future transportation

Article

Evaluating Preferences towards Electromobility in Greece

Fotini Kehagia [1,*], Ioannis Karagiotas [2] and Sofia Giotaki [3]

[1] School of Civil Engineering, Division of Transportation and Construction Management, Highway Laboratory, Aristotle University of Thessaloniki, 54124 Theesaloniki, Greece
[2] School of Mathematics, Faculty of Sciences, Aristotle University of Thessaloniki, 54124 Thessaloniki, Greece; ioanniskaragiotas@gmail.com
[3] School of Applied Arts and Sustainable Design, Hellenic Open University, 26335 Patras, Greece; sgiotaki@yahoo.gr
* Correspondence: fkehagia@civil.auth.gr

Abstract: The electrification of transport is a step towards the transition to efficient, cleaner, and low-carbon mobility, as it decreases negative environmental effects and greenhouse gas emissions. In many countries, the adoption and the deployment of electric vehicles was based on a combination of policy measures and incentives. To promote the uptake of electrification, it is important to understand consumers' opinions about electric vehicles. The aim of the present research is to investigate the factors influencing EV purchase decisions in a city of Greece. The analysis of this paper was based on the data collected using a structured questionnaire, addressed to the active population of Thessaloniki, the second largest city in Greece. A small percentage of the respondents own an electric vehicle. Appropriate statistical analysis identified correlations between the intention to purchase an electric vehicle and a number of critical factors.

Keywords: electric vehicles; respondents; urban area; legislation and regulations

Citation: Kehagia, F.; Karagiotas, I.; Giotaki, S. Evaluating Preferences towards Electromobility in Greece. *Future Transp.* **2024**, *4*, 856–873. https://doi.org/10.3390/futuretransp4030041

Academic Editor: Luigi dell'Olio

Received: 27 May 2024
Revised: 25 July 2024
Accepted: 31 July 2024
Published: 7 August 2024

1. Introduction

The acceleration of the transition to sustainable and intelligent mobility is necessary and is a crucial demand of the European Union (EU) in order to reduce the carbon dioxide (CO_2) emissions caused by transport by 90% by 2050 [1,2]. The substitution of renewable energy-powered automobiles for those running on fossil fuels is one revolutionary idea that is gaining traction. Vehicles that run on renewable energy fuels, like electricity, hydrogen, or biofuels, provide an opportunity to move toward more environmentally friendly and sustainable modes of transportation [3].

The electrification of transport is a step towards the transition towards more efficient, clean, and low-carbon mobility, as it decreases negative environmental effects and greenhouse gas emissions. Transport is a major source of unsustainable energy use due to the fact that it is dependent on carbon-based fuels. While other sectors of the economy have achieved decarbonization, transport has continued to increase its consumption of energy and CO_2 emissions [4].

Electric-powered vehicles are gaining an increasing share of the passenger and commercial vehicle market. Electric vehicles (EVs) include battery electric cars (BEVs), vehicles in which an internal combustion engine cooperates with an electric drive (HEVs—hybrid electric vehicles, PHEVs—plug-in hybrid electric vehicles), or vehicles equipped with fuel cells or electrochemical batteries (FCEVs—fuel cell electric vehicles). For many years, European manufacturers were skeptical as to the value of hybrid–electric vehicles and preferred the diesel alternative. Equipped with a full range of high-efficiency diesel vehicles, the felt they were already ahead of many gasoline passenger car fleets produced in other parts of the world. However, with the relentless advance of emission standards, the diesel advantage is being handicapped by growing costs. Simultaneously, the cost of batteries for electric vehicles has been decreasing very rapidly, and there are viable options for electric vehicles to deliver a range of more than 300 km.

Several challenges can be identified ahead of electric propulsion technology at present, with optimism regarding its future. Innovative technologies used in electric vehicle propulsion systems have the ability to reduce energy consumption and emissions under a range of road conditions, as well as to considerably contribute to the development of intelligent and sustainable transportation [5,6].

Undoubtedly, the advantages of EVs include zero emissions of pollutants and noise. Electric propulsion is quieter, uses less energy, and does not produce air emissions [7–9]. The low operational noise levels due to its quiet engine decrease the noise pollution in cities [10]. The driver experiences driving comfort and lower operational costs [11]. However, there are also many other environmental concerns, including the impact of EVs on the environment during the production phase, the purity of the electricity used to charge these vehicles, and the risks associated with recycling [12,13].

In many countries, the adoption and the deployment of electric vehicles was based on a combination of policy measures and incentives. Incentives for the auto industry motivate it to develop competitive new vehicle technology and methods to improve the capacity and charging speed of batteries. Incentives for consumers motivate them to develop a positive approach to electric vehicles, including policies such as special discounts for parking and tax fees, access to dedicated lanes, purchase grants for buying, and tax exemptions [14].

Several studies have explored consumer opinions concerning the challenges and opportunities of EV deployment, as well as existing barriers to market uptake [15,16].

The technical performance of EVs is one of the most important factors that affects consumers' preferences regarding EV acceptance. Other crucial factors in EVs adoption are the driving range [17], the deployment of electric vehicle infrastructure (availability of charging points in the public space and battery stations), and high battery cost [18,19]. The availability of charging infrastructure alleviates the range anxiety of drivers concerning their trip completion [20–22]. Purchasing and operational costs (energy expenses and fuel prices) are also determinant categories that affect consumer willingness to invest in EVs [23].

Government financial policies such as fiscal support, subsidies, tax exemptions, electricity price subsidies, and oil price policies generally play a critical role in promoting the adoption of EVs. Consumer attitudes and behaviors may be influenced by policies and measures, where purchase intentions are primarily driven by techno-economic considerations, including cost factors, charging time, driving range, and operating costs [24,25]. Rietmann and Lieven (2019) [26] analyzed data from 20 countries worldwide in order to evaluate the influence of various policy measures on EV market share. Specifically, they examined monetary measures (purchase subsidies, tax incentives), infrastructural incentives (tax deductions for charging stations), and traffic regulations (free use of bus lanes, fast lanes, or parking spots). The effectiveness of implementing different policy measures and incentives in order to affect consumers' purchase intentions towards EVs is influenced by socio-demographic profiles, attitudes, subjective norms, and perceived behavioral control of consumers [18,27]. An empirical study was carried out with 404 potential consumers in Spain with regard to their beliefs, attitudes and purchase intention. The results show that range, incentives, and reliability are the most reliable predictors of purchase intention [28].

Liao et al. (2016) [29] presented a comprehensive review of studies on consumer preferences for EVs, analyzing influential factors such as socio-economic variables, psychological factors, mobility condition, and social influence. However, the authors critically acknowledge that uncertainties influence adoption decisions and behaviors.

The aim of the present research is to investigate the factors influencing EV purchase decisions in a city of Greece. Greece (as a member of the EU) has established specific energy and climate goals for 2030, namely, for the share of electric passenger vehicles to comprise 30% of new registrations and a minimum participation of renewable energy sources (RESs) in the gross final energy consumption of at least 35%. The Greek Ministry of Environment and Energy has implemented institutional, administrative, and financial incentives in order to meet the goals set by the National Energy and Climate Plan for low-emission mobility with the enactment of Law 4710/2020 (FEK A 142-23.07.2020). This was announced as the first National E-mobility Plan, marking a significant step to face e-mobility in a more comprehensive approach. The plan promotes new incentives for production units and other e-mobility activities, provides generous tax-based incentives for businesses to purchase electric vehicles, establishes a regulatory framework for the electric vehicle-charging services market, and includes urban planning regulations for charging infrastructure (known as the subsidy program "I move electrically") [14]. The study of Kyparissis et al. (2022) showed that citizens of Athens (the capital of Greece) feel positive about low and zero-emission vehicles and appreciate these incentives [30].

However, the replacement of the current vehicle fleet with EVs is a long process that requires specific policy, strategy, and incentives in the electromobility market [31].

2. Materials and Methods

2.1. Sample and Collection Method

To promote the uptake of electrification, it is important to understand consumers' opinions about electric vehicles. The analysis of this paper was based on the data collected using a structured questionnaire, addressed to the active population of Thessaloniki, the second largest city in Greece. According to the recent census (2021), the metropolitan area has a population of approximately one million inhabitants, which roughly corresponds to the 10% of the country's total population (ELSTAT 2021) [32].

Thessaloniki has a high density of population, buildings, activities, and transport infrastructure. The economically active population (15–60 years old) represents 74% of the total city's population. The gross domestic product per capita, in current prices, is estimated at EUR 14,590, and the unemployment rate remains high (17.4%) as a consequence of the past financial crisis. In 2019, before the pandemic, the modal split of passenger transport in Thessaloniki was as follows: private car, 41.3%; public transport, 33.7%; walking, 9.2%; taxi, 3.0%; and cycling, 1.7%. The car ownership rate is about 494 private cars per 1000 inhabitants, and car occupancy rates are below 1.5 persons per vehicle. Public transport is currently provided by buses only [33].

This questionnaire consists of four parts. The first part records the socio-demographic data of the respondents, the second includes questions regarding respondents' everyday travel and mobility habits, and the third part includes introductory questions concerning how familiar the respondents are with electric vehicles. Finally, the fourth part explores the respondents' perceptions about the incentives towards the acquisition of an electric vehicle.

The survey questionnaire consists of closed-ended questions, and the majority of the responses are measured using a five-point Likert scale ranging from 1 to 5: 1: "not at all", 2: "little", 3: "moderately", 4: "much", 5: "very much" or 1: "much less", 2: "a little less", 3: "the same", 4" "a little more", 5: "much more".

The survey was conducted from 9 February to 23 April 2023 in Thessaloniki city. The questionnaire was part of the framework of a master thesis of the Environmental Design MSc program of Hellenic Open University. Only active respondents aged over 18 years old and living in urban area of Thessaloniki participated.

The sample size, in the case of a finite population, was calculated using the following Equation (1) [34]:

$$n = \frac{z^2 \times p \times (1-p) \times N}{ME^2 \times (N-1) + z^2 \times p \times (1-p)} \tag{1}$$

where:

- n is the sample size;
- ME is the desired margin of error (for desired reliability, the acceptable maximum error is 0.05, with an associated 95% confidence interval);
- N is the population size (adult population of Thessaloniki, Greece: (319,045 inhabitants);

- p is the preliminary estimate of the proportion of the population (as the value of p was not known, a maximum value of 0.50 was assumed);
- z is the two-tailed value of the standardized normal deviate associated with the desired level of confidence (for the 95% confidence interval, the value of z was equal to 1.96).

In our case, the desired margin of error of 5% resulted in 334 questionnaires. A total of 304 valid questionnaires were collected and analyzed using Statistical Package for the Social Sciences [35].

2.2. Descriptive Analysis

Table 1 shows the frequency distribution of the socio-demographic profiles of the respondents, specifically the gender, the age distribution, marital status, education, and occupation.

Table 1. Socio-demographic profile of the respondents.

Variables	Value	% (Sample)
Gender	Male	47.0
	Female	53.0
Age group	18–25	3.5
	26–35	13.0
	36–45	48.0
	46–55	30.5
	56–	5.0
Marital status	Married	53.6
	Single	46.4
Education	Primary/Secondary school	2.1
	High school	24.4
	Higher education	35.4
	Master's diploma/PhD	38.1
Occupation	Civil servant	19.9
	Private employee	49.0
	Freelancer	23.2
	Unemployed	7.9
Family income, EUR	0–15,000	40.7
	15,001–30,000	39.1
	>30,000	20.2

In the survey, there were questions related to the respondents' transportation habits and conditions. Participants were asked questions about the number of cars in their household, the status of their driver's license, their daily driving time, the number of weekly trips by car, and the frequency of trips exceeding 100 km. In terms of private car ownership, the majority of respondents own one private car (61.3%), while the percentage of respondents who owned two cars was 24.8% and a small percentage of the respondents (10.9%) did not own any car. A total of 70% of the respondents declared that they preferred the vehicle as a transport mode for everyday mobility, and only 8.9% preferred public transportation and 8.6% walking.

The survey investigated how familiar the respondents are with electric vehicles. A significant part of the respondents had not driven an electric vehicle (76.2%), despite the fact that they expressed their willingness to drive one. The survey investigated the factors influencing the willingness of respondents to purchase a new vehicle and decisive factors regarding the low percentage of electric vehicle sales. In Table 2, the list of examined factors is presented. The results of the responds were analyzed statistically in order to explore significant results, as presented in the following section.

Table 2. List of factors examined.

Factors Positively Influencing the Purchasing of an Electric/Hybrid Vehicle	Decisive Factors that Influence the Low Percentage of Electric/Hybrid Vehicle Sales
Battery charging/Fast charging time	Few charging stations
Available charging stations	High purchase cost
Vehicle autonomy	Anxiety of covering kilometers before the next chargeHigh charging cost
Battery life guarantee	Maintenance cost
Charging cost	Limited models
Performance	Outward appearance
Potential of buying a used electric vehicle	Unavailability of used models
Maintenance cost	
Initial purchase cost	
Outward appearance	
Environmental benefits	

3. Results

3.1. Data Analysis Methodology

Descriptives statistics metrics were calculated for each variable of interest, leading to the evaluation of importance for each impact factor presented in the current study. In order to identify groups of factors with homogeneous behavior, an exploratory factor analysis with the method of principal components (EFA-PCA) was implemented [36,37]. The estimated factor orthogonal model lies in the mathematical expression (Equation (2)):

$$X = LF + \varepsilon \tag{2}$$

where:

- X is the px1 vector of the initial variables (p is the number of variables);
- F is the kx1 vector of the extracted factors (k is the number of factors);
- L is the pxk matrix with elements of the factor loadings and the element L_{ij} represents the loading of factor $F_j,\ j = 1, 2, \ldots, k$ on variable $X_i,\ i = 1, 2, \ldots, p$);
- ε is the error of the model, and it represents the variability of a variable that cannot be explained by the extracted factors.

At first, the sampling adequacy for the implementation of EFA-PCA was tested using the Kaiser–Meyer–Olkin (*KMO*) coefficient and Bartlett's Test of Sphericity, with the results showing high adequacy ($KMO > 0.800$) for the factor analysis [36,37]. Following that, for the identification of the extracted number of factors, both the Kaiser Eigenvalue and Total Variance Explained criteria were used, while for the estimation of factor's scores the Anderson–Rubin estimator was used, which always leads to totally uncorrelated factors. Finally, in order to identify the variables that structure every single extracted factor based on the factor loading values, it is a necessity to rotate the Factor Score Coefficient Matrix, and so in the current survey the Equamax method was implemented [36,37].

Using the extracted uncorrelated factors from the EFA-PCA, both for positive and negative impact ones, a Structure Equation Modeling (SEM) [38] analysis was implemented using IBM SPSS AMOS Graphics with independent variables (IVs), the extracted factors and dependent variable (DV), and the willingness to purchase an EV/HEV vehicle. After the implementation of SEM, a new set of variables representative of the extracted factors was estimated by calculating the mean score of the variables that led to the formation of each factor according to the EFA-PCA results, a methodology that is widely used in social and psychometric studies [36]. For these new variables, descriptive statistics were estimated, while the normality of their distribution was tested using Kolmogorov–Smirnov and Shapiro–Wilk normality tests. The results showed that the normality of the distributions was being rejected, and as a result, in order to test for statistically significant differences among the estimated mean score variables, a related-samples non-parametric analysis was implemented using the Related-Samples Friedman's Two-Way Analysis of Variance by Ranks Test and the Related-Samples Wilcoxon Signed Rank Test. The results for both tests showed that there was a statistically significant difference among the distributions of mean score variables, and so for the Friedman Criterion, a post-hoc analysis was implemented by estimating the related-samples pairwise comparisons using the Bonferroni method, while for the Wilcoxon Signed Rank test a comparison between the estimated descriptive values of medians was used. Both the Friedman Criterion and the Wilcoxon Signed Rank Test were implemented due to the violation of the normality of distributions, and as a result, they are the appropriate tests to examine whether a set of more than three and a set of two variables, respectively, have the same distributions. The following Figure 1 represents the core of the main analysis, as described above.

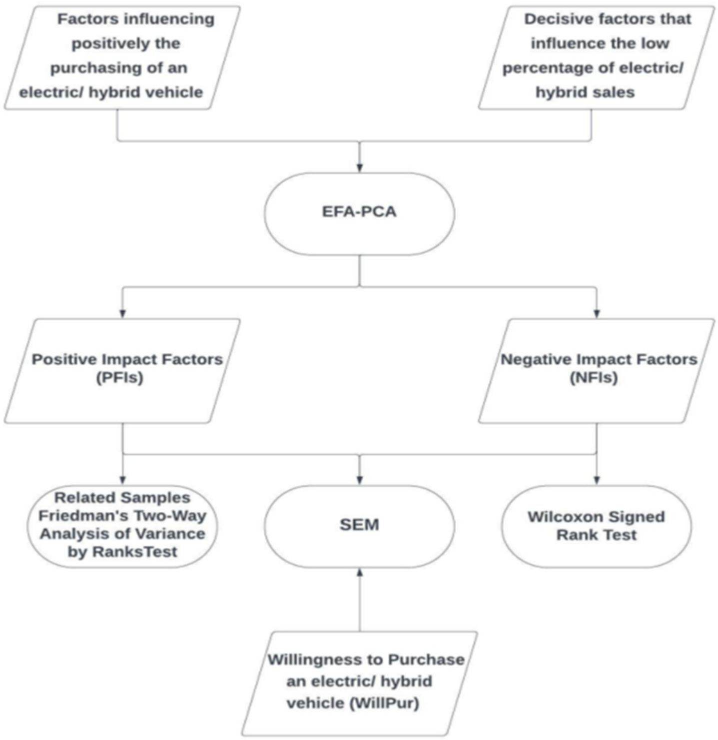


Figure 1. Flow chart that depicts the data analysis process.

Following that, in order to test for the independence between categorical variables, a Chi-square Test of Independence was implemented with Cramer's *V* Coefficient of Association, while in order to test for statistically significant differences in DVs using categorical IVs with two and three levels, the non-parametric Mann–Whitney U-test and the Kruskal–Wallis test were implemented with their respective effect size measures of the rank biserial correlation coefficient (rbc) and eta-squared (η^2).

In order to test for moderation effects in the relationship between impact factors and the willingness to purchase, with the moderator variable being the occupation of an electric/hybrid vehicle, a moderation analysis was implemented using linear regression modeling approximation [39]. Also, in order to present the results graphically, a structural path diagram was used, and the distributions of the quantitative variables were estimated using the Kernel Density Estimator (KDE) along with 95% confidence intervals for the means. The KDE is a non-parametric method for probability distribution estimation, and it is an appropriate technique to use when data are drawn from unknown distributions. Also, to further present the results graphically for the categorical variables, clustered bar charts were created. It has to be mentioned that through lack of sample size and low fit in certain cases in the following analysis, the level of significance often needed to be adjusted from 0.05 to 0.10 in order to identify potential trends and relations between the examined variables. Finally, the above-mentioned data analysis methodology was conducted with IBM Statistical Package for the Social Sciences (SPSS), IBM SPSS AMOS Graphics, IBM SPSS extension PROCESS v4.2 (by Andrew V. Hayes), and Python programming.

3.2. Data Analysis Results

Based on the factors that participants believe are important before deciding to buy an EV/HEV vehicle, an EFA-PCA was implemented using the Kaiser Eigenvalue Criterion in order to identify the number of extracted factors. Issues with communalities and MSA values appeared regarding the variables "outward appearance" and "environmental benefits", leading to inappropriate levels of variable adequacy [37].

The extracted number of independent factors was equal to 2, creating issues with its appropriateness due to low factor loading (<0.300) of the variables "outward appearance" and "environmental benefits", so it needed to be further examined. As a result, in order to deal with this situation and create a set of independent extracted factors, a new EFA-PCA (KMO = 0.923, X^2_{55} = 2095.97, p < 0.05) was performed by adjusting the number of extracted factors from 2 to 4, leading to acceptable values of factor analysis adequacy metrics (communalities > 0.700, MSA > 0.600) and 79.27% of total variance explained. The first extracted factor, called "vehicle overall operation and charging stations" (alpha = 0.940, N of items = 6), consisted of the variables "battery charging/fast charging time", "available charging stations", "vehicle autonomy", "battery life guarantee", "charging cost", and "performance"; the second factor, called "purchase and maintenance cost" (alpha = 0.774, N of items = 3), consisted of the variables "potential of buying a used electric vehicle", "maintenance cost", and "initial purchase cost"; while the third (alpha = –, N of items = 1) and fourth (alpha = –, N of items = 1) extracted factors both consisted of one single variable, "outward appearance" and "environmental benefits", respectively, and so were named after them.

Following the same process for the factors that participants believed are responsible for the low sales of electric/hybrid vehicles in Greece, according to the EFA-PCA (KMO = 0.804, X^2_{28} = 1073.38, p < 0.05), the factor model consisted of two independent factors, which explained 65.88% of the total variation. The first factor, called "operating cost and charging stations" (alpha = 0.866, N of items = 5), consisted of the variables "few charging stations", "high purchase cost", "anxiety of covering kilometers before the next charge", "high charging cost", and "maintenance cost", while the second factor, called "model availability and appearance" (alpha = 0.722, N of items = 3), consisted of the variables "limited models", "outward appearance", and "unavailability of used models". For the rest of the analysis, the extracted factors from the EFA-PCA will be called positive impact factors (PIFs) and negative impact factors (NIFs), representing the factors that are important in order to buy an e/h vehicle and the factors that are responsible for low sales, respectively, in Thessaloniki, Greece (Table 3).

Following that, to identify the impact of the extracted factors on the willingness of purchasing an electrical or hybrid vehicle, a Structural Equation Modeling (SEM) approach was taken by estimating two different models, with "willingness to purchase" (WillPur) as the dependent variable and the sets of positive and negative impact factors (PIFs and NIFs, respectively) as the independent variables. As mentioned before, the extracted factors, both PIFs and NIFs, were calculated with the Anderson–Rubin method, which always leads to totally uncorrelated factors [30]. As a matter of fact, the respective variance–covariance matrices were equal to the diagonal unit matrix, so the covariance of factors was equal to 0. As a result, by implementing SEM, the estimated model was equivalent to the Independence Model, which assumes that every independent variable has covariates equal to 0 with every other independent variable in the model.

Table 3. Exploratory Factor Analysis–Principal Component Analysis (EFA-PCA): sampling adequacy statistics using KMO and Bartlett's Test of Sphericity, reliability analysis table, positive and negative impact factors (PIFs and NIFs, respectively).

Factors	Factor Loadings	Sampling Adequacy Statistics		
Positive Impact Factor 1 (PIF-1)– **Overall Vehicle Operation and Charging Stations**	***Value***	*KMO*	X^2_{55}	*p*
Battery charging/Fast charging time	0.779	0.923	2095.97	0.000
Available charging stations	0.727			
Vehicle autonomy	0.713			
Battery life guarantee	0.705			
Charging cost	0.670			
Performance	0.571			
Cronbach's Alpha Internal Consistency Coefficient	0.940			
Positive Impact Factor 2 (PIF-2)– Purchase and Maintenance Cost	*Value*			
Potential of buying a used electric vehicle	0.832			
Maintenance cost	0.701			
Initial purchase cost	0.638			
Cronbach's Alpha Internal Consistency Coefficient	0.774			
Positive Impact Factor 3 (PIF-3)– Outward Appearance	*Value*			
Outward appearance	0.989			
Cronbach's Alpha Internal Consistency Coefficient	-			
Positive Impact Factor 4 (PIF-4)– Environmental Benefits	*Value*			
Environmental benefits	0.938			
Cronbach's Alpha Internal Consistency Coefficient	-			
Negative Impact Factor 1 (NIF-1)– Operating Cost and Charging Stations	*Value*	*KMO*	X^2_{28}	*p*
Few charging stations	0.845	0.804	1073.38	0.000
High purchase cost	0.837			
Anxiety of covering kilometers before the next charge	0.814			
High charging cost	0.759			
Maintenance cost	0.682			
Cronbach's Alpha Internal Consistency Coefficient	0.866			
Negative Impact Factor 2 (NIF-2)– Model Availability and Appearance	*Value*			
Limited models	0.857			
Outward appearance	0.768			
Unavailability of used models	0.708			
Cronbach's Alpha Internal Consistency Coefficient	0.722			

According to the first model (CMIN/DF = 2.614, $p > 0.05$, GFI = 0.968, AGFI = 0.952, FMIN = 0.087, RMR = 0.08, RMSEA = 0.073), with PIFs as the independent variable (IV) and WillPur as the dependent variable (DV), there were indications in model fit indices that led to a poor fit of the model, a decision that is related to high levels of variation in WillPur (CV = 0.46 > 0.10). As a result, the current model was estimated to identify the potential impact of the extracted factors on the willingness to purchase an electrical vehicle. Adjusting the significance level to $\alpha = 0.10$, it was estimated that PIF-1 ($b_1 = -0.130$, $p < 0.10$) and PIF-2 ($b_2 = -0.238$, $p < 0.10$) had a negative effect on the DV, while PIF-3 ($b_3 = 0.119$, $p < 0.10$) and PIF-4 ($b_4 = 0.181$, $p < 0.10$) had a positive one. The higher the importance for an individual before buying an e/h vehicle in "vehicle overall operation and charging stations" (PIF-1) and in "purchase and maintenance cost" (PIF-2), the lower the levels of willingness to purchase an electric vehicle, while on the other hand, the higher the importance for an individual before buying an e/h vehicle in "outward appearance" (PIF-3) and in "environmental benefits" (PIF-4), the higher the level of willingness.

Regarding the second model (CMIN/DF = 2.614, $p > 0.05$, GFI = 0.997, AGFI = 0.995, FMIN = 0.004, RMR = 0.01, RMSEA = 0.001) and the estimation of the effect of the negative impact factors (NIFs), it was estimated that there was an acceptable fit, while neither the factor NIF-1 ($b_1 = -0.060$, $p > 0.10$) nor the factor NIF-2 ($b_2 = 0.01$, $p > 0.10$) had a statistically significant effect on the willingness to purchase an electric vehicle. Figure 2 below presents the respective structural diagrams for the above estimated models.

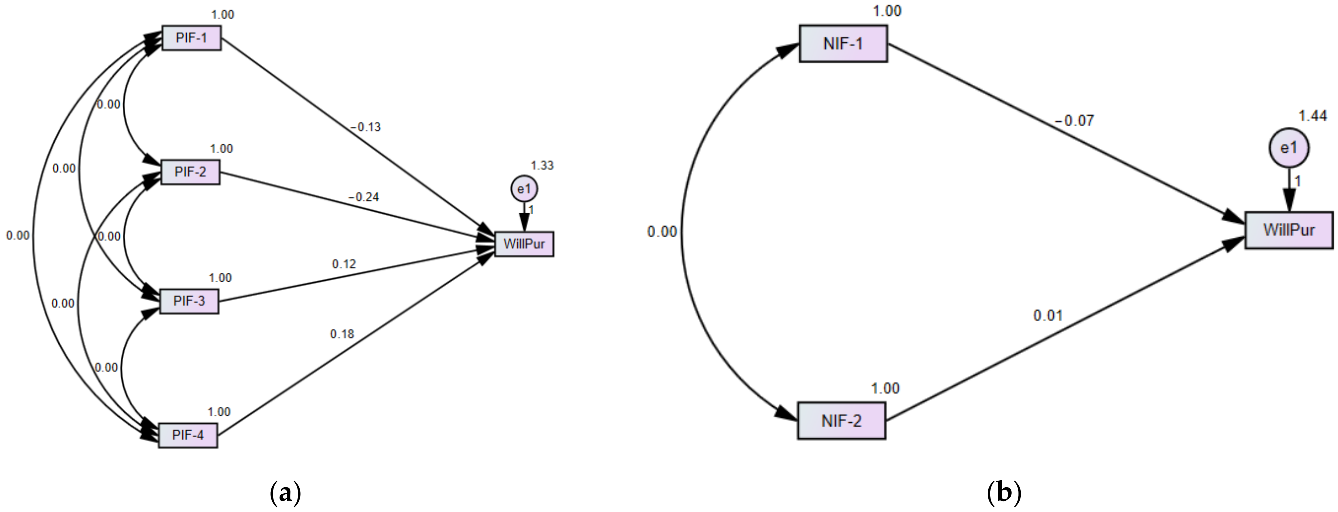


Figure 2. Structural path diagram: positive impact factors (PIFs) and willingness to purchase (WillPur) (**a**), negative impact factors (NIFs) and willingness to purchase (WillPur) (**b**).

Based on the estimated structure of the extracted factors from the exploratory factor analysis (EFA-PCA), the mean score of the respective variables was calculated for each set of variables. As a result, for the positive impact factors (PIFs), it was estimated that the factor "overall vehicle operation and charging stations" (PIF-1) had the highest estimated importance scores, followed by the factors "environmental benefits" (PIF-4) and "purchase and maintenance cost" (PIF-2), while the lowest estimated scores belonged to the factor "outward appearance" (PIF-3) (Table 4).

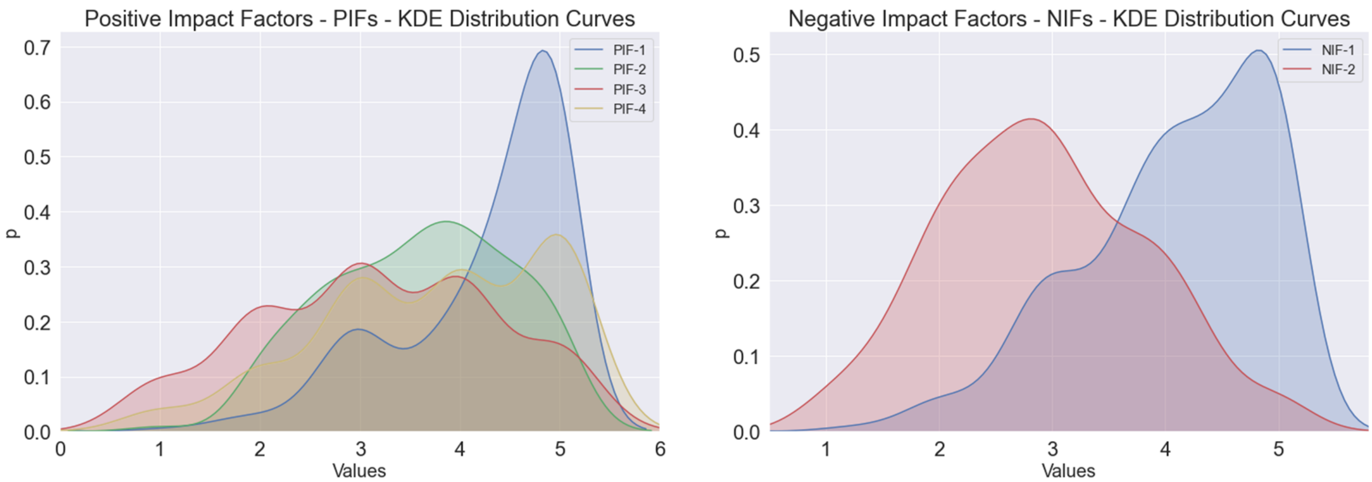
Regarding the estimated mean score variables for the negative impact factors (NIFs), it was estimated that the factor "operating cost and charging stations" (NIF-1) had the highest estimated scores, while the factor "model availability and appearance" (NIF-2) had the lowest estimated ones. Finally, according to normality tests, the hypothesis of normality of distribution for each estimated mean score variable factor was rejected ($p < 0.05$) (Table 4).

To test for statistically significant differences among the estimated factors, a set of related non-parametric methods was implemented for PIFs and NIFs. At first, for PIFs, according to the Related-Samples Friedman's Two-Way Analysis of Variance by Ranks Test, there was a statistically significant difference in distributions ($X_3^2 = 192.24$, $p < 0.05$). In order to prioritize the importance of PIFs, non-parametric pairwise comparisons were implemented with the Bonferroni method, where it was estimated that each factor had a statistically significant different distribution from every other one ($p < 0.01$), leading to the result that the PIF-1 factor had the statistically highest importance scores, with the factors PIF-4 and PIF-2 following, while the lowest importance scores belonged to PIF-3. Regarding the NIFs, according to the Related-Samples Wilcoxon Signed Rank Test, there was a statistically significant difference between distributions (T = 554.000, $p < 0.05$), where the importance of NIF-1 was statistically significantly higher than the importance of NIF-2. Figure 3 below presents the estimated distribution curves using the Kernel Density

Estimator (KDE) for each group of impact factors, where the x-axis represents the values of the variables and the y-axis represents the respective probabilities.

Table 4. Descriptive statistics: Kolmogorov–Smirnov (K-S) test and Shapiro–Wilk (S-W) test of normality on the significance of positive and negative impact factors (PIFs and NIFs, respectively).

	Descriptives Statistics								Normality Tests p	
Positive Impact Factors (PIFs)	**M**	**SE**	**95% CI**		**Md**	**SD**	α_3	α_4	**K-S**	**S-W**
			LB	**UB**						
Overall vehicle operation and charging stations (PIF-1)	4.25	0.049	4.15	4.34	4.50	0.85	−1.22	0.71	0.000	0.000
Purchase and maintenance cost (PIF-2)	3.60	0.052	3.50	3.71	3.67	0.90	−0.25	−0.74	0.000	0.000
Outward appearance (PIF-3)	3.17	0.068	3.04	3.31	3.00	1.18	−0.12	−0.86	0.000	0.000
Environmental benefits (PIF-4)	3.76	0.065	3.63	3.89	4.00	1.14	−0.55	−0.57	0.000	0.000
Negative Impact Factors (NIFs)										
Operating cost and charging stations (NIF-1)	4.08	0.049	3.99	4.18	4.20	0.83	−0.81	0.02	0.000	0.000
Model availability and appearance (NIF-2)	2.91	0.052	2.80	3.01	3.00	0.91	0.18	−0.44	0.000	0.000



(**a**) (**b**)

Figure 3. KDE distribution curves: positive impact factors (**a**) and negative impact factors (**b**).

Setting as an independent variable (IV) the occupation of an electric/hybrid (e/h) vehicle, Mann–Whitney U-tests were implemented with dependent variables (DVs) the positive and negative impact factors (PIFs and NIFs, respectively) and the willingness to purchase a vehicle, in order to test for significant differences between owners and non-owners in the levels of our variables of interest. According to Table 5 below, there was a statistically significant difference between the distributions of e/h vehicle owners and those who did not own such a vehicle in PIF-2 ($Z = -2.043$, $p < 0.05$, rbc = 0.250), NIF-1 ($Z = -1.977$, $p < 0.05$, rbc = 0.241), and "willingness to purchase" ($Z = -4.072$, $p < 0.05$, rbc = 0.486), while on the other hand, there was not a difference in PIF-1 ($Z = -0.482$, $p > 0.05$, rbc = 0.059), PIF-3 ($Z = -1.511$, $p > 0.05$, rbc = 0.181), or PIF-4 ($Z = -0.475$, $p > 0.05$, rbc = 0.056).

Table 5. Descriptives statistics table: non-parametric Mann–Whitney U-tests and rbc effect size coefficient, PIFs and NIFs, and occupation of an e/h vehicle.

	Occupation of e/h Vehicle						Mann–Whitney U-Test		Effect Size
	No			Yes					
	M	SD	Md	M	SD	Md	Z	*p*	rbc
PIF-1	4.25	0.86	4.50	4.24	0.83	4.67	−0.482	0.630	0.059
PIF-2	3.64	0.90	3.67	3.24	0.85	3.33	−2.043	0.041	0.250
PIF-3	3.14	1.18	3.00	3.50	1.22	4.00	−1.511	0.131	0.181
PIF-4	3.77	1.13	4.00	3.67	1.17	4.00	−0.475	0.635	0.056
NIF-1	4.11	0.83	4.20	3.80	0.82	4.00	−1.977	0.048	0.241
NIF-2	2.93	0.92	3.00	2.61	0.67	2.67	−1.698	0.089	0.208
Willingness to purchase	2.52	1.17	3.00	3.62	1.17	4.00	−4.072	0.000	0.486

Also, by adjusting the significance level α from 0.05 to 0.10, it was established that there was a fair statistically significant difference between the distributions at NIF-2 (Z = −1.698, $p < 0.10$, rbc = 0.208). Considering the statistically significant differences between e/h vehicle owners and non-owners, it was further estimated that for the factor PIF-2 and the factor NIF-1, e/h vehicle owners had statistically significantly lower scores compared with non-owners for the factor "willingness to purchase" and owners of EV/HEV vehicles had statistically significantly higher scores compared with non-owners, while for the factor NIF-2 there was evidence that current owners tended to be more willing to buy an EV/HEV vehicle in the future compared to non-owners, who had lower levels of willingness.

Figure 4 below presents the estimated distribution curves using the Kernel Density Estimator (KDE) for the different groups of e/h occupation according to their scores for PIF, NIF, and "willingness to purchase" variables, where the x-axis represents the values of the variables and the y-axis represents the respective probabilities.

Regarding the relationship between the occupation of an e/h vehicle and income, a Chi-Square Test of Independence (X_2^2 = 14.375, $p < 0.05$, V = 0.221) was performed, and a statistically significant dependence relation emerged. More precisely, 19.67% of participants with income higher than EUR 30,000 owned an e/h vehicle compared to the 4.07% and 5.88% of participants with incomes varying between EUR 0 and 15,000 and between EUR 15,000 and 30,000, respectively (Figure 5).

Regarding the investigation of income and its effect on PIFs, NIFs, and WillPur, Kruskal–Wallis tests were implemented with dependent variables (DVs), positive and negative impact factors (PIFs and NIFs, respectively), and the willingness to purchase an EV/HEV vehicle, while the IV was set as the annual income. According to Table 6 below, there was a statistically significant difference between the distributions of groups of income in PIF-2 ($p < 0.05$) and "willingness to purchase" ($p < 0.05$), while on the other hand, there was not a difference in PIF-1 ($p > 0.05$) or NIF-2 ($p > 0.05$). Also, by adjusting the significance level α from 0.05 to 0.10, it was established that there was a fairly statistically significant difference between the distributions at PIF-4 ($p < 0.10$).

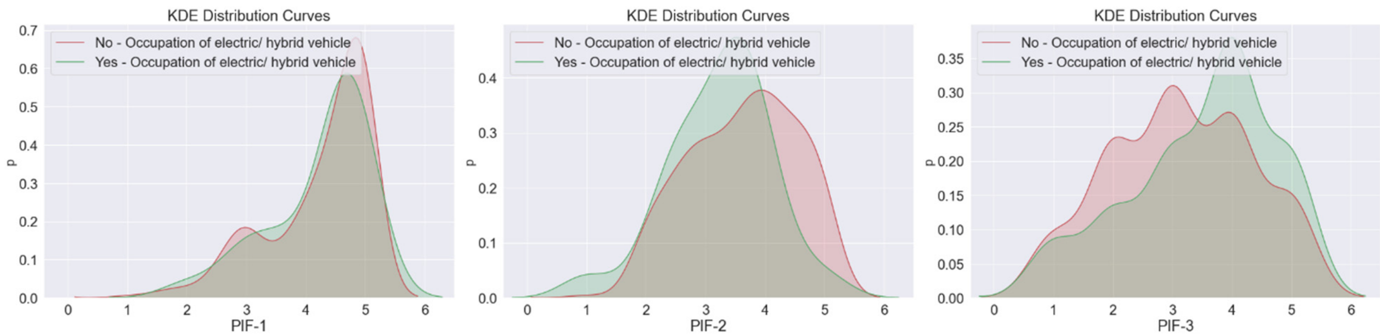


Figure 4. *Cont.*

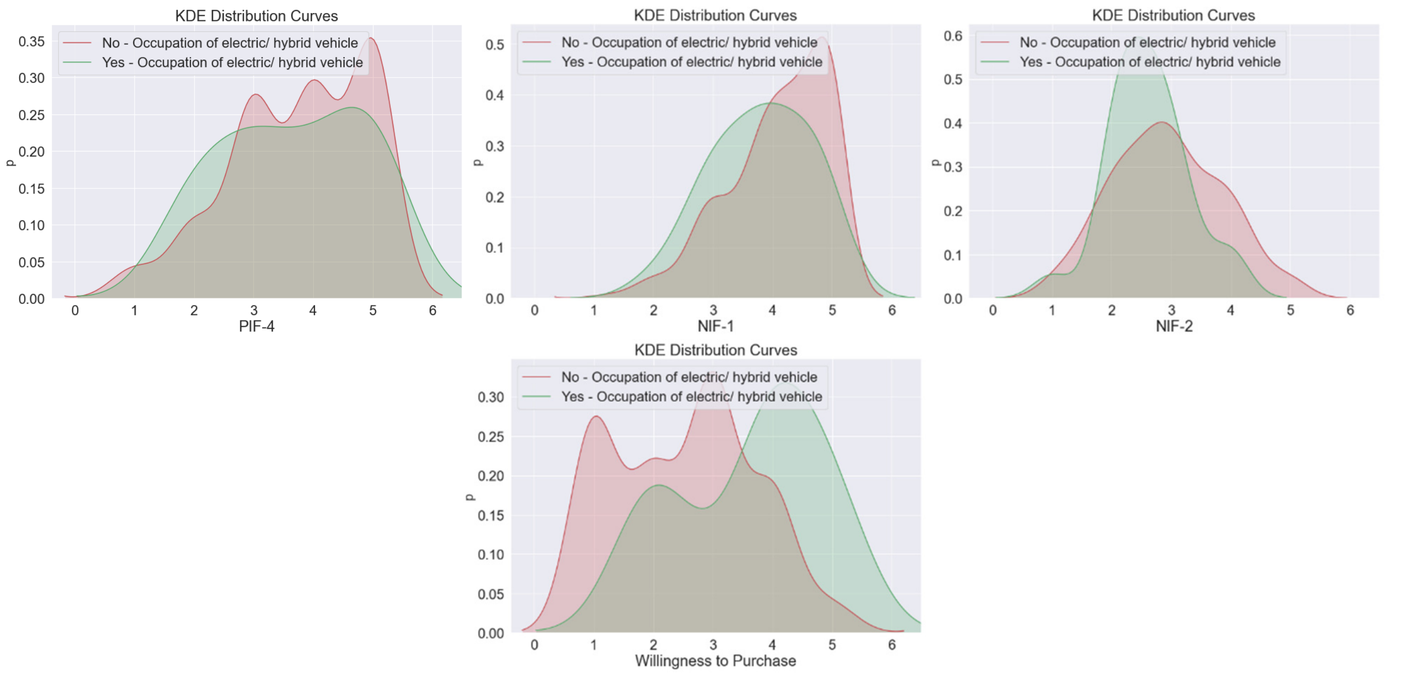


Figure 4. KDE Distribution curves: PIFs, NIFs, and willingness to purchase (WillPur) for occupation of an e/h vehicle.

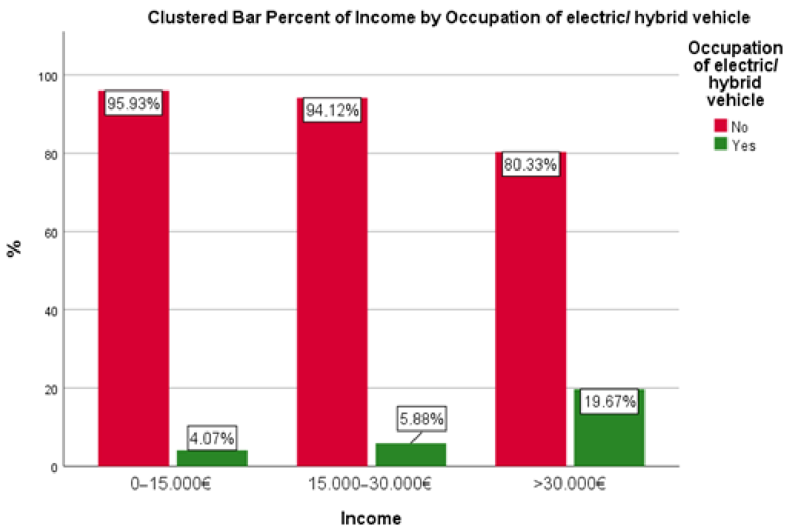


Figure 5. Clustered bar chart (%): income–occupation of an e/h vehicle.

Table 6. Descriptives statistics table: non-parametric Kruskal–Wallis tests and eta-squared effect size coefficient for PIFs and NIFs for income.

	Income									Kruskal–Wallis Test		Effect Size
	EUR 0–15,000			EUR 15,000–30,000			EUR > 30,000					
	M	SD	Md	M	SD	Md	M	SD	Md	H(2)	p	η^2
PIF-1	4.32	0.88	4.67	4.18	0.83	4.33	4.23	0.84	4.67	3.793	0.150	0.013
PIF-2	3.69	0.91	3.67	3.70	0.88	3.67	3.24	0.86	3.33	12.248	0.002	0.041
PIF-3	3.07	1.19	3.00	3.09	1.19	3.00	3.52	1.12	4.00	6.926	0.031	0.023
PIF-4	3.92	1.16	4.00	3.63	1.13	4.00	3.69	1.07	4.00	5.284	0.071	0.017
NIF-1	4.07	0.86	4.20	4.14	0.81	4.20	4.01	0.81	4.20	1.369	0.504	0.005
NIF-2	2.89	0.96	2.67	3.01	0.87	3.00	2.75	0.85	2.67	4.104	0.128	0.014
Willingness to purchase	2.47	1.16	3.00	2.52	1.16	3.00	3.03	1.29	3.00	8.732	0.013	0.029

As a result, for the statistically significant cases, post-hoc non-parametric analysis was implemented using Bonferroni's method. At first, for PIF-2, the income groups of EUR 15,000–30,000 and EUR 0–15,000 had equal scores ($p > 0.05$) and were statistically significantly ($p < 0.05$) higher compared with the scores of the EUR >30,000 income group; for PIF-3 and "willingness to purchase", the income groups EUR 15,000–30,000 and EUR 0–15,000 had equal scores ($p > 0.05$) and were statistically significantly ($p < 0.05$) lower compared with the scores of the EUR >30,000 income group; and for PIF-4, there was evidence that the income groups EUR 15,000–30,000 and EUR >30,000 had equal scores ($p > 0.05$) and were statistically significantly ($p < 0.05$) higher compared with the scores of the EUR 0–15,000 income group.

Figure 6 below presents the estimated distribution curves using the Kernel Density Estimator (KDE) for the different groups of income according to their scores for the PIF, NIF, and "willingness to purchase" variables, where the x-axis represents the values of the variables and the y-axis represents the respective probabilities.

Regarding the investigation of the impact of occupation of an electric vehicle on the relationship between the impact factors and willingness to purchase an electric vehicle, a moderation analysis [39] was implemented, with the dependent variable (DV) being the willingness to purchase an electric vehicle, the independent variables (IVs) being the positive and negative impact factors (PIFs and NIFs, respectively), and the moderator being the occupation of an e/h vehicle (OccV). In order to further proceed to the estimation of the interaction effect between an independent variable and a moderator to the dependent variable, it is necessary to test for a statistically significant linear relation between the IV and DV. According to the following Table 7, it was estimated that the factors PIF-2 ($r(303) = -0.169$, $p < 0.05$) and PIF-3 ($r(303) = 0.148$, $p < 0.05$) had a statistically significant linear relationship with the DV, which led to poor fit of a linear model. So, in order to perform a moderation analysis, it was necessary to adjust the level of significance to $\alpha = 0.10$, and the upcoming conclusion will be explained as an expected trend in the Greek environment. As a result, from the following moderation analysis table, it was estimated that there was a statistically significant moderation effect ($b_{Int} = -0.504$, $p < 0.10$, 90% BLBCI = -0.989, 90% BUBCI = -0.184) on the linear relationship between PIF-2 and WillPur, while there was no moderation effect ($b_{Int} = -0.094$, $p > 0.10$, 90% BLBCI = -0.437, 90% BUBCI = -0.249) on the linear relationship between PIF-3 and WillPur. Taking into consideration the facts that the current owners of e/h vehicles consider the factor "purchase and maintenance cost" (PIF-2) as less important in comparison with non-owners, current owners of e/h vehicles had statistically significantly higher willingness to purchase (WillPur) scores compared with non-owners, and that there was a negative statistically significantly fair linear correlation between PIF-2 and WillPur, we came to the conclusion that the occupation of an e/h vehicle ($b_{Mod} = 2.677$, $p < 0.10$) tended to have a positive impact on the relationship between PIF-2 and WillPur by reducing its negative strength. Also, it has to be mentioned that owners with higher incomes are more likely to own an e/h vehicle, as stated before, but due to a lack of sample units, an interaction between occupation and income cannot be estimated for PIF-2 and WillPur.

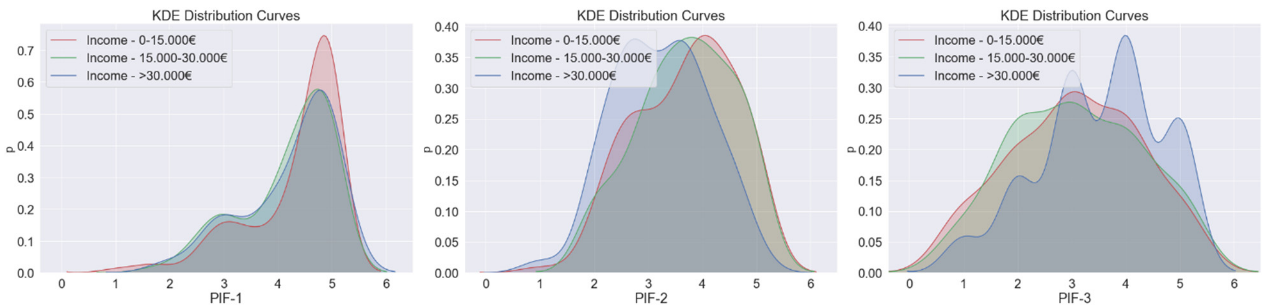


Figure 6. *Cont.*

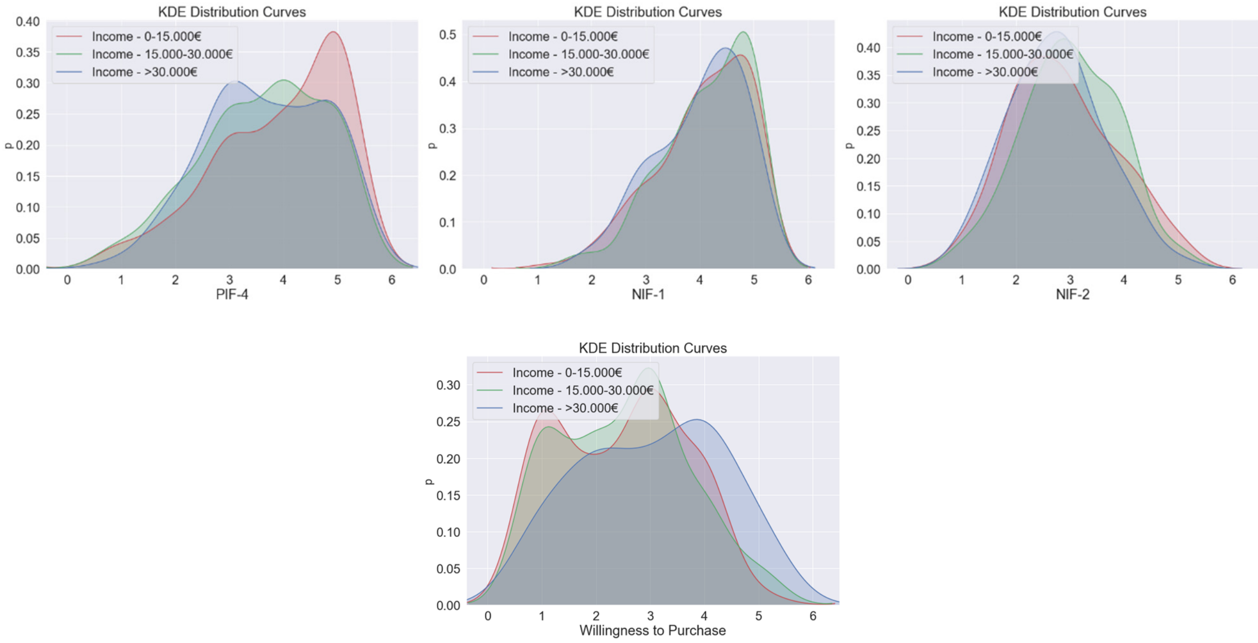


Figure 6. KDE distribution estimations: PIFs, NIFs and willingness to purchase (WillPur) for income.

Table 7. Descriptives statistics table: non-parametric Kruskal–Wallis tests and eta-squared effect size coefficient for PIFs and NIFs for income.

Moderation Effect Structural Path ($IV * Mod \to DV$)	Estimated Coefficient $IV \to DV$	p	Moderator Coefficient	Interaction Coefficient	S.E.	p	90% Bootstrap CI	Result
PIF1 ∗ OccV → WillPur	−0.058	0.474	-	-	-	-	-	-
PIF2 ∗ OccV → WillPur	−0.225	0.003	2.677	−0.504	0.294	0.088	[−0.989, −0.184]	Moderation effect
PIF3 ∗ OccV → WillPur	0.150	0.010	1.389	−0.094	0.208	0.652	[−0.437, 0.249]	No moderation
PIF4 ∗ OccV → WillPur	0.044	0.473	-	-	-	-	-	-
NIF1 ∗ OccV → WillPur	−0.092	0.268	-	-	-	-	-	-
NIF2 ∗ OccV → WillPur	0.008	0.920	-	-	-	-	-	-

Figure 7 below represents the relationship between the PIF-2 and WillPur according to the moderator factor as it was estimated in the respective moderation analysis table.

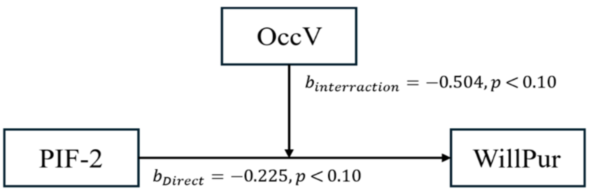


Figure 7. PIF-2 and WillPur relationship.

4. Discussion

According to the inferential results, factors that had a significant positive impact on potential e/h vehicle buyers' judgment before buying such a vehicle can be grouped into four independent factors, identified as PIFs, which represent the overall homogeneous behavior of variables regarding overall vehicle operation and charging stations (PIF-1), purchase and maintenance cost (PIF-2), outward appearance (PIF-3), and environmental benefits (PIF-4). By further analyzing their scores, a statistically significant difference was discovered among PIFs, which led to the result that the highest impact belonged to overall vehicle operation and charging stations, followed by environmental benefits and purchase and maintenance cost, while the lowest scores belonged to the outward appearance factor.

The factors that had a significant negative impact on the low sales of e/h vehicles can be grouped into two independent factors, identified as NIFs, which represent the overall homogeneous behavior of variables regarding the operating cost and charging stations (NIF-1), and also the model availability and appearance (NIF-2). By further analyzing their scores, it was found that the factors regarding the operating cost and charging stations had statistically significantly higher scores regarding the factor that represented model availability and appearance.

Following that, by analyzing the impact of PIFs and NIFs on the willingness to purchase an e/h vehicle, there was evidence that the purchase and maintenance factor had the highest negative impact on the willingness to purchase a vehicle, followed by the overall operation and charging stations, while on the other hand, environmental benefits and outward appearance tended to have a positive impact. Regarding the impact of NIFs, there was not an estimated statistically significant impact on the willingness to purchase an e/h vehicle.

Regarding the investigation of differences between the owners of e/h vehicles and non-owners in the impact factors—both PIFs and NIFs—both significant and non-significant cases were estimated. More precisely, current owners of e/h vehicles tended to have lower scores for purchase and maintenance cost (PIF-2), operating cost and charging stations (NIF-1), and model availability and appearance (NIF-2), while on the other hand, they had higher scores for willingness to purchase an additional e/h vehicle compared to non-owners.

Regarding the income of the participants and its impact on PIFs and NIFs, it was estimated that for the factor of outward appearance (PIF-3) and willingness to purchase a vehicle, the income groups of EUR 15,000–30,000 and EUR 0–15,000 had equal scores and were statistically significantly lower compared with the scores of the EUR > 30,000 income group for the factor of purchase and maintenance cost (PIF-2), the income groups EUR 15,000–30,000 and EUR 0–15,000 had equal scores and were statistically significantly higher compared with the scores of the EUR > 30,000 income group, and there was evidence that for the factor of environmental benefits (PIF-4), the income groups EUR 15,000–30,000 and EUR > 30,000 had equal scores and were statistically significantly higher compared with the scores of the EUR 0–15,000 income group.

Also, considering the above estimates, an additional statistically significant dependency was estimated between income and the occupation of an e/h vehicle, where 19.67% of participants with an income higher than EUR 30,000 owned an e/h vehicle compared to the 4.07% and 5.88% of participants with incomes varying between EUR 0 and 15,000 and between EUR 15,000 and 30,000, respectively. Finally, it was estimated that the occupation of an e/h vehicle had is a statistically significant moderation effect on the relationship between purchase and maintenance cost (PIF-2) and willingness to purchase an e/h vehicle, leading to the result that the moderation reduced the strength of the negative impact of PIF-2 on WillPur.

5. Conclusions

Our study tried to investigate, identify, and interrelate the factors defining the choice of adopting an electric/hybrid vehicle. Drivers who prioritize the overall operational performance of the vehicle and the charging station availability are more likely to be willing to buy an electric vehicle. On the other hand, the factor of the high operating cost acts as a significant deterrent. Income has some impact. People of higher income have a higher likelihood of being attracted to an electric vehicle.

Despite the study's valuable insights into electric vehicles, it is important to note that there are limitations to consider. Firstly, the data collected and the respective analysis are limited to one city, with specific sociodemographic and mobility characteristics. Also, the primary data, as any self-reported survey data, may suffer to a degree from social desirability, optimism, and volunteer biases. Future research could use qualitative methods to collect more in-depth insights about the topic. However, the research's findings are still valuable because they provide an insight into drivers' opinions. As Greece's electric vehicle market grows, new research in the future may investigate opinions, attitudes, and safety concerns.

Our findings suggest that government financial policies such as fiscal support, subsidies, tax exemptions, electricity price subsidies, or oil price policies generally play a critical role in promoting the adoption of EVs. Targeted communication and information-sharing campaigns influence consumers' attitudes and behaviors, where purchase intentions are primarily driven by techno-economic considerations.

Author Contributions: Conceptualization, F.K. and S.G.; methodology F.K.; formal analysis, I.K.; investigation, S.G. and I.K.; resources, S.G.; data curation, I.K.; writing—original draft preparation, F.K. and I.K.; writing—review and editing, F.K. and I.K.; supervision, F.K. All authors have read and agreed to the published version of the manuscript.

Funding: This research received no external funding.

Institutional Review Board Statement: Not applicable.

Informed Consent Statement: Not applicable.

Data Availability Statement: Data are contained within the article.

Conflicts of Interest: The authors declare no conflicts of interest.

Nomenclature

EV	Electric vehicle
BEV	Battery electric vehicle
HEV	Hybrid electric vehicles
PHEV	Plug-in hybrid electric vehicles
FCEV	Fuel cell electric vehicles
EV/HEV	Electric vehicle or hybrid electric vehicle
ME	Marginal error
IV	Independent variable
DV	Dependent variable
EFA-PCA	Exploratory Factor Analysis with the method of Principal Components
KMO	Kaiser–Meyer–Olkin Coefficient
SEM	Structure Equation Modeling
V	Cramer's V Coefficient of Association
Rbc	Rank biserial correlation coefficient
η^2	Eta-squared
KDE	Kernel Density Estimator
Alpha	Cronbach's Alpha internal consistency coefficient

References

1. European Commission. *A European Strategy for Low-Emission Mobility*; COM (2016) 501 Final; European Commision: Brussels, Belgium, 2017.
2. EEA. *Electric Vehicles in Europe. Report*; EEA: Brussels, Belgium, 2016.
3. Reddy, V.J.; Hariram, N.P.; Maity, R.; Ghazali, M.F.; Kumarasamy, S. Sustainable Vehicles for Decarbonizing the Transport Sector: A Comparison of Biofuel, Electric, Fuel Cell and Solar-Powered Vehicles. *World Electr. Veh. J.* **2024**, *15*, 93. [CrossRef]
4. EEA. *Transport and Environment Report 2021. Decarbonising Road Transport-the Role of Vehicles, Fuels and Transport Demand, Report 2022*; EEA: Brussels, Belgium, 2022.
5. Guzek, M.; Jackowski, J.; Jurecki, R.S.; Szumska, E.M.; Zdanowicz, P.; Żmuda, M. Electric Vehicles—An Overview of Current Issues—Part 1—Environmental Impact, Source of Energy, Recycling, and Second Life of Battery. *Energies* **2024**, *17*, 249. [CrossRef]
6. Longo, M.; Viola, F.; Miceli, R.; Zaninelli, D.; Romano, P. Replacement of vehicle fleet with evs using pv energy. *Int. J. Renew. Energy Res.* **2015**, *5*, 1146–1153.

7. Abdul-Manan, A.F.N. Uncertainty and differnces in GHG emissions between electric and conventional gasoline vehicles with implications for transport policy making. *Energy Policy* **2015**, *87*, 1–7. [CrossRef]
8. Figenbaum, E.; Assum, T.; Kolbenstvedt, M. Electromobility in Norway: Experiences and Opportunities. *Res. Transp. Econ.* **2015**, *50*, 29–38. [CrossRef]
9. Jochem, P.; Doll, C.; Fichtner, W. External costs of electric vehicles. Transp. *Res. Part D Transp. Environ.* **2016**, *42*, 60–76. [CrossRef]
10. Campello-Vicente, H.; Peral-Orts, R.; Campillo-Davo, N.; Velasco-Sanchez, E. The effect of electric vehicles on urban noise maps. *Appl. Acoust.* **2017**, *116*, 59–64. [CrossRef]
11. Thiel, C.; Tsakalidis, A.; Jager-Waldau, A. Will Electric vehicles be killed (again) or are they the next mobility killer app? *Energies* **2020**, *13*, 1828. [CrossRef]
12. Yu, A.; Wei, Y.; Chen, W.; Peng, N.; Peng, L. Life cycle environmental impacts and carbon emissions: A case study of electric and gasoline vehicles in China. *Transp. Res. Part D Transp. Environ.* **2018**, *65*, 409–420. [CrossRef]
13. Held, M.; Schücking, M. Utilization effects on battery electric vehicle life-cycle assessment: A case-driven analysis of two commercial mobility applications. *Transp. Res. Part D Transp. Environ.* **2019**, *75*, 87–105. [CrossRef]
14. Lamprianidou, M.; Kehagia, F.; Pitsiava-Latinipoulou, M. The Transition to Electromobility in Greece. In Proceedings of the 11th International Congress on Transportation Research, ICTR2023, Heraklion, Greece, 20–22 September 2023.
15. Sierzchula, W.; Bakker, S.; Maat, K.; Van Wee, B. The influence of financial incentives and other socio-economic factors on electric vehicle adoption. *Energy Policy* **2014**, *68*, 183–194. [CrossRef]
16. Kumar, R.; Alok, K. Adoption of electric vehicle: A literature review and prospects for sustainability. *J. Clean. Prod.* **2020**, *253*, 119911. [CrossRef]
17. Fjendbo, J.; Cherchi, A.; Mabit, E.; Lindhard, S. On the stability of preferences and attitudes before and after experiencing an electric vehicle. *Transp. Res. Part D Transp. Environ.* **2013**, *25*, 24–32.
18. Zhao, X.; Ma, Y.; Shao, S.; Ma, T. What determines consumers' acceptance of electric vehicles: A survey in Shanghai, China. *Energy Econ.* **2022**, *108*, 105805. [CrossRef]
19. Danielis, R.; Rotaris, L.; Giansoldati, M.; Scorrano, M. Drivers' preferences for electric cars in Italy. Evidence from a country with limited but growing electric car uptake. *Transp. Res. Part A Policy Pract.* **2020**, *137*, 79–94. [CrossRef]
20. Latinopoulos, C.; Sivakumar, A.; Polak, J. Modeling Electric Vehicle Charging Behavior: What Is the Relationship Between Charging Location. Driving Distance and Range Anxiety? No. 17–05273. In Proceedings of the 96th Annual Meeting of the TRB, Washington, DC, USA, 8–12 January 2017.
21. Sommer, S.; Vance, C. Do more chargers mean more electric cars? *Environ. Res. Lett.* **2021**, *16*, 064092. [CrossRef]
22. Brückmann, G.; Willibald, F.; Blanco, V. Battery Electric Vehicle adoption in regions without strong policies. *Transp. Res. Transp. Environ.* **2021**, *90*, 102615. [CrossRef]
23. Singh, V.; Singh, V.; Vaibhav, V. A review and simple meta-analysis of factors influencing adoption of electric vehicles. *Transp. Res. Part D* **2020**, *86*, 102436. [CrossRef]
24. Wicki, M.; Brückmann, G.; Bernauer, T. How to accelerate the uptake of electric cars? Insights from a choice experiment. *J. Clean. Prod.* **2022**, *355*, 131774. [CrossRef]
25. Wang, N.; Tang, L.; Pan, H. Effectiveness of policy incentives on electric vehicle acceptance in China: A discrete choice analysis. *Transp. Res. A* **2020**, *105*, 210–218. [CrossRef]
26. Rietmann, N.; Lieven, T. How policy measures succeeded to promote electric mobility e Worldwide review and outlook. *J. Clean. Prod.* **2019**, *206*, 66–75. [CrossRef]
27. Li, L.; Wang, Z.; Wang, Z. Do policy mix characteristics matter for electric vehicle adoption? A survey-based exploration. *Transp. Res. Part D* **2020**, *87*, 102488. [CrossRef]
28. Higueras-Castillo, E.; Guillén, A.; Herrera, L.J.; Liébana-Cabanillas, F. Adoption of electric vehicles: Which factors are really important? *Int. J. Sustain. Transp.* **2020**, *15*, 799–813. [CrossRef]
29. Liao, F.; Molin, E.; van Wee, B. Consumer preferences for electric vehicles: A literature review. *Transp. Rev.* **2016**, *37*, 252–275. [CrossRef]
30. Kyparissis, I.; Kontaxi, A.; Deliali, A.; Yannis, G. Electric or not? Factors affecting Greek Drivers' Preference when Purchasing a New Vehicle. In Proceedings of the Transport Research Arena TRA 2022 Conference, Lisbon, Portugal, 14–17 November 2022.
31. Shaban, F.; Siskos, P.; Tjortjis, C. Electromobility Prospects in Greece by 2030: A Regional Perspective on Strategic Policy Analysis. *Energies* **2023**, *16*, 6083. [CrossRef]
32. Hellenic Statistical Agency (ELSTAT). Report on Results of Population and Housing Census 2021. 2021. Available online: https://elstat-outsourcers.statistics.gr/Census2022_GR.pdf (accessed on 5 March 2024).
33. Senikidou, N.; Basbas, S.; Georgiadis, G.; Campisi, T. The Role of Personal Identity Attributes in Transport Mode Choice: The Case Study of Thessaloniki, Greece. *Soc. Sci.* **2022**, *11*, 564. [CrossRef]
34. Kothari, C.R. *Research Methodology, Methods and Techniques*, 2nd ed.; New Age International Publishers: New Delhi, India, 1990.
35. Parke, C. *Essential First Steps to Data Analysis: Scenario-Based Examples Using SPSS*; Duquesne University: Pittsburgh, PA, USA, 2013.
36. Shrestha, N. Factor Analysis as a Tool for Survey Analysis. *Am. J. Appl. Math. Stat.* **2021**, *9*, 4–11. [CrossRef]
37. Karlis, D. *Multidimensional Statistics*; Athens University of Economics and Business: Athens, Greece, 2003.

38. Abrahim, S.; Mir, B.A.; Suhara, H.; Mohamed, A.F.; Sato, M. Structural equation modeling and confirmatory factor analysis of social media use and education. *Int. J. Educ. Technol. High. Educ.* **2019**, *16*, 32. [CrossRef]
39. Memon, M.A.; Cheah, J.; Ramayah, T.; Ting, H.; Chuah, F.; Cham, T. Moderation Analysis: Issues and Guidelines. *J. Appl. Struct. Equ. Model.* **2019**, *3*, 1–11. [CrossRef]