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The Effect of Drivers and Barriers on Electric Vehicle Usage in Romania: Findings from PLS-SEM and MGA

Abstract. *In recent years, the popularity of electric vehicles among consumers has been steadily increasing. In 2023, electric cars accounted for a market share of 24.4% on the Romanian automotive market. In Europe, the share of electric vehicles (EVs) represents more than 22.3% of the automotive market, setting a record percentage. This study investigates the effect of determining factors on the intention to use and actual usage of electric vehicles by Romanian consumers, considering two distinct latent variables and integrating attributes related to the acceptance of new technologies. Based on an online questionnaire and using the "Snowball Sampling" method, 413 valid questionnaires were collected from Romanian users. Statistical hypothesis testing and validation of the proposed new model were conducted using the Partial Least Squares Structural Equation Modelling (PLS-SEM) and multi-group analysis (PLS-MGA). Data processing and analysis were performed using Smart PLS 4 and SPSS 28 software. The results highlight the positive and significant effect of latent variables (perceived ease of use, perceived usefulness, as well as the drivers) on the intention of electric vehicle usage behaviour among Romanian users. These results provide valuable insights for developing strategies to increase the use of electric vehicles in the future. The findings align with existing literature confirming the significant role of perceived usefulness and ease of use in technology adoption while highlighting the impact of contextual drivers and barriers.*

Keywords: *electric vehicle, perceived ease of use, perceived usefulness, drivers and barriers, behavioural intention to use, Romanian users.*

JEL Classification: C12, C35, D11, L62, M31.

1. Introduction

Electric vehicles (EVs) are reshaping the automotive landscape, presenting key solutions to pressing issues such as climate change, air pollution, and the depletion of fossil fuels (Wolfram et al., 2021; Simmons, 2022; Carbon Brief, 2020). The rise in EV popularity is fuelled by technological advancements, attractive government incentives, and growing environmental consciousness among consumers, as detailed by Gillingham (2023), Lieven & Hügler (2021), and Patil (2020). In 2023, EVs represented 24.4% of all new car sales in Romania, mirroring broader trends across

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Europe, where they accounted for more than 22.3% of the market (Energynomics, 2024; International Energy Agency (IEA), 2024; Toader et al., 2023).

Choi & Jiao (2024) show that despite this growth, the rate of EV adoption still shows significant variation by region and demographic group. For those aiming to boost sustainable transportation, it is critical to understand the diverse factors that influence consumer decisions to adopt EVs (Popa et al., 2018). The process is complex, affected by a variety of factors that sway consumer attitudes and behaviours (Moise et al., 2020).

2. Literature review

The Technology Acceptance Model (TAM), crafted by Davis (1989), serves as a fundamental framework for evaluating how consumers embrace new technologies. It identifies PE and PU as the main drivers of technology adoption. PE measures how easy an individual thinks it will be to use a technology, while PU assesses whether they believe that the technology will enhance their job performance.

When it comes to EVs, **perceived usefulness** (PU) is especially critical. It encompasses the degree to which consumers perceive EVs as offering concrete advantages like improved efficiency, increased safety, reduced traffic and pollution, lower stress levels, and enhanced driving dynamics (Bockarjova and Steg, 2014; Xiao & Goulias, 2022).

Several studies have highlighted the significance of PU in the adoption of EVs, Yousif and Alsamydai (2019) found that benefits such as decreased fuel costs and maintenance significantly affect consumers' intentions to use EVs. Furthermore, Adhikari et al. (2020) showed that the environmental benefits of EVs (their role in reducing emissions and pollution) greatly enhance their perceived usefulness and motivate adoption. Dudenhöffer (2013) also confirms that the technological maturity and perceived advantages of EVs play a crucial role in their acceptance, illustrating the broad impact of PU on decision-making processes related to EV adoption.

Perceived Ease of Use (PE) is another key determinant in the TAM framework. In the context of EVs, PE relates to the ease with which consumers can learn to drive EVs, the clear and easy understanding of the interaction with EVs, the ease to become proficient in using EVs and ease in using and operating EVs, including aspects such as charging, maintenance, and driving experience (Dudenhöffer, 2013; Xu et al., 2020).

Research has shown that PE plays a significant role in influencing consumer attitudes toward EVs. Bunce, Harris, and Burgess (2014) highlighted that drivers' views on the ease of using electric vehicles (EVs)—including how easy it is to charge them and the intuitiveness of their controls—positively influence their willingness to adopt these vehicles. Yousif and Alsamydai (2019) also identified that the perceived simplicity and user-friendliness of EV technology are key factors that encourage consumers to consider adopting EVs. Moreover, Adhikari et al. (2020) reinforced this viewpoint by demonstrating that the ease with which EVs can be integrated into everyday routines significantly impacts their adoption.

Drivers (D) are the motivating factors that encourage consumers to adopt EVs. These include environmental concerns, financial incentives, technological advancements, and social influences (Ottesen et al., 2022; Bunce et al., 2014; Dima, 2023). Environmental benefits, such as reduced emissions, pollution, noise, and improved air quality, are significant drivers for many consumers (Rezvani et al., 2015).

Financial incentives, such as subsidies, tax reductions, and lower operating costs, also play a crucial role in promoting EV adoption (Sierzchula et al., 2014). Technological advancements, including improvements in battery technology and the expansion of charging infrastructure, quieter operation, and smoother driving experience further incentivise consumers to switch to EVs (Adhikari et al., 2020). Social influences, such as the desire to align with environmentally conscious peers, and the added level of safety in traffic can also drive EV adoption (Gould and Golob, 1998). These drivers collectively contribute to shaping positive attitudes and intentions towards EV usage.

Barriers (B) are factors that hinder the adoption of EVs. Common barriers include high initial costs, limited charging infrastructure, range anxiety, limited variety of EVs models, and lack of consumer awareness (Tarei et al., 2021). The extended charging time, often associated with insufficient aftermarket support (pars and/or mechanics) and the cost of battery technology, can deter potential buyers (Egbue & Long, 2012; Liao et al., 2017).

Limited charging options in rural or less densely populated areas present a significant obstacle to the larger adoption of electric vehicles (EVs) (Adhikari et al., 2020). Another major barrier is range anxiety—the worry that the battery will run out before reaching a charging station (Bunce, Harris, and Burgess, 2014). Moreover, a general lack of understanding about EV technology and its benefits, coupled with an unawareness of government incentives, can also turn consumers away (Rezvani, Jansson, and Bodin, 2015). Tackling these issues is essential for building consumer trust and encourage the widespread adoption of EVs.

The **intention to use electric vehicles (IU)** plays a crucial role in predicting actual usage. This intent is primarily fuelled by the perceived usefulness and ease of use of EVs, as identified by Xu et al. (2020). External factors such as environmental benefits and financial incentives also play a significant role in strengthening this intention (Ottesen et al., 2022; Picatoste et al., 2023). However, challenges such as high costs and inadequate infrastructure can dampen this intention (Tarei et al., 2021).

Electric Vehicle Use (EV Use) measures how extensively consumers have incorporated EVs into their everyday lives, including for commuting and other activities (Xu et al., 2020). The journey from merely intending to use EVs to actual consistent usage is shaped by several factors, such as the availability of infrastructure, economic incentives, and community support (Xiao & Goulias, 2022).

Studies have shown that a strong IU often translates into EV Use. For example, Bockarjova and Steg (2014) demonstrated that consumers with a high intention to adopt EVs are more likely to follow through and integrate EVs into their transportation routines. Additionally, ongoing support and improvements in technology and infrastructure, and the offering of financial incentives can facilitate the transition from intention to use to actual usage (Sierzchula et al., 2014). Understanding these dynamics is crucial for fostering sustained EV adoption and addressing the practical challenges that users may face.

3. Research Questions/Aims of the Research

The study aims to identify and evaluate the impact of drivers, barriers, perceived ease of use, and perceived usefulness on EV usage behaviour among Romanian consumers. It includes two objectives: (Q1) identifying the determinants and evaluating their common effect on the intention to use electric vehicles in Romania; (Q2) identifying significant differences between the Male (M) and Female (F) groups for correlation paths (PU → IU; PE → IU; PE → PU; D → IU; D → EV Use; B → IU; B → EV Use; IU → EV Use).

The study brings three contributions to the field of electric vehicle research. It addresses a trending topic by evaluating the impact of determinant factors on EV usage behaviour, complementing existing literature on EV acceptance. It extends the TAM model by integrating driver and barrier variables, demonstrating its robustness and versatility in the automotive sector. The study includes empirical data from experienced drivers, providing valuable implications for future research, as well as for the design of regulations and promotion and sales strategies for EVs.

In accordance with the two research objectives, 16 statistical hypotheses were formulated, as follows:

Hypothesis 1 ($H1_0$): Perceived usefulness (PU) has a positive and significant impact on Intention to use electric vehicle (EV).

Hypothesis 2 ($H2_0$): Perceived ease to use (PE) has a positive and significant impact on Intention to use electric vehicle (EV).

Hypothesis 3 ($H3_0$): Perceived ease to use (PE) has a positive and significant impact on Perceived usefulness (PU).

Hypothesis 4 ($H4_0$): Drivers (D) has a positive and significant impact on Intention to use electric vehicle (EV).

Hypothesis 5 ($H5_0$): Drivers (D) has a positive and significant impact on Electric Vehicle Use (EV Use).

Hypothesis 6 ($H6_0$): Barriers (B) has a positive and significant impact on Intention to use electric vehicle (EV).

Hypothesis 7 ($H7_0$): Barriers (B) has a positive and significant impact on Electric Vehicle Use (EV Use).

Hypothesis 8 ($H8_0$): Intention to use electric vehicle (EV) has a positive and significant impact on Electric Vehicle Use (EV Use).

Hypothesis 9_0 -16_0 ($H9_0$ - $H16_0$): There are no significant differences between "Male" (M) and "Female" (F) groups in the eight constructs of the proposed model

(PU → IU; PE → IU; PE → PU; D → IU; D → EV Use; B → IU; B → EV Use; IU → EV Use).

Figure 1 presents the correlation paths between the latent variables of the proposed construct model.

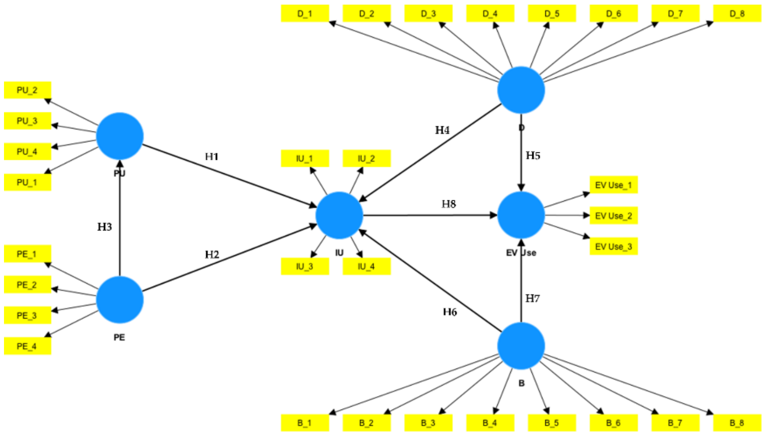

Figure 1. Proposed Construct Model

Source: Model created by the authors using the Smart PLS 4 software.

4. Research Methods

The study was carried out from December 1st, 2023, to March 30th, 2024, in Bucharest, Romania. Data was gathered using an online questionnaire that included three demographic questions and 31 questions focusing on content. The target population included both male and female drivers aged between 18 and 65+ years, who had held a valid driving license for at least one year. The online questionnaire was distributed to the respondents via email or WhatsApp, considering these means appropriate to obtain the necessary research data. A pilot test involving 50 respondents was conducted to pre-test the questionnaire in order to improve its content and structure (Ottesen et al., 2022). Specific items for the driver and barrier variables were constructed by the authors, while the other variables (PE, PU, IU, and EV Use) were adapted from Davis's model published in 1989.

Using a non-probabilistic sampling method – snowball sampling, the authors distributed the online questionnaire, via a link, to the target population. Out of the 1200 questionnaires distributed, 453 were collected, of which 39 were incomplete, resulting in a response rate of 16.88%. The final sample size was 413 respondents, exceeding the minimum accepted threshold of 170 responses (34 items x 5 = 170 responses < 315 responses) (Kristensen & Eskildsen, 2010). There were 55% women and 45% male respondents. Among the participants, 32.4% were aged 18-30, 29.8% were 31-40, and 37.8% were over 41 years old. Regarding driving experience, 27.1% had held a driving license for at least one year, while 72.9% had been driving for more than five years. Details of the questionnaire are provided in Table 1A in the

Appendix. There were utilized nominal and ordinal (Likert) scales ranging from 1 ("Very unimportant") to 5 ("Very important") to measure responses. Data analysis was conducted using Smart PLS 4 and SPSS 28 software tools.

Additionally, the study included an evaluation of Common Method Bias (CMB) using the Variance Inflation Factor (VIF) and the Harman single-factor test to ensure the robustness of the findings. The VIF measures falling within the range of 0.250 to 4.000 indicate that the correlations between exogenous and endogenous variables in the regression analysis were strong and robust (Hair et al., 2024). The results of the Harman single-factor test showed that the total variance for a single factor was 40.82%, which is below 50%, the maximum acceptable value (Podsakoff et al., 2003).

5. Findings and Discussion

The analysis applied Partial Least Squares Structural Equation Modelling (PLS-SEM) to explore connections among six latent variables. The reliability and validity of these constructs were examined. Cronbach's Alpha, which assesses internal consistency, ranged from 0.664 to 0.889. These scores surpass the exploratory research threshold of 0.60, demonstrating strong convergent validity for the latent variables (Hair et al., 2024). Recognising that Cronbach's Alpha might not always provide an accurate reliability estimate, composite reliability (CR) scores were also calculated for each latent variable to ensure a more robust evaluation in the proposed reflective model. As can be seen in Table 2, composite reliability (CR) measures ranged from 0.798 to 0.912, exceeding the acceptable threshold of 0.60 set by Chin (2010) and Hair et al. (2024). The average variance extracted (AVE) measures ranged between 0.502 and 0.630, surpassing the minimum threshold of 0.5 proposed by Hair et al. (2024). The results above, obtained by running the data through the PLS algorithm, demonstrate that the proposed construct model meets the conditions for convergent reliability and validity (see Table 2).

Table 2. Construct Reliability and Validity results

	Cronbach's Alpha*	**Composite Reliability***	**Average Variance Extracted (AVE)***	**R-square***	**R-square adjusted***
Barriers (B)	0.854	0.888	0.502	-	-
Drivers (D)	0.889	0.912	0.567	-	-
Electric Vehicle Use (EV Use)	0.705	0.836	0.630	0.562	0.559
Intention to use (IU)	0.664	0.798	0.505	0.675	0.672
Perceived Ease of Use (PE)	0.785	0.861	0.608	-	-
Perceived Usefulness (PU)	0.770	0.852	0.591	0.390	0.389

*Note: * Cronbach's Alpha >0.60; Composite Reliability ≥ 0.60; Average Variance Extracted (AVE) >0.5; R-square (R^2); R-square adjusted.*

Source: Analysis conducted by the authors using the Smart PLS 4 software.

The square root of the AVE (Average Variance Extracted) regarding the latent variable Barriers (B) was greater than its correlation with the latent variables (D), (EV Use), (IU), (PE), and (PU) (0.623; 0.625; 0.676; 0.630; 0.663 < 0.709) (Sarstedt et al., 2021). The variable EV Use exhibited the highest correlation with itself (0.794), while the shared variations with variables IU, PE, and PU were lower (0.647; 0.526; 0.565 < 0.794). The situation is similar for the other latent variables of the proposed construct model. The magnitude of the AVE indicators demonstrates, once again, that the proposed reflective model meets the condition of discriminant validity (see Table 3).

Table 3. Fornell-Larcker criteria results

	B	**D**	**EV Use**	**IU**	**PE**	**PU**
Barriers (B)	**0.709**					
Drivers (D)	0.623	**0.753**				
Electric Vehicle Use (EV Use)	0.625	0.662	**0.794**			
Intention to use (IU)	0.676	0.556	0.647	**0.710**		
Perceived Ease of Use (PE)	0.630	0.633	0.526	0.674	**0.780**	
Perceived Usefulness (PU)	0.663	0.630	0.565	0.615	0.625	**0.769**

Source: Analysis conducted by the authors using the Smart PLS 4 software.

The highest variance inflation factor (VIF) was obtained by item B_6 (2.920), while the lowest was attributed to item IU_1 (1.151). All VIF coefficients fell within the range of 0.250 – 4.000, as proposed by Hair et al. (2024), demonstrating that there is no problematic multicollinearity. The endogenous variable PU achieved an R-square of 0.390, with its variance entirely explained by the action of the exogenous variable PE. In Figure 1, it is observed that 67.5% of the variance in IU (R-square = 0.675) was explained by the joint action of the variables PE and PU, while 56.2% of the variance in EV Use was demonstrated by the joint action of the latent variables D, B, and IU. The Goodness-of-Fit (GoF) was 0.555 (GoF > 0.50), indicating a good fit between the collected sample data and the predicted data, as well as a good validity of the proposed reflective model (Henseler & Sarstedt, 2013). Strong positive effects on EV Use were demonstrated by the variables IU ($\beta = 0.503$) and D ($\beta = 0.213$), respectively. Conversely, the lowest positive influence on EV Use was exerted by the exogenous variable B ($\beta = 0.090$) (see Figure 2).

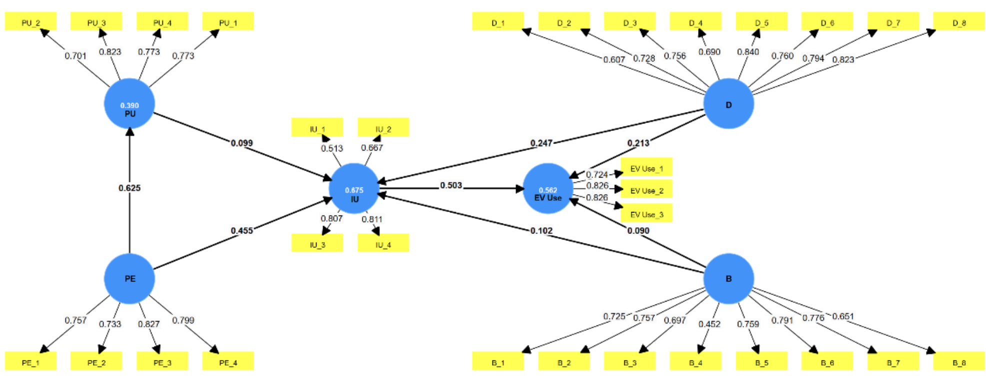

Figure 2. Results of the PLS-SEM model

Source: Results determined by the authors using the Smart PLS 4 software.

The bootstrapping results demonstrate that the effects of the variables PU (β = 0.099, t= 2.213, p = 0.027), PE (β = 0.455, t= 10.136, p = 0.000), and D (β = 0.247, t= 3.926, p = 0.000) on IU are positive and significant at a probability level of 0.50 (where t-Value > 1.96 or p-Value < 0.05 in accordance with Hair et al. (2024). Therefore, the null hypotheses $H1_0$, $H2_0$, and $H4_0$ were accepted. The correlation path PE PU (β = 0.625, t= 19.363, p = 0.000) is also significant, and the null hypothesis $H3_0$ is accepted. The exogenous variable EV Use was significantly influenced by the variables D (β = 0.213, t= 2.798, p = 0.005) and IU (β = 0.503, t= 7.382, p = 0.000), thus hypotheses $H5_0$ and $H8_0$ were also accepted. A positive but nonsignificant impact was exerted by the exogenous variable B on the endogenous variables IU (β = 0.102, t= 1.627, p = 0.104) and EV Use (β = 0.090, t= 1.538, p = 0.000), leading to the rejection of null hypotheses $H6_0$ and $H7_0$ (See Table 4).

Table 4. Results obtained after testing the statistical hypotheses

Correlations	β	Sample Mean (M)	t-value*	p-value*	Result of the hypothesis
PU → IU	0.099	0.099	2.213	0.027	$H1_0$ – Supported
PE → IU	0.455	0.453	10.136	0.000	$H2_0$ – Supported
PE → PU	0.625	0.627	19.363	0.000	$H3_0$ – Supported
D → IU	0.247	0.247	3.926	0.000	$H4_0$ – Supported
D → EV Use	0.213	0.216	2.798	0.005	$H5_0$ - Supported
B → IU	0.102	0.106	1.627	0.104	$H6_0$ – Unsupported
B → EV Use	0.090	0.092	1.538	0.124	$H7_0$ – Unsupported
IU → EV Use	0.503	0.500	7.382	0.000	$H8_0$ – Supported

*Note: *t-value >1.96; p-value < 0.001 or 0.05.*

Source: Analysis conducted by the authors using the Smart PLS 4 software.

The differences between the dispersion of estimated values across the paths of exogenous variables (PE, D, B) and endogenous variables (PU, IU, EV Use) were depicted in the histograms in Figure 3. The iterations of paths B → IU (f) and B → EV Use (g) exhibit a less complex distribution regarding the path loading coefficients, unlike those significantly correlated (a-e and h) (see Figure 3).

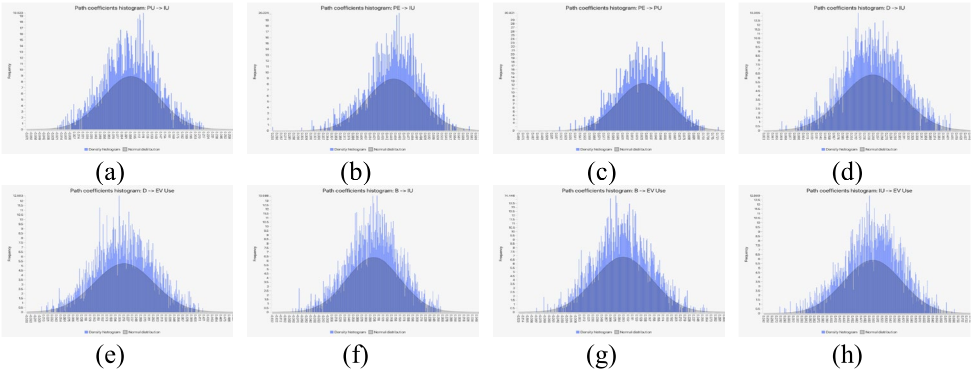

Figure 3. Path Coefficients Histograms – The distribution of path loading coefficients for the path model path from: (a) PU → IU; (b) PE → IU; (c) PE → PU; (d) D → IU; (e) D → EV Use; (f) B → IU; (g) B → EV Use; (h) IU → EV Use.

Source: Results determined by the authors using the Smart PLS 4 software.

Following variable gender, the sample was divided into two groups, namely "Male" (M) and "Female" (F). Multigroup analysis (MGA) was used to identify potential differences between the newly created groups, based on independent samples t-tests (Kiel et al., 2000). Statistical hypotheses $H9_0$ - $H16_0$ were formulated and tested, stating that there are no significant differences between the "Male" (M) and "Female" groups, for the proposed model constructs (see Table 5).

Table 5. Differences between groups "Male" (M) – "Female"(F)

		Path Coefficients Difference (M-F)	PLS-MGA	Parametric Test		Welch-Satterthwait Test	
			Male (M) - Female (F)				
			p -value new (M vs. F)	t value new (M vs. F)	p -value new (M vs. F)	t value new (M vs. F)	p -value new (M vs. F)
H9	PU → IU	0.001	0.497	0.006	0.498	0.006	0.498
H10	PE → IU	0.070	0.269	0.651	0.258	0.621	0.268
H11	PE → PU	-0.022	0.367	0.331	0.370	0.334	0.369
H12	D → IU	0.208	0.070	1.498	0.067	1.474	0.071
H13	D → EV Use	0.180	0.105	1.219	0.112	1.253	0.106
H14	B → IU	-0.232	0.035	1.791	0.037	1.833	0.034
H15	B → EV Use	-0.320	0.003	2.653	0.004	2.670	0.004
H16	IU → EV Use	0.068	0.302	0.501	0.308	0.512	0.305

Source: Results determined by the authors using the Smart PLS 4 software.

The non-parametric significance test PLS-MGA demonstrates that there are significant differences between the "Male" (M) and "Female" (F) groups for the constructs B → IU and B → EV Use, with p-values below 0.05 (B → IU, p-value new = 0.035 < 0.050; B → EV Use, p-value new = 0.003 < 0.050). These results are confirmed by the Parametric Test (0.037; 0.004 <0.050) and the Welch-Satterthwait Test (0.034; 0.004<0.050), therefore null hypotheses $H14_0$ and $H15_0$ are rejected. The situation is different for the constructs PU → IU; PE → IU; PE → PU; D → IU; D → EV Use; and IU → EV Use, where there are no significant differences between the two groups (M vs. F).

6. Conclusions

The present study aimed to explore the effect of drivers (D), barriers (B), perceived usefulness (PU), and perceived ease of use (PE) on the intention (IU) and usage (EV Use) behaviour of electric vehicles among Romanian consumers.

Scientific Implications. The study brings several contributions to the current literature on EVs and usage behaviour of new technologies. Previous studies have focused on understanding the acceptance and usage of EVs (Xu et al., 2020; Xiao & Goulias, 2022). However, these studies have not assessed the combined effect of D and B on the behavioural intention to use EVs. This study addresses this gap by including both constructs in the TAM model, providing new perspectives on the phenomenon. For example, awareness of climate change, CO_2 emissions reduction, pollution, noise, and congestion (D1) has a significant effect on the intention to use EVs, stimulating demand for electric vehicles. The results of the study demonstrate how important it could be to conduct awareness campaigns about the benefits and capabilities of electric vehicles (B6), in the context of urbanisation growth (D6). Furthermore, the development and improvement of the theoretical model to anticipate future trends in the adoption and usage of electric vehicles could contribute to stimulating demand and overcoming existing barriers.

Practical Implications. The study results demonstrate that drivers have a significant positive impact on the usage behaviour of Romanian consumers regarding electric vehicles. These findings are in line with the observations of Ottesen et al., (2022), who showed that an increasing number of consumers may consider using EVs in the future because they are faster, quieter, safer, and more environmentally friendly. Evaluating the drivers allows for the best strategic decisions to be made by the government, municipalities, automotive industry, and other stakeholders. For example, by understanding specific driver items, such as quiet functionality and smooth driving experience (D8); added safety in traffic (D7); reduction of CO_2 emissions, pollution, noise, and congestion (D1), etc., automotive companies could develop more effective strategies to promote EVs. Furthermore, automakers can use information from the model to develop more options/styles of EVs (D5) and new battery technologies, contributing to increased range, decreased charging times (D3), and increased demand for EVs. By expanding the charging station network (D4) in locations where it may be needed, municipalities can alleviate range anxiety and encourage the adoption and usage of EVs.

Although insignificant, the influence of barriers on the adoption and usage behaviour of EVs was demonstrated within the proposed construct model. Results of the study demonstrate that there were significant differences between the "Male" (M) and "Female" (F) groups for the constructs B → IU and B → EV Use. Tarei et al., (2021) demonstrated that low battery autonomy, high ownership costs, poor charging infrastructure, and consumer awareness about EV technology were the main barriers that slowed down the EV adoption process. Therefore, understanding specific barrier items allows for the implementation of projects and interventions aimed at overcoming barriers and strengthening factors for EV adoption and usage. For example, providing financial incentives to automotive manufacturers to support the development of EV models and battery technology, with a focus on improving autonomy (B3), aftermarket support (B4), resale value (B8), and reducing costs (B1), could increase consumer accessibility to electric vehicles. To address the issue of lack of home charging facilities or infrastructure in rural/less populated areas (B2) and limited awareness of government incentives (B7), relevant public institutions could conduct awareness campaigns about the expansion of charging infrastructure, accessing financial incentive systems, and reducing environmental impact. The development and implementation of educational and awareness programmes for Romanian consumers on the benefits and capabilities of electric vehicles (B6), safety features, performance and comfort of electric vehicles (B5) could contribute to improving their understanding and acceptance of them.

The significant effect of PU, PE, and D on IU and EV Use, complemented by specific barriers to EV usage, can contribute to improving policies and regulations in the automotive sector and related areas. The results were consistent with the research of Xu et al. (2020), Xiao & Goulias (2022), demonstrating that perceived relative advantage and ease of use have a significant influence on behavioural intentions to adopt EVs. Furthermore, respondents with higher annual incomes, who live and work in urban areas with access to charging stations, show a stronger intention to adopt and use EVs. Therefore, the government, municipalities, and financial institutions could offer Romanian EV users future financial and fiscal incentives, such as: abolishing excise taxes on EVs, VAT deduction, exemption from EV tax, bonuses for purchasing EVs and/or various types of charging infrastructure, fiscal credits, exemptions from registration fees, special environmental taxes, property taxes, annual circulation taxes, parking taxes, etc.

Limits and Future Research. The study presents several limitations related to situational and spatial constraints. The sample consisted only of respondents from Bucharest with a driving license of at least one year. It is recommended that future studies address other market segments and geographical regions to generalize the results. Increasing the sample size and applying probabilistic sampling methods could contribute to ensuring better representativeness and diversity of research results. Furthermore, using less structured questionnaires, analysing the moderator effect of sociodemographic characteristics, and integrating new latent variables, such as intrinsic and extrinsic motivation, could contribute to understanding the overall determinants influencing consumer adoption and usage behaviour of EVs.

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Appendix

Table 1A. Measures of variables used in the research

Variables and items	**Outer loadings**
Drivers	
D1- Increasing awareness about climate change, reducing CO2 emissions, pollution, noise, and congestion will stimulate demand for electric vehicles.	0.607
D2 - Providing government incentives will contribute to encouraging the adoption and usage of electric vehicles.	0.728
D3 - The development of battery technologies will contribute to increasing the autonomy and reducing the charging times of electric vehicles.	0.756
D4 - The demand for electric vehicles will increase with the expansion of the charging station network.	0.690
D5 - The development of more options/styles of electric vehicles will influence customers to consider electric vehicles.	0.840
D6 - The increase in urbanization and the popularity of electric vehicles will facilitate widespread adoption of electric vehicles.	0.760

D7 - Electric vehicles bring an added level of safety in traffic, being as safe as other gasoline/diesel/hybrid cars.	0.794
D8 - The quieter operation and smoother driving experience contribute to increasing the demand for electric vehicles.	0.823
Barriers	
B1 - The perceived high cost of electric vehicles due to battery technology costs.	0.725
B2- The lack of home charging facilities or infrastructure in rural/less populated areas.	0.757
B3 - The extended charging time of electric vehicles and limited autonomy.	0.697
B4 - Insufficient aftermarket support: parts and mechanics.	0.452
B5 - The lack of consumer education programs regarding the safety, performance, and comfort features of electric vehicles.	0.759
B6 - Lack of awareness regarding the benefits and capabilities of electric vehicles	0.791
B7 - Limited awareness of government incentives	0.776
B8 - Limited variety of EV models, resale value, and depreciation discourages potential customers	0.651
Perceived usefulness (PU)	
PU1 - I feel that using an electric vehicle would allow me to be more productive.	0.773
PU2 - I feel that using an electric vehicle would allow me to be safer while driving.	0.701
PU3 - I believe that using an electric vehicle contributes to reducing traffic-related issues and pollution.	0.823
PU4 - I feel that using an electric vehicle reduces my stress and improves my performance.	0.773
Perceived ease to use (PE)	
PE1 - I believe it would be easy for me to learn to drive an electric vehicle.	0.757
PE2 - I believe my interaction with an electric vehicle would be clear and easy to understand.	0.733
PE3 - I believe it would be easy for me to become proficient in using an electric vehicle.	0.827
PE4 - I believe an electric vehicle is easy to use.	0.799
Intention to use (IU)	
IU1 - I predict I will use electric vehicle	0.513
IU2 - I intend to use electric vehicle	0.667
IU3 - I plan to use electric vehicle	0.807
IU4 - I intend to recommend the use of the electric vehicle	0.811
Electric Vehicle Use (EV Use)	
EV Use1 - I plan to use electric vehicle in the future	0.724
EV Use2 - I currently use electric vehicle	0.826
EV Use3 - I will continue to use electric vehicle	0.826