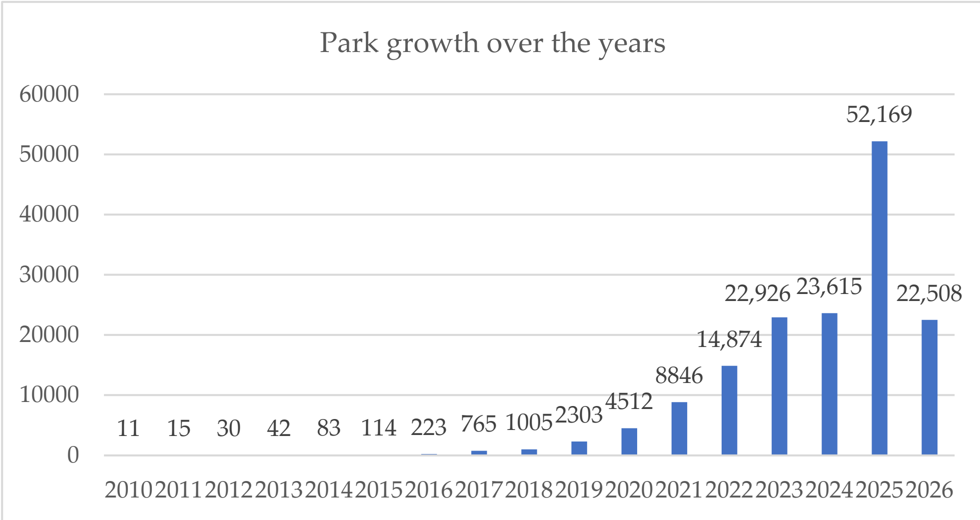

Figure 2. Annual increase in the number of BEVs in Poland in 2010–2026 * [40]. * Legend: The values represent the number of newly registered battery electric vehicles (BEVs) in Poland in individual years, from 2010 to June 2026.

In Poland, the charging infrastructure is systematically developing alongside the growing number of electric vehicles. According to PSNM data from the end of June 2026, a total of 154,947 passenger and commercial all-electric vehicles (BEVs) were registered in Poland [39]. In the first half of this year, their number increased by 22,737, which is 22% more than in the same period in 2025.

Table 3 presents the cities' positions in the national ranking of the number of charging stations. Cities with the largest number of charging points (as of July 2026): Warsaw (338), Poznań (181), Gdańsk (177), Szczecin (158), Wrocław (152), and Kraków (146), followed by Łódź (144) and Katowice (108). In the Lubuskie Voivodeship, Gorzów Wielkopolski has the largest number of stations (44 stations, 14th place in Poland), while Zielona Góra has 33 stations, taking 15th place in the national ranking [38].

In summary, data on the share of BEVs in new registrations in June 2026 show variation across European countries. Denmark (64.9%) clearly dominates the ranking. Sweden (35.0%) and the Netherlands (34.5%) also achieve a high BEV share, exceeding one-third of the market (Figure 1). Poland (5.2%) and Croatia (3.8%) rank last (Figure 1), which may be due to various factors, such as lower subsidies, slower development of charging infrastructure, stronger perceived barriers (price, range, and charger availability), and lower consumer technological awareness.

The contrast between the Scandinavian countries and other European countries shows that the perception of electromobility is strongly dependent on local market conditions, government policies, and infrastructure.

Table 3. Ranking of cities in Poland by number of charging stations (26 July 2026) [38].

City	Number of Stations	Location in Poland
Warsaw	338	1
Poznań	181	2
Gdańsk	177	3

Table 3. *Cont.*

City	Number of Stations	Location in Poland
Szczecin	158	4
Wrocław	152	5
Kraków	146	6
Łódź	144	7
Katowice	108	8
Częstochowa	80	9
Bydgoszcz	75	10
Lublin	63	11
Białystok	61	12
Rzeszów	48	13
Gorzów Wielkopolski	44	14
Zielona Góra	33	15

5. Results

In this part of the study, based on empirical data, the verification of the research hypotheses is presented. The research process explored relationships between variables, analyzed the impact of selected factors on price, and identified differentiated user segments in terms of their perception of electromobility. As mentioned above, the research was conducted using a survey method, which made it possible to collect the data necessary for performing linear regression analysis (Table 4) and cluster segmentation.

Table 4. Linear regression results.

Source	SS	df	MS	Number of Obs. = 510		
Model	59.2346137	8	7.40432671	F(8, 501) = 10.23		
Residual	362.469308	501	0.723491633	Prob > F = 0.0000 R-squared = 0.1405 Adj. R-squared = 0.1267 Root MSE = 0.85058		
Total	421.703922	509	0.828494934			
Price	Coefficient (β)	Std. err.	t	$p > \|t\|$	[95% conf. interval]	
Infrastructure	0.1490952	0.0425425	3.50	0.000	0.0655115	0.232679
Charging time	−0.1024067	0.04277	−2.39	0.017	−0.1864373	−0.0183761
Range	0.1091855	0.0463122	2.36	0.019	0.0181954	0.2001756
Availability of chargers	−0.0226046	0.0518998	−0.44	0.663	−0.1245726	0.0793634
Charging access at home	−0.0427279	0.0377213	−1.13	0.258	−0.1168393	0.0313835
Operating costs	0.0668543	0.0497705	1.34	0.180	−0.0309304	0.1646389
Environmental awareness	0.1121394	0.0353542	3.17	0.002	0.0426786	0.1816002
Purchase incentives	0.0647861	0.0407546	1.59	0.113	−0.0152848	0.1448571
_cons	2.433876	0.1880149	12.95	0.000	2.064481	2.803271

As part of the linear regression model diagnostics, we assessed the collinearity of variables, tested for homoscedasticity, analyzed influential observations, and verified the normality of residuals, confirming that the model met all the key assumptions of the classic linear model.

The strongest and most significant factors ($p < 0.05$) indicate that respondents are willing to accept a higher price when they positively evaluate the infrastructure ($\beta = 0.149$; $p < 0.001$), when the vehicle offers a longer range ($\beta = 0.109$; $p = 0.019$), and when they are more environmentally aware ($\beta = 0.112$; $p = 0.002$). At the same time, longer charging times reduce price acceptance ($\beta = -0.102$; $p = 0.017$), demonstrating that charging speed is a real constraint on the perceived value of a vehicle. These four variables constitute a key set of factors shaping price assessments in the study group. The remaining predictors, such as charger availability ($p = 0.663$), home charging capability ($p = 0.258$), operating costs ($p = 0.180$), and purchase incentives ($p = 0.113$), did not reach statistical significance. This means that their clear impact on price acceptance was not demonstrated in the study sample. It is worth noting the purchase incentives variable, which, with a p-value of 0.113, is close to the significance threshold but still does not meet the $p < 0.05$ criterion, suggesting that its impact may be weaker or more variable among respondents. It is worth noting that although the model as a whole proved to be statistically significant, it explains only about 14% of the variability in the analyzed variable, namely price, which indicates a weak level of fit and suggests that price is also influenced by other determinants not included in the model (Table 3). The literature emphasizes that a low coefficient of determination (R^2) does not determine the model's quality or statistical significance [36–40]. This means that even with limited fit, the model can accurately reflect important relationships and be valuable for analysis. Consistent with the approach presented in the literature, this level of R^2 does not undermine the validity of the analysis but suggests that other factors not included in the model also associated with price. Therefore, the resulting regression model, despite its weak level of fit ($R^2 = 0.14$), retains its cognitive value because it allows for the identification of statistically significant price determinants. The results indicate that infrastructure, charging time, range, and environmental awareness are significantly associated with price, confirming the validity of their inclusion in the model. The remaining variables were found to be insignificant, but their presence allows for a more comprehensive understanding of the research context. The model as a whole is statistically significant, meaning that the relationships captured are not coincidental, while the limited fit suggests that other factors not included in the analysis also associated with price. This indicates the need for continued analysis in the future, which may be an important direction for further research.

In the next stage of the analysis, we assessed whether the variables used in the linear regression model were overly correlated. To this end, the VIF was calculated for each predictor (Table 5). The obtained values ranged from 1.19 to 2.45, with an average VIF of 1.63, indicating a low level of multicollinearity between the variables. This means that none of the predictors disturbed the stability of the model through strong relationships with other variables, and the estimated regression coefficients can be considered reliable.

These values clearly confirm that the model is not affected by multicollinearity.

Next, the model was tested for compliance with key assumptions of linear regression. First, the presence of heteroscedasticity was verified using the Breusch–Pagan/Cook–Weisberg test. The test result ($\chi^2 = 0.18$; $p = 0.6700$) does not support the rejection of the null hypothesis of constant variance, meaning that the model residuals have homogeneous variance and the homoscedasticity assumption was met.

Table 5. VIF values for model variables.

Variable	VIF	1/VIF
Availability of chargers	2.45	0.407367
Operating costs	2.01	0.498022
Infrastructure	1.77	0.565323
Range	1.58	0.631452
Charging access at home	1.39	0.720003
Environmental awareness	1.36	0.737004
Purchase incentives	1.27	0.787384
Charging time	1.19	0.837283
Mean VIF	1.63	

Additionally, Cook's distance values (Table 6) were analyzed to assess whether there were any observations in the dataset that had an excessive impact on the model fit. The mean Cook's distance value was 0.001979, and the maximum was 0.0334, indicating that no observation exerted an excessive impact on the model.

Table 6. Cook's distance (cooksd) values.

Variable	Obs	Mean	Std. Dev.	Min	Max
cooksd	510	0.001979	0.0033116	1.03×10^{-7}	0.0334058

In the next part of the diagnostics, the normality of the distribution of residuals was checked using the skewness and kurtosis test (Table 7). The obtained values ($p = 0.8763$ for skewness; $p = 0.3118$ for kurtosis; joint test $\chi^2 = 1.05$; $p = 0.5910$) indicate that the distribution of residuals does not differ significantly from normal, which means that another assumption of the classical linear regression model is met.

Table 7. Skewness and kurtosis tests for normality.

				Joint Test	
Variable	**Obs.**	**Pr (Skewness)**	**Pr (Kurtosis)**	**Adj. Chi^2 (2)**	**Prob > Chi^2**
resid	510	0.8763	0.3118	1.05	0.5910

In summary, the diagnostic tests performed confirm the model's validity: the residuals are homoscedastic, do not show excessively influential observations, and are normally distributed. Therefore, the model can be considered reliable.

The marginal effects graph shows the predicted price acceptance of an electric vehicle depending on the level of infrastructure and environmental awareness (Figure 3).

The results of the regression analysis and the visualization of the marginal effects allow us to formulate several important observations regarding the factors associated with the price acceptance of electric vehicles. The analysis indicates that both the perceived quality of charging infrastructure and the level of environmental awareness are positively associated with higher levels of price acceptance. This means that individuals who evaluate the infrastructure more favorably and who report higher environmental awareness tend to declare greater acceptance of the purchase price of an electric vehicle.

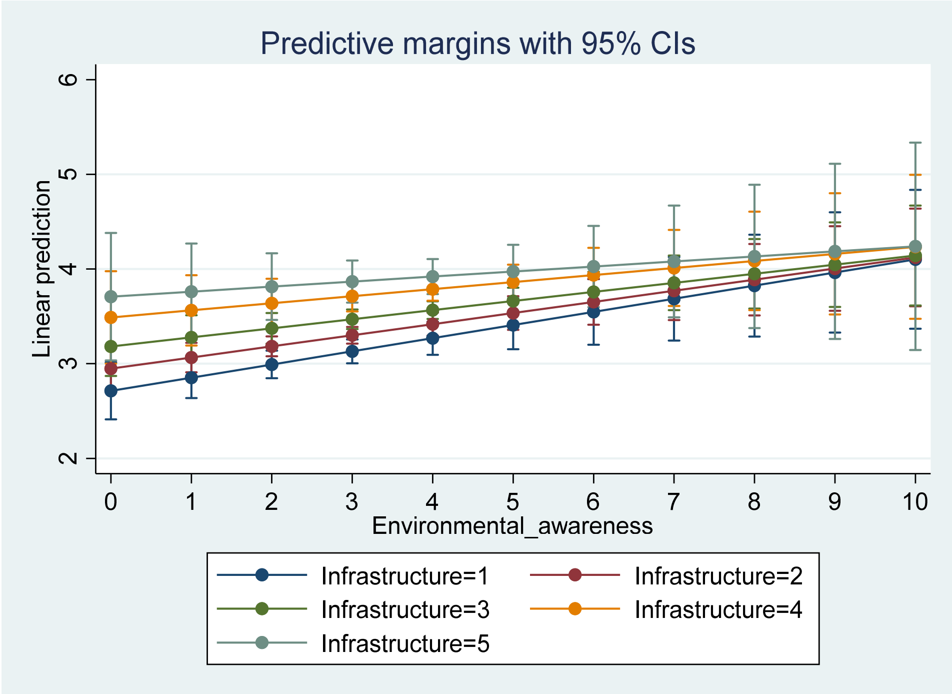

Figure 3. Predictive values of electric vehicle price acceptance depending on the level of environmental awareness and the quality of charging infrastructure *. * Note: The vertical axis (linear prediction) represents the values predicted by the regression model for the dependent variable (price acceptance), reflecting the initial five-point Likert scale. The horizontal axis represents the cumulative environmental awareness index in the range 0–10, generated in 1-unit increments (0(1)10). Individual lines represent the marginal effects for the five levels of the moderating variable (Infrastructure). Markers around the points indicate 95% confidence intervals, abbreviated as Cls on the graph. The number of observations in the model is $n = 510$.

The first step before cluster extraction is principal component analysis (PCA). Principal component analysis (PCA) was conducted to assess the structure of the variables (Table 8). The first component explains 39.39% of the total variance, while the first four components together explain 71.68%. The remaining components (from Comp 5 to Comp 9) gradually add up to 100% (cumulative = 1.0000). For further analyses, it was decided to retain all nine components (Comp 1–Comp 9). This allows accounting for 100% of the total variance of the studied system (as confirmed by the cumulative value of 1.0000 at Comp 9) and ensures that no information from the original variables was lost before the clustering stage.

The results indicate that the variables are multidimensional and reflect various aspects of perceptions of electromobility, such as infrastructure, functional features, operating costs, and environmental motivations. The first component represents the general attitude toward electromobility, while the subsequent components differentiate the assessment of infrastructure, charging time, range, and financial incentives. The PCA structure supports the use of cluster analysis, as the data demonstrate diversity that justifies segmenting respondents.

A graphical interpretation of the division of data into clusters in the principal component space is presented in Figure 4.

Table 8. Principal component analysis (PCA) results: eigenvalues and proportion of variance explained.

Number of obs. = 510				
Principal components/correlation Number of comp. = 9				
Trace = 9				
Rotation: (unrotated = principal) Rho = 1.0000				
Component	Eigenvalue	Difference	Proportion	Cumulative
Comp1	3.54508	2.44308	0.3939	0.3939
Comp2	1.102	0.189668	0.1224	0.5163
Comp3	0.912334	0.0208223	0.1014	0.6177
Comp4	0.891512	0.198272	0.0991	0.7168
Comp5	0.69324	0.0816205	0.0770	0.7938
Comp7	0.544263	0.119694	0.0605	0.9222
Comp8	0.424568	0.149184	0.0472	0.9694
Comp9	0.275385	.	0.0306	1.0000

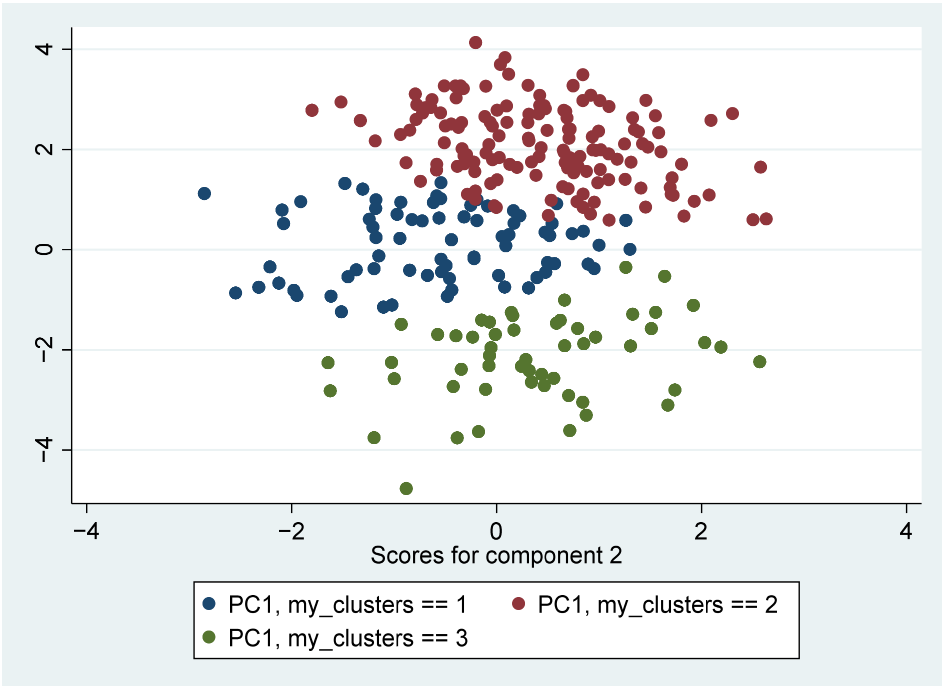

Figure 4. Scatterplot of the first components divided into three clusters.

To determine the optimal number of segments, a validation procedure was performed for the three- and four-cluster solutions (Table 9). Comparative analysis clearly indicated the superiority of the three-cluster division. This is supported by the significantly higher Calinski–Harabasz index (pseudo-F), which reached 143.48 for the three-cluster model, while for the four-cluster model it decreased to 109.83. This proves that the centers of the three distinguished groups are much better separated from each other and the intergroup variance is stronger. The overall average silhouette score for the three clusters is 0.29. Division into three groups ensures an even distribution of the number of objects within the segments (n = 187, 160, and 163, respectively). Decomposing the data into four groups results in a significant deterioration in the overall model quality. The overall silhouette score drops to 0.24. The introduction of the fourth cluster led to excessive fragmentation of the data and isolation of smaller groups (n = 154, 162, 96, 98, respectively), which destabilized the structure of the remaining clusters.

Table 9. Validation results of three clusters.

Number of Clusters	Calinski–Harabasz Index	Overall Average Silhouette Score *
3 clusters	143.48	0.29
4 clusters	109.83	0.24

* The average overall Silhouette score was calculated as a weighted average of the size of individual groups.

In line with Rousseeuw [35], silhouette values illustrate the coherence of individual observations within clusters, and the average silhouette width supports evaluating whether the selected number of clusters reflects a natural partition of the data. Figure 5 confirms the balanced size of the groups and the relatively higher internal consistency of clusters 2 and 3.

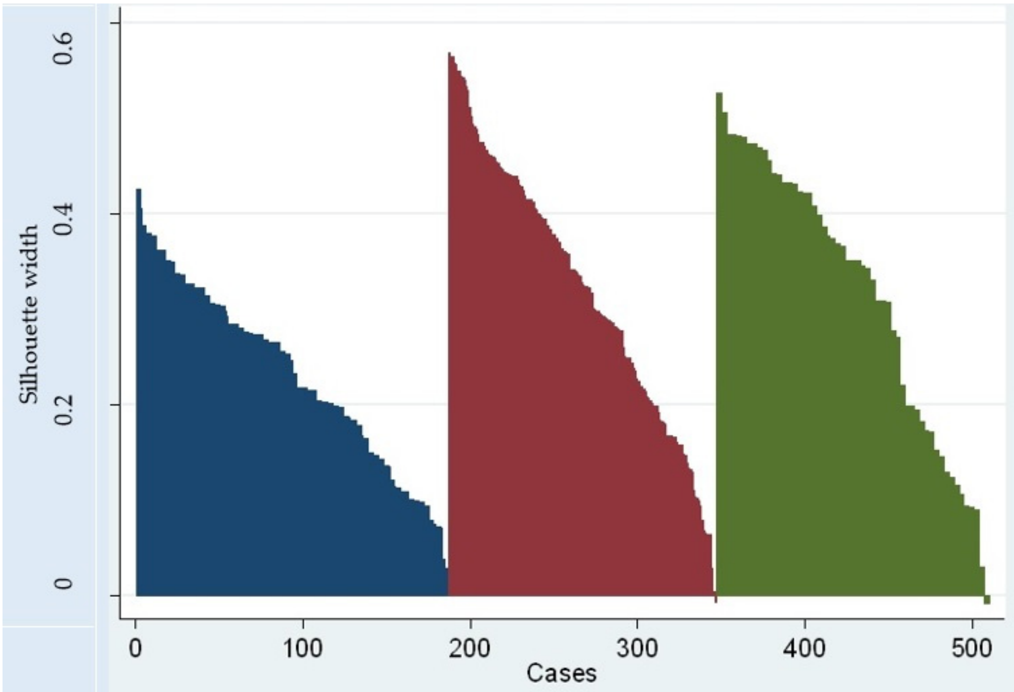

Figure 5. Graph for the three-class solution *. * Note: Colors represent distinct clusters (blue = Cluster 1, red = Cluster 2, and green = Cluster 3); n = 510.

Figure 5 presents a synthetic, model-based summary of key criteria that differentiate three distinct customer clusters. Each group has a distinct approach to ecology, infrastructure, incentives, and costs, allowing us to capture its specific motivations and barriers related to electromobility.

The next stage of the analysis involved the identification of clusters, which allowed for the grouping of respondents with similar preference profiles (Tables 10–12).

The first cluster turned out to comprise 187 individuals (Table 10). This group has a balanced, practical approach to electric vehicles. Respondents approve of the purchase price (3.10), but their ratings for other aspects are moderate.

The most striking are the average ratings for infrastructure (2.27) and charger availability (3.21), which indicate some concerns about charging options, though not as strong as in the skeptical cluster. At the same time, this segment stands out for its moderately positive ratings of utility features:

– Charging time (3.57)—acceptable, though not ideal;
– Range (3.23)—sufficient for everyday needs;
– Operating costs (3.03)—rated as more favorable than for combustion cars;
– Environmental awareness (3.04)—moderate, but higher than in the skeptical cluster;
– Incentives (3.56)—perceived as an important, though not decisive, argument.

The normalized values indicate that Cluster 1 achieves average results in most areas, with no extreme scores. This group views electromobility primarily through the lens of practicality and economic viability, but its decisions are constrained by moderate concerns about infrastructure.

Overall, this segment approaches electromobility through the lens of everyday usability and economic rationality.

Table 10. Electromobility pragmatists (Cluster 1).

Variable	Obs.	Mean	Std. Dev.	Min	Max
Price	187	3.096257	0.7906285	1	5
Infrastructure	187	2.272727	0.8134981	1	4
Charging time	187	3.572193	0.7469486	2	5
Range	187	3.235294	0.847663	1	5
Availability of chargers	187	3.213904	0.6934558	2	5
Charging access at home	187	2.780749	1.036979	1	5
Operating costs	187	3.032086	0.5857056	2	5
Environmental awareness	187	3.037433	1.104093	1	5
Purchase incentives	187	3.55615	1.005791	1	5
z_Price	187	−0.3487836	0.8686154	−2.651813	1.742743
z_Infrastructure	187	−0.2161141	0.6901924	−1.295928	1.249348
z_Charging time	187	0.3313982	0.7753686	−1.300613	1.813531
z_Range	187	0.3579144	0.8274294	−1.824024	2.080497
z_Availability of chargers	187	0.1379792	0.6092834	−0.9285796	1.707277
z_Charging access at home	187	0.1517867	0.8803711	−1.360027	2.035879
z_Operating costs	187	−0.0833642	0.5456549	−1.044876	1.749984
z_Environmental awareness	187	−0.1356086	0.8888408	−1.775827	1.444339
z_Purchase incentives	187	−0.0683925	0.9647601	−2.520265	1.316557
Custer		1	0	1	1

Cluster two comprises 160 individuals (Table 11). This group has the most positive attitudes towards electromobility. Respondents in this segment stand out for their high ratings of almost all aspects related to the use of electric vehicles.

The most notable are the very high scores for infrastructure (3.78), charger availability (4.10), and operating costs (4.22). This indicates that individuals in this segment perceive electromobility as a well-developed, ecological, and economically viable solution.

Key characteristics of this segment:

– Infrastructure (3.78)—perceived as sufficient;
– Availability of chargers (4.10)—no worries about charging;
– Operating costs (4.22)—clear perception of savings;

– Environmental awareness (4.19)—environmental sustainability is a key motivator;
– Purchase incentives (4.23)—financial incentives reinforce positive attitudes;
– Price acceptance (3.94)—willingness to pay higher purchase costs.

Normalized values confirm that Cluster 2 achieves the highest scores in the areas of infrastructure, charger availability, operating costs, and environmental awareness. This group perceives electromobility as a modern, ecological, and economically attractive solution, and its motivations are both practical and environmentally friendly.

Overall, high evaluations of infrastructure, charger availability, operating costs, environmental awareness, and purchase incentives indicate strong confidence in the technological maturity and ecological benefits of electric vehicles. Respondents in this group also show high price acceptance, reflecting readiness to invest in electric transport solutions. This segment views electromobility as modern, environmentally responsible, and economically advantageous.

Table 11. Electromobility enthusiasts (Cluster 2).

Variable	Obs.	Mean	Std. Dev.	Min	Max
Price	160	3.94375	0.7709088	1	5
Infrastructure	160	3.775	0.7684829	1	5
Charging time	160	3.50625	1.00937	1	5
Range	160	3.2375	0.9744374	1	5
Availability of chargers	160	4.1	0.7371541	2	5
Charging access at home	160	3.325	1.130203	1	5
Operating costs	160	4.21875	0.8139652	1	5
Environmental awareness	160	4.19375	0.756497	1	5
Purchase incentives	160	4.225	0. 6534861	3	5
z_Price	160	0.5823057	0.8469505	−2.651813	1.742743
z_Infrastructure	160	1.058452	0.6520004	−1.295928	2.097773
z_Charging time	160	0.2629467	1.047775	−2.338661	1.813531
z_Range	160	0.3600676	0.9511778	−1.824024	2.080497
z_Availability_of_chargers	160	0.9165202	0.6476776	−0.9285796	1.707277
z_Charging access at home	160	0.6138433	0.9595156	−1.360027	2.035879
z_Operating costs	160	1.022156	0.758306	−1.976495	1.749984
z_Environmental awareness	160	0.7952746	0.6090116	−1.775827	1.444339
z_Purchase incentives	160	0.5731723	0.6268274	−0.6018544	1.316557
Cluster		2	0	2	2

The third cluster includes 163 individuals (Table 12). Analysis of the mean values of the variables indicates that this group has the most negative attitudes towards electromobility. Respondents from this segment consistently give the lowest ratings for most aspects related to electric vehicle use.

The most characteristic are very low scores for infrastructure (1.60), charger availability (1.85), and home charging options (1.68). This indicates a strong belief that electromobility is a technologically underdeveloped solution and not adapted to their everyday needs. Ratings for operating costs (2.15) and range (2.08) are also low.

The distinguishing features of this segment include:

– Infrastructure (1.60)—perceived as a major barrier;
– Availability of chargers (1.85)—lack of charging options in practical conditions;

– Environmental awareness (2.43)—environmental protection is not a significant factor;
– Purchase incentives (3.12)—financial incentives are insufficient;
– Price acceptance (3.26)—price remains a barrier.

The normalized values confirm that Cluster 3 achieves the lowest scores in the areas of infrastructure, charger availability, operating costs, and environmental awareness. This group perceives electromobility as a problematic, expensive, and impractical solution.

Table 12. Electromobility skeptics (Cluster 3).

Variable	Obs.	Mean	Std. Dev.	Min	Max
Price	163	3.257669	0.940114	2	5
Infrastructure	163	1.595092	0.7339899	1	4
Charging time	163	2.638037	0.8448982	1	5
Range	163	2.08589	0.7965882	1	4
Availability of chargers	163	1.852761	0.6501009	1	3
Charging access at home	163	1.687117	0.6896185	1	3
Operating costs	163	2.147239	0.6501009	1	4
Environmental awareness	163	2.429448	1.132948	1	5
Purchase incentives	163	3.122699	1.104273	1	5
z_Price	163	−0.1714501	1.032846	−1.553174	1.742743
z_Infrastructure	163	−0.791037	0.6227357	−1.295928	1.249348
z_Charging time	163	−0.6383003	0.8770449	−2.338661	1.813531
z_Range	163	−0.7640541	0.7775738	−1.824024	1.104367
z_Availability of chargers	163	−1.057947	0.571191	−1.807199	−0.0499607
z_Charging access at home	163	−0.7766812	0.5854699	−1.360027	0.3379259
z_Operating costs	163	−0.9077045	0.6056469	−1.976495	0.818364
z_Environmental awareness	163	−0.6250621	0.9120705	−1.775827	1.444339
z_Purchase incentives	163	−0.4841605	1.059225	−2.520265	1.316557
Cluster		3	0	3	3

Overall, this segment views electric vehicles as costly and insufficiently adapted to everyday needs.

The three identified clusters differ in their level of price acceptance, as well as their assessment of infrastructure, utility features, and environmental motivations (Table 13). Cluster 2 demonstrates the most positive attitude toward electric vehicles, while Cluster 3 represents the most critical segment. Cluster 1 occupies an intermediate position, combining moderate evaluations of infrastructure with a pragmatic, economically oriented perspective. Cluster 1 evaluates electromobility mainly through economic and functional criteria. Cluster 2 stands out for its strong ecological motivations and positive perception of both infrastructure and operating costs. Cluster 3 is primarily driven by concerns about charging infrastructure and everyday usability.

The Figure 6 presents a synthetic, model-based summary of key criteria that differentiate three distinct customer clusters. Each group has a distinct approach to ecology, infrastructure, incentives, and costs, allowing us to capture their specific motivations and barriers related to electromobility.

Table 13. Summary of average values for the four clusters.

Variable	Cluster 1	Cluster 2	Cluster 3
Price	3.10	3.94	3.26
Infrastructure	2.27	3.78	1.60
Charging time	3.57	3.51	2.64
Range	3.24	3.24	2.09
Availability of chargers	3.21	4.10	1.85
Charging access at home	2.78	3.33	1.69
Operating costs	3.03	4.22	2.15
Environmental awareness	3.04	4.19	2.43
Purchase incentives	3.56	4.23	3.12

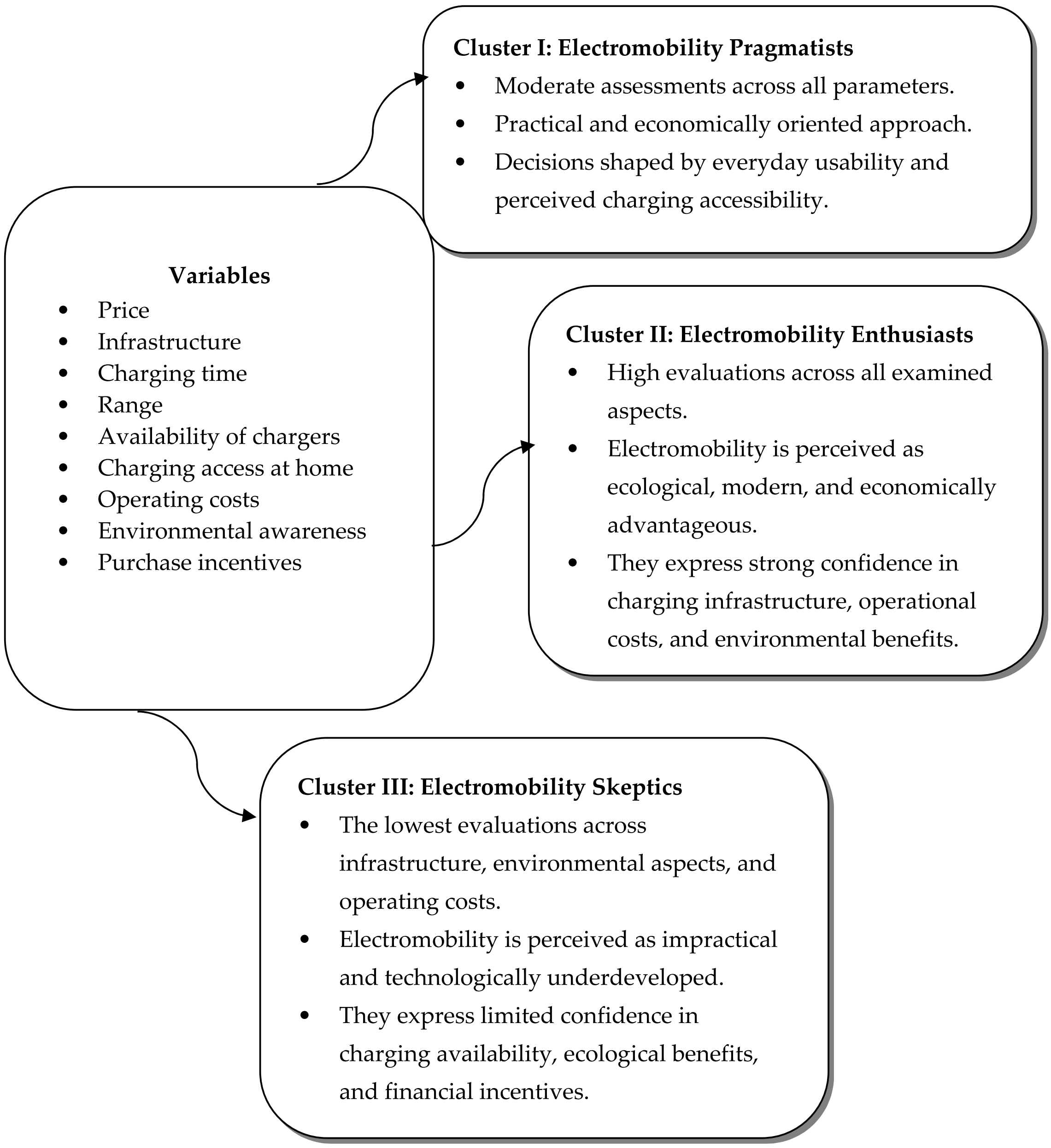

Figure 6. A model approach to the evaluation criteria of the three clusters. *. * Note: The arrows indicate the association between the analyzed variables and the identified respondent attitude profiles (Clusters I–III).

6. Discussion

In light of the conducted research, as well as previous findings by other authors, factors associated with the perception of electromobility can be identified. Śmiech [13] undertook to examine the perception of electromobility among Polish society using a survey questionnaire. The study revealed [13] that the greatest barriers preventing further consideration of purchasing an electric car include high price (75.3%), followed by lack of infrastructure (61.3%), short range (59.1%), cumbersome charging (52.7%), unsustainable car production (43%), energy costs (40.9%), and high-emission electricity (coal) (39.8%). A small percentage of respondents (3.2%) indicated that electric cars have no disadvantages.

Śmiech's research results correlate with some of the results obtained during the regression analysis, which show that in both cases, respondents indicated high price, poor infrastructure, short range and long charging times as the main barriers. Regression analysis indicates that both the perceived quality of charging infrastructure and respondents' environmental awareness are positively and significantly associated with price acceptance. This means that individuals who perceive infrastructure as more developed and who are characterized by higher environmental awareness are willing to accept a higher cost of purchasing an electric vehicle. The strongest and most significant factors ($p < 0.05$) indicate that respondents are willing to accept a higher price when they positively evaluate the infrastructure ($\beta = 0.149$; $p < 0.001$), when the vehicle offers a longer range ($\beta = 0.109$; $p = 0.019$), and when they are characterized by higher environmental awareness ($\beta = 0.112$; $p = 0.002$). At the same time, extended charging times reduce price acceptance ($\beta = -0.102$; $p = 0.017$), demonstrating that charging speed is a real limitation in the perception of vehicle value. These four variables constitute a key set of factors associated with price assessment in the study group. Other predictors, such as charger availability ($p = 0.663$), home charging ($p = 0.258$), operating costs ($p = 0.180$), and purchase incentives ($p = 0.113$), did not reach statistical significance, indicating that they did not clearly associated with price acceptance. Therefore, respondents are willing to accept a higher purchase price for an electric vehicle if they perceive the infrastructure as developed, the vehicle as functional, and the environmental benefits as important. At the same time, other variables, such as charger availability, home charging, operating costs, and purchase incentives, did not reach statistical significance, indicating that they do not play a key role in shaping price acceptance.

As researchers have noted [41–45], a low R^2 does not necessarily mean that the model is inadequate or that its statistically significant predictors are of no value. They emphasize that R^2 should be interpreted in the context of the phenomenon being studied, the variability of human behavior, and the type of data used [41–45]. In domains requiring complex decision-making, such as consumer preferences, low R^2 values are common because individual choices are shaped by numerous unobserved factors. Cross-sectional models often exhibit limited fit due to heterogeneity and omitted influences that cannot be fully captured in survey data [44]. From a data mining perspective, Pegoraro and Andrea [41] suggest that models with low R^2 can still reveal significant patterns, provided the identified predictors are statistically reliable.

Importantly, a low R^2 does not undermine the validity of the observed statistically significant relationships but rather highlights that these effects operate in parallel with other determinants beyond the scope of the current model. Future research could incorporate additional variables such as brand perception, prior experience with electric vehicles, and risk attitudes, among others, to increase explanatory power and provide a more comprehensive understanding of price acceptance. Therefore, although this model offers important insights into key factors influencing price evaluation, its limited fit highlights the complexity of consumer decision-making in the electric vehicle market.

This research also correlates with studies conducted by Firlej, Firlej, Luty and Kabaja [10], who identified the insufficient number of charging stations (56.8%) as the main obstacle to the development of electromobility, which, despite improvements, still fails to keep pace with growing demand. Other barriers include the insufficient range of vehicles (46.3%) and the high price of electric cars (45.5%). Other difficulties, such as long charging times, limited driver knowledge, and limited availability of specific models, were also cited in the responses. The most important benefits of electric cars were primarily the lack of exhaust emissions, along with other amenities, such as free parking. Those skeptical of these advantages tended to have a negative attitude toward electric cars compared to combustion vehicles [10].

An analysis of in-depth interviews conducted among Polish drivers by Pabian and Pabian [12] shows that the development of electromobility still faces numerous barriers. Respondents most frequently cited high purchase costs, limited range, long charging times, and insufficient infrastructure. These results are consistent with this research, which identified the same factors as key barriers to the widespread adoption of electric vehicles.

Similar results were also obtained by Łuszczyk, Sulich, Siuta-Tokarska, Zema and Their [6] using secondary data, which confirmed that infrastructure plays a crucial role in the development of electromobility.

A study conducted in November 2025 using an online survey (CAWI) on the SW Panel, covering a sample of 1014 adult Poles, identified factors influencing the perception of electric cars that correlate with these results [46]. The results show that Poles are increasingly less likely to evaluate electric cars solely based on price. Short range (33.6%), high purchase cost (33.3%), long charging times (31.8%), and lack of home charging options (27.3%) are cited almost equally often, suggesting the growing importance of practical aspects of electric vehicle use [46].

At the same time, this study allows us to identify barriers considered most significant. Range is key for 64.3% of respondents, and the ability to charge at home for 70% [46]. A high percentage also cited safety issues, such as the risk of fire (60.5%) and battery failure (54.8%) [46]. The results show that the challenge lies not only in the technology itself but also in user confidence in its reliability. Price remains a factor, but its relative importance is gradually declining.

As Adamczyk, Dzikuć, Dylewski and Varese [17] note, a subsidy system for the purchase of electric vehicles (BEVs) may temporarily increase sales, but its effect lasts only for the duration of the program. However, the sustained increase in interest in electric cars is driven by long-term benefits, such as lower failure rates, relatively low energy costs, slower depreciation, and the ability to enter urban low-emission zones.

The literature review conducted by Biresselioglu, Demirbag Kaplan and Yilmaz [5] confirms the results of previous studies and largely aligns with the conclusions reached in this study, which suggest that the most important barriers to the development of electromobility include, among others, insufficient charging infrastructure, economic factors and cost concerns, technical and operational constraints, low trust, lack of knowledge, limited energy and raw material resources, and doubts about their feasibility. On the other hand, the environmental, economic, and technological benefits of using electric vehicles prove to be significant motivators [5].

Similar findings were reached by researchers Sotnyk, Hulak, Yakushev, Yakusheva, Prokopenko and Yevdokymov [7], who point out that one of the key factors hindering the faster development of the electric vehicle market is the continued high price of these vehicles, resulting from the lack of mass production. The authors [7] also highlight limited battery capacity, relatively high energy consumption per kilometer, and insufficiently developed charging infrastructure. They also noted that rising household incomes are dampening

https://doi.org/10.3390/en19184410

electric vehicle sales, which they attribute to low awareness of the benefits of electric cars and consumers' attachment to traditional combustion engines [7].

These findings are also confirmed by Bielski, Marks-Bielska, Wiśniewski, Kurowska and Sobieraj [15], who point out that one of the key factors hindering the faster development of the electric vehicle market is the continued high price of these vehicles, resulting from the lack of mass production. The authors [15] also point to limited battery capacity, relatively high energy consumption per kilometer, and underdeveloped charging infrastructure. All these elements combine to keep demand for electric vehicles lower than it could be under more favorable market conditions.

Unlike many studies, this analysis focuses specifically on regression analysis, which reveals that price acceptance increases with better infrastructure ratings, longer range, and higher environmental awareness, and decreases with longer charging times, a finding not demonstrated in studies conducted by other authors. Cluster analysis, in turn, enabled the identification of diverse user segments with distinct profiles of preferences, motivations, and barriers related to electromobility. Segmentation allowed us to identify three groups of consumers: electromobility pragmatists, electromobility enthusiasts and electromobility skeptics. The use of both analytical approaches enabled us to determine which factors are associated with price acceptance and to explore how these determinants vary across social segments.

The results of the analyses conducted by Sobiech-Grabka, Stankowska and Jerzak show that [16]:

- Manufacturers should more strongly emphasize the environmental benefits of BEV use;
- Targeted information and educational campaigns are necessary to clarify the real incentives and conditions for using electric vehicles;
- Market development requires improved battery technology and charging systems to make them more attractive and functional for users.

Therefore, it seems that the key to increasing interest in BEVs is a combination of education, environmental communication, and technological development, rather than just offering short-term financial incentives.

The segmentation identified in this study is consistent with market-based cluster analyses presented in the literature. While studies by Henderi, Zailani, Tuah, and Abas [20] distinguished groups of electric vehicle users based on vehicle attributes, geographic distribution, and demographic profiles, the clusters identified in this study differentiate consumers based on their price acceptance, infrastructure evaluation, perceived usefulness, and environmental motivations. Despite focusing on different dimensions, both approaches reveal similar structural patterns: a highly positive segment, a critical segment, and two intermediate groups with distinct priorities.

A different approach was employed by Kozłowski and Czerepicki [21], who used latent structure analysis to reveal deeper patterns in how respondents evaluated autonomous vehicles. Based on the multidimensional structure of technology perception, they concluded that consumer attitudes are not driven by demographics but by a set of consistent evaluations and priorities [21], which is consistent with the results of this study, despite the different analytical methodology.

7. Conclusions

With reference to the primary objective of the research, which aimed to determine the level of electromobility development in the Lubuskie Voivodeship, and in response to research Problem 1 (P1), the analysis of secondary data allowed for the assessment of the region's situation against national and European trends. Data on the share of BEVs in new registrations indicate significant variation across EU countries, with the highest figures in Denmark (64.9%) and a low level in Poland (5.2%). The increase in the number of BEVs in Poland between 2010 and 2026 confirms the market's systematic development, although its pace remains moderate. Analysis of charging infrastructure shows a gradual expansion of the network, placing the Lubuskie Voivodeship—which includes Gorzów Wielkopolski and Zielona Góra as its main centers—in the early stages of electromobility development. A comparison of European, national and regional data indicates that the level of electromobility development in the region is strongly determined by nationwide trends, the pace of infrastructure development and support policies, while differences between the Scandinavian countries and Poland highlight the importance of local market conditions, subsidies and technological barriers to the adoption of electromobility.

Integrating these secondary data with the survey-based regression and segmentation results enables an analytical connection between national and European electromobility indicators and individual-level perceptions, showing how macro-scale market conditions and infrastructure development correspond to the factors shaping price acceptance and consumer profiles identified in the empirical analysis.

An analysis of publications regarding the perception of electric mobility indicates a number of factors associated with the choice of an electric vehicle. After conducting an empirical analysis, both main hypotheses were verified. In line with the main objective of identifying factors statistically associated with the perception of electromobility, and in direct response to research Problem 2 (P2), the first main hypothesis (H1), concerning factors statistically associated with price acceptance, was broken down into a set of specific hypotheses, some of which received statistical support, while others were rejected. The following hypotheses were accepted ($p < 0.05$):

H1a. *A better assessment of charging infrastructure is statistically associated with higher price acceptance of an electric vehicle.*

H1b. *Longer charging times are statistically associated with lower price acceptance of an electric vehicle.*

H1c. *A longer vehicle range is statistically associated with higher price acceptance.*

H1d. *Higher environmental awareness is statistically associated with higher price acceptance of an electric vehicle.*

The following hypotheses were not supported by the data ($p > 0.05$):

H1e. *Greater availability of public chargers is statistically associated with higher price acceptance.*

H1f. *The ability to charge a vehicle at home is statistically associated with higher price acceptance.*

H1g. *Lower operating costs are statistically associated with higher price acceptance.*

H1h. *Attractive purchase incentives are statistically associated with higher price acceptance of an electric vehicle.*

Linear regression analysis showed that, among all variables considered, only infrastructure, charging time, range, and environmental awareness demonstrated a statistically significant relationship with price acceptance. Better infrastructure, longer vehicle range, and higher environmental awareness were statistically associated with higher price acceptance, whereas longer charging times were associated with lower price acceptance. Other factors such as charger availability, home charging, operating costs, and purchase incentives were not found to be significantly related to price acceptance, indicating that the data do not support the hypotheses regarding their expected associations.

As part of the study's primary objective, namely identifying factors statistically associated with its perception, and in response to research questions regarding the diversity of residents' attitudes (P3 and P4), cluster analysis verified hypothesis H2. The results confirmed the existence of three distinct user segments, differing in their assessment of technical, economic, and environmental parameters, as well as their price acceptance of electric vehicles.

1. Cluster 1—electromobility pragmatists. This segment gave moderate ratings across all analyzed aspects. Users perceive electromobility through the prism of everyday functionality and economic viability, while simultaneously expressing moderate concerns about the availability of charging infrastructure.
2. Cluster 2—electromobility enthusiasts. This group gave the most positive ratings for infrastructure, charger availability, operating costs, environmental aspects, and incentives. Users perceive electromobility as a modern, ecological, and economically advantageous solution, demonstrating high price acceptance of electric vehicles.
3. Cluster 3—electromobility skeptics. This segment gave the lowest scores across most parameters, including infrastructure, charger availability, operating costs, environmental aspects, and incentives. This group perceives electromobility as expensive, impractical, and technologically underdeveloped.

The results confirm that the electromobility market in the Lubusz Voivodeship is not homogeneous but consists of distinct user segments with clearly differentiated attitudes and expectations.

Regardless of the adopted methodology and the analyzed technology area, perception segmentation reveals similar patterns, i.e., from highly positive segments, through intermediate groups with different priorities, to the most critical segments, which are confirmed by the results of this research and those of other researchers.

The results of the survey on the perception of electromobility allow for practical implications to be drawn for the design of public policies, marketing strategies, and investment activities in the area of sustainable transport. The analysis indicates that developing charging infrastructure and strengthening environmental awareness are two independent, yet equally effective, avenues of influence that can lead to increased price acceptance of electric vehicles. This means that investments in both public and residential charging networks, as well as educational activities that raise awareness of the environmental benefits of electromobility, can independently generate positive effects on the perception of purchase costs.

Based on the obtained results, it is possible to identify directions of action for local governments, central administration, the automotive industry, and infrastructure operators who build, manage, maintain, and develop electric vehicle charging infrastructure. These actions constitute a valuable element of public assessment of electromobility activities as a crucial element of sustainable transport development in the Lubusz Voivodeship. The results indicate that actions aimed at developing charging infrastructure and strengthening environmental awareness can independently contribute to increased price acceptance of electric vehicles, which may be significant for designing public policies and marketing strategies.

The presented results should be considered in the context of certain limitations of the study, which also define directions for further analysis. First, the study covers only residents of the Lubusz Voivodeship, which limits the generalizability of the results to other regions with different infrastructure and social conditions. Second, respondents' statements may be biased, and their knowledge of electromobility may vary, which impacts the reliability and validity of the data obtained. Third, the dynamic growth of the electric vehicle market and changing regulations mean that the obtained results reflect perceptions only at the time of the study. Fourth, the research methods used do not allow for the full capture of complex motivations and barriers, particularly unconscious ones, which may lead to simplifications in user segmentation.

Therefore, it is worthwhile to expand future research on electromobility in the Lubusz Voivodeship, focusing on the impact of psychological factors such as trust in technology, fear of novelty, and perceived risk, as well as to examine how individual segments respond to specific actions in the areas of infrastructure investments, financial incentives, and educational campaigns.

Funding: This research received no external funding.

Data Availability Statement: The original contributions presented in this study are included in the article. Further inquiries can be directed to the author.

Conflicts of Interest: The author declares no conflicts of interest.

References

1. Vuchic, V.R. *Transportation for Livable Cities*; Centre for Urban Policy Research: New Brunswick, NJ, USA, 1999.
2. Miller, P.; De Barros, A.; Kattan, L.; Wirasinghe, S.C. Public transportation and sustainability: A review. *KSCE J. Civ. Eng.* **2016**, *20*, 1076–1083. [CrossRef]
3. Low, N. Is Urban Transport Sustainable? In *Urban Transport Sustainable*; Global Issues Series; Palgrave Macmillan: London, UK, 2003; pp. 1–22. [CrossRef]
4. Motowidlak, U. Zielona mobilność 4.0–dokąd zmierzamy? In *W Poszukiwaniu Zielonego Ładu*; Burchard-Dziubińsk, M., Ed.; Wydawnictwo Uniwersytetu Łódzkiego: Łodź, Poland, 2022.
5. Biresselioglu, M.E.; Demirbag Kaplan, M.; Yilmaz, B.K. Electric mobility in Europe: A comprehensive review of motivators and barriers in decision making processes. *Transp. Res. Part A Policy Pract.* **2018**, *109*, 1–13. [CrossRef]
6. Łuszczyk, M.; Sulich, A.; Siuta-Tokarska, B.; Zema, T.; Thier, A. The Development of Electromobility in the European Union: Evidence from Poland and Cross-Country Comparisons. *Energies* **2021**, *14*, 8247. [CrossRef]
7. Sotnyk, I.; Hulak, D.; Yakushev, O.; Yakusheva, O.; Prokopenko, O.V.; Yevdokymov, A. Development of the US electric car market: Macroeconomic determinants and forecasts. *Polityka Energ. Energy Policy J.* **2020**, *23*, 147–164. [CrossRef]
8. Krupa, J.S.; Rizzo, D.M.; Eppstein, M.J.; Brad, L.D.; Gaalema, D.E.; Lakkaraju, K.; Warrender, C.E. Analysis of a consumer survey on plug-in hybrid electric vehicles. *Transp. Res. Part A Policy Pract.* **2014**, *64*, 14–31. [CrossRef]
9. Graham-Rowe, E.; Gardner, B.; Abraham, C.; Skippon, S.; Dittmar, H.; Hutchins, R.S. Mainstream consumers driving plug-in battery-electric and plug-in hybrid electric cars: A qualitative analysis of responses and evaluations. *Transp. Res. Part A Policy Pract.* **2012**, *46*, 140–153. [CrossRef]
10. Firlej, C.; Firlej, K.A.; Luty, L.; Kabaja, B. Awareness and perception of electromobility among young consumers: Survey results. *Krakow Rev. Econ. Manag.* **2026**, *2*, 97–116. [CrossRef]
11. Rezvani, Z.; Jansson, J.; Bodin, J. Advances in consumer electric vehicle adoption research: A review and research agenda. *Transp. Res. Part D Transp. Environ.* **2015**, *34*, 122–136. [CrossRef]
12. Pabian, A.; Pabian, B. Challenges for Managing Electromobility System-A Case Study from the Central European Region. *Energies* **2026**, *19*, 2484. [CrossRef]
13. Śmiech, L. Perception of electric mobility in Poland. In *Zrównoważony Rozwój Organizacji*; Lis, M., Kot-Radojewska, M., Popławska, E., Eds.; Polskie Towarzystwo Ekonomiczne w Katowicach, Akademia WSB: Dąbrowa Górnicza, Poland, 2023; pp. 143–163.
14. Zhang, Y.; Yu, Y.; Zou, B. Analyzing public awareness and acceptance of alternative fuel vehicles in China: The case of EV. *Energy Policy* **2011**, *39*, 7015–7024. [CrossRef]
15. Bielski, S.; Marks-Bielska, R.; Wiśniewski, P.; Kurowska, K.; Sobieraj, P. Determinants of Consumer Decisions in the Electric Vehicle Market. *Energies* **2026**, *19*, 667. [CrossRef]
16. Sobiech-Grabka, K.; Stankowska, A.; Jerzak, K. Determinants of Electric Cars Purchase Intention in Poland: Personal Attitudes v. Economic Arguments. *Energies* **2022**, *15*, 3078. [CrossRef]
17. Adamczyk, J.; Dzikuć, M.; Dylewski, R.; Varese, E. Assessment of selected environmental and economic factors for the development of electro-mobility in Poland. *Transportation* **2024**, *51*, 2199–2223. [CrossRef]
18. Piotrowski, P. Electromobility Market Development in Selected European Countries: Long-Term Forecasts to 2035. *Sustainability* **2026**, *18*, 5340. [CrossRef]
19. Wu, M.; Chen, W. Forecast of Electric Vehicle Sales in the World and China Based on PCA-GRNN. *Sustainability* **2022**, *14*, 2206. [CrossRef]

20. Henderi; Zailani, A.U.; Tuah, N.M.; Abas, A. Segmentation and profiling of electric vehicle market using clustering analysis: A case study with implications for digital marketing in the EV sector. *J. Digit. Mark. Digit. Curr.* **2025**, *2*, 323–342. [CrossRef]
21. Kozłowski, M.; Czerepicki, A. Autonomous Vehicles in Poland: A Latent-Structure Analysis of Technology Perception Based on Survey Data and Focus Group Validation. *Urban Sci.* **2026**, *10*, 243. [CrossRef]
22. Malik, M.A.I.; Kalam, M.A.; Ikram, A.; Zeeshan, S.; Zahidi, S.Q.R. Energy Transition towards Electric Vehicle Technology: Recent Advancements. *Energy Rep.* **2025**, *13*, 2958–2996. [CrossRef]
23. Gis, W.; Waśkiewicz, J.; Pawlak, P. Assumptions of eMAP project-the prospects for electromobility in selected European countries. *Combust. Engines* **2013**, *154*, 266–274.
24. Santana-Diaz, A. Electric Vehicles Are a Zero-Emission Technology? In *Green Technologies to Improve the Environment on Earth*; Pacheco, M., Ed.; IntechOpen: London, UK, 2019; pp. 1–11. [CrossRef]
25. Kułyk, P.; Michałowska, M. Integration of Renewable Energy in Central and Eastern Europe: Policy and Efficiency Analysis. *Energies* **2025**, *18*, 6557. [CrossRef]
26. Czyżewski, A.; Michałowska, M. The Impact of Agriculture on Greenhouse Gas Emissions in the Visegrad Group Countries after the World Economic Crisis of 2008. Comparative Study of the Researched Countries. *Energies* **2022**, *15*, 2268. [CrossRef]
27. International Energy Agency (IEA). Renewables in District Energy. 2026. Available online: https://www.iea.org/ (accessed on 11 July 2026).
28. Kurytka, M. Rozwój elektromobilności w Polsce w kontekście wyzwań współczesnej polityki gospodarczej. In *Elektromobilność w Rozwoju Miast*; Drożdż, W., Ed.; PWN: Warszawa, Poland, 2018.
29. Pawłowska, B. Sustainable Transport Development as an Example of Improvement in Environmental Resource Allocation Efficiency. *Acta Univ. Lodziensis. Folia Acon.* **2015**, *2*, 63–78.
30. Kaiser, C.; Lepinteur, A. Measuring the Unmeasurable? Systematic Evidence on Scale Transformations in Subjective Survey Data. *arXiv* **2025**, arXiv:2507.16440. [CrossRef]
31. Ferrer-i-Carbonell, A.; Frijters, P. How Important is Methodology for the estimates of the determinants of Happiness? *Econ. J.* **2004**, *114*, 641–659. [CrossRef]
32. Agresti, A. *Analysis of Ordinal Categorical Data*, 2nd ed.; Wiley: Hoboken, NJ, USA, 2010. [CrossRef]
33. Lantz, B. Equidistance of Likert-type scales and validation of inferential methods using experiments and simulations. *Electron. J. Bus. Res. Methods* **2013**, *11*, 16–28.
34. StataCorp LLC. *Stata Statistical Software: Release 17*; StataCorp LLC.: College Station, TX, USA, 2021.
35. Caliński, T.; Harabasz, J. A dendrite method for cluster analysis. *Commun. Stat.* **1974**, *3*, 1–27. [CrossRef]
36. Rousseeuw, P.J. Silhouettes: A graphical aid to the interpretation and validation of cluster analysis. *J. Comput. Appl. Math.* **1987**, *20*, 53–65. [CrossRef]
37. Globenergia. Polska i Chorwacja Nie Chcą Elektryków-Oba Kraje na Końcu Europejskiego Rankingu. Available online: https://globenergia.pl/polska-i-chorwacja-nie-chca-elektrykow-oba-kraje-na-koncu-europejskiego-rankingu/ (accessed on 26 July 2026).
38. UDT/EIPA. 2026. Available online: https://stacjeladowaniapojazdow.pl/ (accessed on 26 July 2026).
39. PSNM. Licznik Elektromobilności: Bardzo Wysoki Wzrost Rejestracji Autobusów Zeroemisyjnych w I Półroczu 2026 r. Available online: https://psnm.org/2026/informacja/licznik-elektromobilnosci-bardzo-wysoki-wzrost-rejestracji-autobusow-zeroemisyjnych-w-i-polroczu-2026-r/ (accessed on 20 July 2026).
40. Hadyś, M. Park Samochodów Elektrycznych–Czerwiec 2026. IBRM Samar. 2026. Available online: https://www.samar.pl/rynek-w-liczbach/park-samochodow-elektrycznych-2026-2026 (accessed on 26 July 2026).
41. Pegoraro, E.; Andrea, C.R. *Data Mining*; Packt Publishing: Birmingham, UK, 2017.
42. Kutner, M.H.; Nachtsheim, C.J.; Neter, J. *Applied Linear Regression Models*; McGraw-Hill: New York, NY, USA, 2004.
43. James, G.; Witten, D.; Hastie, T.; Tibshirani, R. *An Introduction to Statistical Learning*; Springer: New York, NY, USA, 2021.
44. Wooldridge, J.M. *Econometric Analysis of Cross Section and Panel Data*; MIT Press: Cambridge, MA, USA, 2010.
45. Draper, N.R.; Smith, H. *Applied Regression Analysis*; Wiley: Hoboken, NJ, USA, 1998.
46. Barometr Nowej Mobilności 2026, OTOMOTO, 9. Edycja Badania Dotyczącego Opinii Polaków na Temat Elektromobilności. 2026. Available online: https://psnm.org/?raporty=barometr-nowej-mobilnosci-2026 (accessed on 20 June 2026).