

Issue 26(4), 2026
ISSN: 1567-7141
DOI: 10.59490/ejtir.2026.26.4.8708

TU Delft | OPEN Publishing

Research article

Understanding post-adoption heterogeneity in electric vehicle use: A perception-based user segmentation

Ecem Ozkan [1,*], Arda Gurus [2]

[1] Department of Econometrics, Faculty of Economics and Administrative Sciences, Bursa Uludağ University, Turkey
[2] Department of Political Science and Public Administration, Faculty of Economics and Administrative Sciences, Bursa Uludağ University, Turkey
* corresponding author ecemozkan@uludag.edu.tr

Keywords
perceptual segmentation
electric vehicles
post-adoption experience
cluster analysis

Publishing history
Submitted: 3 March 2026
Revised date(s): 1 June 2026
Accepted: 18 September 2026
Published: 21 November 2026

Cite as
Ozkan, E., & Gurus, A. (2026). Understanding post-adoption heterogeneity in electric vehicle use: A perception-based user segmentation. *European Journal of Transport and Infrastructure Research, 26*(4). https://doi.org/10.59490/ejtir.2026.26.4.8708

©2026 Authors. Published by TU Delft OPEN Publishing on behalf of the authors. This work is licensed under a Creative Commons Attribution 4.0 International (CC BY 4.0) license.

Abstract

This study investigates the perceptual dynamics of electric vehicle (EV) use in the post-adoption phase, focusing on how active users evaluate advantages and disadvantages. Moving beyond approaches that assume an inverse relationship between perceived benefits and risks, we argue that these perceptions can coexist and that the multidimensional nature of post-adoption experience should not be overlooked. The study addresses three research questions: (i) How are post-adoption perceptual dimensions shaped among active EV users? (ii) What benefit–risk perceptions emerge across user segments? (iii) What policy recommendations can be derived for Turkish and European urban contexts? Using data collected in early 2025, we examine Turkey's Marmara Region, characterized by rapid EV adoption. Exploratory Factor Analysis and K-means Cluster Analysis identify eight perceptual dimensions and three segments: comfort-oriented satisfied users, performance-oriented users with high perceived technical risk, and cautious pragmatic users. Findings indicate that performance-oriented users exhibit strong sensitivity to technological risks due to high technical awareness despite high satisfaction. The majority perceive infrastructure constraints as a persistent barrier despite prolonged use. The results offer transferable insights for European urban contexts facing increasing EV user heterogeneity and support strategic interventions for decarbonization. To effectively foster a sustainable mobility transition, policy strategies must transition from generic, one-size-fits-all incentives to targeted, segment-specific interventions that simultaneously synchronize infrastructure reliability, address technological uncertainties, and account for the heterogeneity of the user base.

1 Introduction

Growing environmental concerns on a global scale, increasing policy pressures to reduce dependence on fossil fuels, and the significant contribution of the transportation sector to total carbon emissions have positioned EVs as one of the key components of the sustainable mobility transition (Adnan et al., 2017; Mesquita et al., 2025; Singh et al., 2020). In recent years, both developed and developing countries have witnessed a rapid expansion of investments in EV technologies, alongside the widespread implementation of charging infrastructure, financial incentives, and regulatory policies designed to support this transition (Sang & Bekhet, 2015; Sierzchula et al., 2014; Wang et al., 2017). Within this context, EVs are increasingly understood not merely as an alternative technology, but as a multidimensional innovation shaped by economic cost structures, environmental externalities, and perception-based evaluations grounded in user experience (Javanmardi et al., 2023; Schuitema et al., 2013). Accordingly, understanding how users interpret and experience EV technologies has become a critical issue for both transport policy design and the operational effectiveness of sustainable mobility interventions. While factors such as cost, performance, and charging infrastructure play a decisive role in adoption, how these factors are perceived and experienced by users is a central determinant influencing both the pace of diffusion and the continuity of adoption over time (Egbue & Long, 2012; Liao et al., 2017; Noel et al., 2019).

Despite the growing body of research, a substantial part of the EV literature has focused primarily on individuals' adoption intentions, purchase decisions, or the attitudes of potential users (Bektaş & Akyıldız Alçura, 2024; Rezvani et al., 2015). While this intention-focused perspective has provided important insights, it offers limited evidence regarding how perceptions evolve after adoption and how real-world usage experience reshapes technology evaluation. Existing research has often examined user perceptions through single-dimensional variables, frequently assuming that the advantages and disadvantages attributed to EV, such as vehicle performance and range anxiety, function as opposing forces that offset or weaken one another. Within the literature, the affect heuristic framework, as articulated by Alhakami and Slovic (1994) and further developed by Finucane et al. (2000), posits that increasing perceived benefits of a technology are typically associated with decreasing perceived risks. This inverse relationship has received substantial empirical support, particularly in pre-adoption evaluations (Alhakami & Slovic, 1994; Finucane et al., 2000; Loewenstein et al., 2001; Slovic et al., 2007). However, whether this linear relationship remains valid in post-adoption contexts characterized by prolonged usage experience and increasing technical knowledge remains a significant knowledge gap in the literature.

In this regard, Rogers (1962) Diffusion of Innovations Theory offers a valuable perspective, suggesting that user perceptions may evolve alongside experience and that diverse adopter profiles can coexist within a social system (Jansson et al., 2017; Petschnig et al., 2014). From a transport systems perspective, post-adoption heterogeneity represents an underexplored dimension of mobility transitions. Although diffusion theory provides a lens to examine how benefit and risk evaluations co-develop, its application has largely remained confined to intention-based studies (Egbue & Long, 2012; Plötz et al., 2014; Rezvani et al., 2015; Sierzchula et al., 2014). This creates a need for empirical research that simultaneously examines the coexistence of perceived advantages and disadvantages among active EV users.

Against this background, the present study aims to fill this gap in the literature by jointly examining perceived advantages and disadvantages within a multidimensional framework and by conducting perception-based user segmentation. Drawing on survey data from 160 active EV users in Turkey's Marmara Region collected in the first half of 2025, the study utilized purposive sampling to specifically target eligible individuals who own 100% electric vehicles, thereby enabling the assessment of experience-based evaluations instead of hypothetical perceptions. The data collection process was administered by a professional survey organization, which utilized a randomized selection approach within consumer panels to engage eligible respondents. While the sample size is framed by the challenges of reaching a verified and specific user population, it was

selected to enable the implementation of segmentation analyses aimed at examining perceptual heterogeneity rather than population-wide estimation.

The Marmara Region is a particularly relevant setting for this investigation, as EV uptake and charging infrastructure deployment have expanded rapidly relative to other regions, allowing user experience to be examined alongside an evolving policy, infrastructure, and transport systems context. Perceptual dimensions were identified through Exploratory Factor Analysis (EFA), and user segments were subsequently formed using K-means Cluster Analysis. This analytical approach enabled a critical re-examination of the implicit assumption that an increase in perceived benefits necessarily corresponds to a decline in perceived risks. Additionally, One-Way Analysis of Variance (ANOVA) and Chi-square Tests of Independence were employed to further examine post-adoption heterogeneity by identifying significant socio-economic and experience-based differences across the derived segments. These insights are particularly relevant for transport policy debates concerned with designing targeted interventions and enhancing the long-term effectiveness of diffusion strategies.

This study contributes to the literature in several respects. First, by conceptualizing perceived advantages and disadvantages as simultaneous and multidimensional constructs rather than linear opposites, it offers a more comprehensive account of the heterogeneous nature of post-adoption perceptions. Second, it extends the explanatory scope of Diffusion of Innovations Theory by demonstrating its relevance not only for adoption intentions but also for adoption continuity and the confirmation stage of usage. Third, through a perceptual segmentation approach, the study shows that policy frameworks should move beyond one-size-fits-all user assumptions and consider diverse perceptual profiles, including users who maintain high risk perceptions despite high-performance satisfaction and experienced users who exhibit heightened sensitivity to infrastructure constraints. Finally, it illustrates how perception-based segmentation can inform more targeted electrification strategies, generating transferable insights for European urban contexts where the growing density and heterogeneity of EV users call for segment-specific policy interventions aligned with distinct benefit–risk perceptions.

The remainder of the paper is structured as follows. Section 2 establishes the theoretical framework, followed by a literature review in Section 3. Section 4 details the materials and methods. Section 5 presents the empirical findings. Section 6 provides a discussion from a transport policy perspective, and Section 7 concludes with policy implications, the limitations of the study, and directions for future research.

2 Theoretical framework

Diffusion of Innovations Theory represents a foundational approach for explaining how, why, and at what pace individuals adopt new ideas, products, or technologies. Developed by Everett M. Rogers, the theory provides a comprehensive framework for understanding how an innovation spreads over time through specific communication channels among members of a social system (Rogers, 1962, 1995, 2003). Rather than conceptualizing adoption as an instantaneous or random decision, the theory frames it as a process shaped by individuals' perceptual evaluations and experiences, embedded within cognitive and social dynamics.

According to Rogers, the innovation adoption process consists of five sequential stages: knowledge, persuasion, decision, implementation, and confirmation. Throughout this process, individuals evaluate the information they acquire about an innovation in an effort to reduce uncertainty and to assess its suitability in relation to their own needs and circumstances (Rogers, 2003). This evaluative process becomes particularly intensive and multidimensional in the case of innovations characterized by high technical complexity and long-term consequences (Noel et al., 2019).

The theory identifies five key perceptual attributes that influence the rate and pattern of innovation adoption: relative advantage, compatibility, complexity, trialability, and observability (Rogers,

2003). Relative advantage refers to the extent to which an innovation is perceived as superior to existing alternatives, while compatibility denotes the degree to which it aligns with an individual's values, lifestyle, and prior experiences. Complexity reflects the perceived difficulty of understanding and using the innovation, whereas trialability captures the extent to which it can be tested on a limited basis, and observability refers to the visibility of the innovation's outcomes within a social context (Moore & Benbasat, 1991; Rezvani et al., 2015).

Technological and environmental innovations such as EVs constitute complex systems in which all of these perceptual attributes are activated simultaneously. Such innovations are not merely technical products but multidimensional technologies imbued with economic, environmental, and social meanings. Consequently, individuals' attitudes toward EVs are shaped not only by instrumental considerations such as cost and performance, but also by factors including usage experience, habits, symbolic meanings, and social visibility (Petschnig et al., 2014; Rezvani et al., 2015). While EVs offer clear advantages such as lower energy costs and environmental benefits, which correspond to relative advantage, they simultaneously evoke substantial perceptions of disadvantages and difficulty, particularly in relation to driving range, charging infrastructure, and uncertainties surrounding battery technology, which are closely associated with perceived complexity. In this respect, Diffusion of Innovations Theory diverges from linear perspectives commonly found in the literature by offering a flexible framework capable of explaining how an innovation may be perceived as both highly advantageous and highly complex at the same time. Crucially, the theory supports the premise that perceived benefits do not necessarily neutralize perceived risks; instead, they can coexist as independent perceptual dimensions during the active use phase.

One of the central contributions of Diffusion of Innovations Theory lies in its emphasis on the non-homogeneous nature of innovation perception and adoption. The theory acknowledges that different adopter profiles may coexist within a social system and posits that these differences emerge through variations in individuals' perceptual evaluations and experiential trajectories (Rogers, 2003). Unlike studies that assume a uniform transition from risk to trust, DOI Theory allows for the identification of post-adoption heterogeneity, where different user segments may prioritize different attributes of the EV ecosystem. Moreover, the theory recognizes that innovation diffusion is shaped not only by individual perceptions but also by the broader social environment and communication channels. While mass media play a prominent role during the awareness stage, interpersonal interactions are particularly influential during the persuasion and decision stages (Rogers, 1976). In this context, the degree to which an innovation is visible within the social environment and the extent to which it is associated with an individual's social identity, as captured by the concept of observability, constitute important components of the adoption process (Heffner et al., 2007; Moore and Benbasat, 1991).

Within this framework, Diffusion of Innovations Theory offers a comprehensive theoretical lens for examining active users' perceptions of EV technology by jointly addressing individual-level perceptions and social dynamics, rather than focusing solely on adoption intentions. The multi-layered conceptual structure provided by the theory enables perceived advantages and disadvantages to be assessed as simultaneous, non-mutually exclusive dimensions and facilitates a nuanced interpretation of perceptual heterogeneity among EV users (Plötz et al., 2014).

3 Literature review

Diffusion of Innovations Theory is one of the most frequently employed frameworks in the literature for understanding consumer dynamics related to technological innovations. Moore and Benbasat (1991) argue that the attributes identified by Rogers should be measured not in relation to the innovation itself, but rather through perceptions of "using the innovation," leading them to incorporate constructs such as perceived ease of use and voluntariness into scale development processes. In the context of EVs, motivational differences between "early adopters" and the "early majority" are particularly salient. Egbue and Long (2012) report that early adopters tend to be

technology-oriented individuals who focus primarily on technical attributes such as performance and cost rather than environmental benefits. Similarly, Jansson et al. (2017) emphasize the critical role of neighborhood effects and social networks in accelerating diffusion. According to Jansson et al. (2017), innovations spread through interpersonal interactions, and the presence of EV ownership within one's immediate social environment reduces uncertainty and increases the likelihood of adoption.

Consumers' perceptions of EVs are shaped by a complex interplay between rational benefits and emotional barriers. The literature suggests that instrumental, hedonic, and symbolic attributes jointly influence adoption intentions. Schuitema et al. (2013) argue that instrumental characteristics such as price and driving range are not sufficient on their own but gain significance when associated with emotional outcomes such as driving pleasure (hedonic) and identity construction (symbolic). In contrast, Egbue and Long (2012) demonstrate that although consumers frequently articulate environmental concerns, cost and performance considerations continue to outweigh sustainability in actual purchase decisions. With respect to barriers, Mesquita et al. (2025) identify insufficient charging infrastructure as the most influential obstacle through a systematic analysis, followed by high purchase costs and lack of information. Wang et al. (2017), drawing on evidence from Shenzhen, further complicate cost-centered interpretations by showing that the perceived technological advantages and infrastructure accessibility may outweigh the importance of direct financial incentives in sustaining long-term usage.

The paradox between the comfort offered by technology and the stress it generates is widely discussed in the EV literature through the concept of "range anxiety." While the conventional view assumes that anxiety diminishes with increased experience, empirical findings in the literature remain mixed. Franke et al. (2012) show that users perceive driving range not merely as a technical constraint but as a resource to be managed, leading them to develop a psychological buffer zone referred to as a "comfortable range." This finding aligns with Ostlund's (1974) assertion that perceived risk exerts a negative influence on innovative behavior. Adopting a more critical perspective, Noel et al. (2019) argue that range anxiety is not always rooted in technical or psychological fear but may instead function as a form of "reactionary rhetoric" employed by consumers to resist behavioral change. According to Noel et al. (2019), even when technical range is sufficient and charging infrastructure improves, users may continue to express irrational resistance through the "jeopardy thesis", providing a compelling theoretical explanation for why risk perceptions may persist even among experienced users who acknowledge the benefits of the technology.

In classifying EV users, perception- and attitude-based segmentation approaches have increasingly gained prominence over purely demographic classifications. Sierzchula et al. (2014) find that socio-economic factors such as financial incentives and charging infrastructure influence market share, whereas demographic variables such as education and income do not constitute significant predictors in cross-country comparisons. Javanmardi et al. (2023) establish a direct relationship between countries' Sustainable Development Goals index scores and EV market shares, demonstrating that nations with higher sustainability performance tend to occupy more advanced stages of adoption. Additionally, Jansson et al. (2017) segment users according to social interaction domains, including neighbors, family members, and coworkers, and identify neighborhood effects as a stronger predictor of adoption than family or workplace influences.

Emerging markets are typically characterized by infrastructural and economic constraints in the context of EV adoption. Focusing on Turkey, Bektaş and Akyıldız Alçura (2024), employing the Technology Acceptance Model, examine adoption intentions among Turkish users and find that social norms and image exert direct effects on usage intention, while perceived compatibility remains low due to charging and range-related challenges. They further note that although tax reductions exist for EVs in Turkey, direct purchase subsidies comparable to those offered in several European Union countries (e.g., Germany and France) are absent, highlighting limitations in economic incentives. These findings parallel the barriers identified by Manjula et al. (2022) in the

Indian context, particularly insufficient infrastructure and high initial purchase costs. In both markets, potential users demonstrate environmental awareness yet postpone adoption due to prevailing economic and technical constraints.

Taken together, the existing literature offers a comprehensive examination of EV adoption by incorporating a wide range of variables, including perceived benefits, barriers, and social influences. However, these factors are often treated as opposing or compensatory constructs, resting on an implicit assumption that increasing perceived advantages will attenuate perceived risks and barriers. Evidence related to range anxiety, infrastructural limitations, and technological uncertainty suggests that, particularly among experienced users, risk perceptions may persist throughout the usage process and may even intensify under certain conditions. Despite this, empirical investigations into how perceived advantages and disadvantages coexist simultaneously among active EV users and how these perceptions cluster into distinct user profiles remain limited. The tendency to neglect the perceptual tensions arising from interactions between perceived benefits and perceived risks within a holistic framework points to a significant research gap. More importantly, prior research has largely focused on pre-adoption intentions, leaving post-adoption perceptual coexistence and segmentation among verified active users—the crucial 'confirmation' stage of the diffusion process—insufficiently explored.

4 Materials and methods

The population of this study consists of individuals residing in Turkey's Marmara Region who actively use EVs. Data collection was conducted during the first half of 2025. The sample comprises 160 individuals who are confirmed EV owners with at least one year of active usage experience. Participants were selected using purposive sampling, a strategy aligned with the study's objective of examining post-adoption perceptions and experience-based evaluations rather than adoption intentions alone.

Given the absence of publicly accessible sampling frames for verified EV users, purposive sampling represents an appropriate strategy for reaching experienced users and obtaining high-quality, experience-based evaluations. While the sample size is framed by the challenges of reaching a verified and specific user population, it was selected to enable the implementation of segmentation analyses aimed at examining perceptual heterogeneity rather than population-wide estimation. Accordingly, the aim of the study is analytical generalization and theory-informed insight generation—consistent with the exploratory nature of post-adoption studies—rather than statistical representativeness. Within this framework, the data collection process was administered by a professional survey organization utilizing randomized selection procedures within consumer panels. To ensure alignment with our purposive sampling criteria, a mandatory screening question was placed at the beginning of the survey; any respondent who did not meet the criteria for active EV ownership was automatically terminated. This screening ensured that all participants were actual EV owners.

Data were collected using a structured, scaled questionnaire developed on the basis of existing literature. The questionnaire includes items measuring participants' basic socio-demographic characteristics and EV usage patterns, as well as items designed to capture perceived advantages and perceived disadvantages. In line with the theoretical framework of this study, perceived advantages are operationalized as the potential benefits identified by users, while perceived disadvantages capture the technical and infrastructural risks associated with sustained EV use. Socio-demographic variables (age, gender, education level, and income level) and indicators of usage experience (duration of use and annual mileage) were incorporated as control variables. Items measuring perceived advantages and disadvantages were assessed using a five-point Likert-type scale ranging from 1 ("Strongly disagree") to 5 ("Strongly agree"). Specifically, the 15-item advantage scale was presented under Question 15 (Q15) with the prompt: "Which features of the electric vehicle you use are more advantageous than gasoline vehicles? Please rate the following statements from 1 (Strongly Disagree) to 5 (Strongly Agree)." Conversely, the 14-item disadvantage

scale was introduced under Question 16 (Q16) with the prompt: "Which features of the electric vehicle you use are more disadvantageous than gasoline vehicles? Please rate the following statements from 1 (Strongly Disagree) to 5 (Strongly Agree)." Prior to the main analyses, the internal consistency of the scales was evaluated using Cronbach's alpha coefficients. As shown in Table 1, both scales exceed the commonly accepted threshold of 0.70, supporting their suitability for subsequent analyses.

Table 1. Cronbach's alpha reliability results

Scale	Cronbach's Alpha
Perceived Advantages Scale	0.841
Perceived Disadvantages Scale	0.791

To establish a comprehensive baseline for user perceptions, the exact formulations, overall sample means, and standard deviations of all individual advantage and disadvantage items are detailed in Appendix A (see Table A1). These baseline descriptive statistics are presented to provide an essential contextual background to understand the overall sample's perceptual tendency before proceeding with the subsequent multivariate analyses.

In line with the theoretical framework, the study followed a three-stage analytical strategy. In the first stage, Exploratory Factor Analysis (EFA) was conducted to assess the construct validity of the items measuring perceived advantages and disadvantages and to reduce the dataset into meaningful latent variables. This analysis was based on the assumption that perceived benefits and risks do not constitute a single-dimensional structure. Accordingly, and drawing on the premise that advantage and disadvantage scales represent theoretically distinct perceptual domains that users evaluate through separate cognitive processes, factor analyses were conducted independently for each scale. This approach allows perceived benefits and risks to be examined as simultaneous yet relatively independent constructs. Within the scope of the Exploratory Factor Analysis, Principal Component Analysis (PCA) was employed as the factor extraction method to identify latent structures and to generate inputs for the subsequent clustering analysis. To enhance factor interpretability and achieve a clearer separation between factors, Varimax orthogonal rotation was applied. The factorability of the dataset was assessed using the Kaiser–Meyer–Olkin (KMO) measure of sampling adequacy, while the suitability of the data for factor analysis was evaluated using Bartlett's Test of Sphericity.

In the second stage, Cluster Analysis was performed using standardized factor scores obtained from the factor analysis as input variables, allowing users to be grouped into homogeneous clusters. This approach aims to reveal user heterogeneity based on perceptual differences, in contrast to the frequently assumed notion of a uniform user profile in the literature. A two-step clustering procedure was adopted. First, Hierarchical Cluster Analysis was conducted using Ward's method and Squared Euclidean Distance to determine the appropriate number of clusters, and the resulting dendrogram was examined. Based on this assessment, the optimal number of clusters was identified as three ($k = 3$). Subsequently, the final segmentation was achieved using the K-means clustering technique.

In the third and final stage, One-Way Analysis of Variance (ANOVA) was employed for continuous variables, and the Chi-square Test of Independence was applied for categorical variables to examine whether the identified user clusters differed significantly in terms of demographic and socio-economic characteristics. This stage enables an assessment of how perceptual segmentation relates to experience-based and socio-economic factors rather than being driven solely by demographic attributes.

5 Empirical findings

5.1 Identification of perceptual dimensions: Factor analysis results

The results of the factor analyses conducted to identify the latent variables underlying EV users' perceptions are presented in Tables 2 and 3. The Kaiser–Meyer–Olkin (KMO) measure of sampling adequacy was calculated as 0.788 for the perceived advantages scale and 0.664 for the perceived disadvantages scale, while Bartlett's Test of Sphericity was statistically significant for both. The analyses yielded four-factor structures for each scale, explaining 63.28% and 66.30% of the total variance, respectively. These rates exceed commonly accepted thresholds, confirming the multidimensional nature of post-adoption evaluations.

Prior to evaluating the specific items, the internal consistency of each individual subdimension was systematically examined. As detailed in Table 2 and Table 3, the Cronbach's alpha coefficients range from 0.613 to 0.876 for the perceived advantages, and from 0.638 to 0.848 for the perceived disadvantages. While a few localized subdimensions exhibit alpha values below the conventional 0.70 threshold, these metrics are generally considered acceptable in exploratory research contexts (Hair et al., 2019). Consequently, the extracted factor structures demonstrate sufficient structural reliability for the subsequent multivariate analyses.

Table 2. Perceived advantages scale: Factor loadings and factor structure

Factor dimensions/ items	Factor loading	Eigenvalue	Variance explained	Cronbach's alpha
Factor 1: Structural and design advantages		5.024	33.49%	0.876
Q15.13. Absence of size/dimension-related problems	0.843			
Q15.11. Compatibility with smartphones and mobile applications	0.819			
Q15.12. Distinctive appearance	0.809			
Q15.6. Availability of designated parking spaces	0.800			
Q15.8. Absence of a gearbox	0.702			
Q15.7. Easy access to low-emission zones	0.559			
Factor 2: Performance and incentives		1.888	12.59%	0.692
Q15.14. Low periodic maintenance costs	0.794			
Q15.10. Rapid acceleration	0.742			
Q15.15. Tax incentives	0.593			
Q15.9. Being at the forefront of new technologies	0.535			
Factor 3: Environmental sustainability and comfort		1.453	9.69%	0.642
Q15.2. Environmentally friendly	0.776			
Q15.5. Comfortable driving and reduced noise levels	0.682			
Q15.1. Low energy costs	0.553			
Factor 4: Accessibility and charging convenience		1.126	%7.51	0.613
Q15.3. Home charging capability	0.757			
Q.15.4. Ease of parking	0.652			
Total variance explained			63.28%	
KMO / Bartlett's test (sig.)			0.788 / 0.000	

The factor analysis results indicate that advantages evaluations are structured across four distinct dimensions: (1) Structural and design advantages; (2) Performance and incentives; (3) Environmental sustainability and comfort; and (4) Accessibility and charging convenience. Similarly, perceived disadvantages are categorized into: (1) Range and infrastructure constraints; (2) Driving experience and sensory limitations; (3) Battery technology and safety; and (4) Economic and technological uncertainty. These findings provide empirical evidence that EV evaluations

cannot be captured by a single-dimensional benefit–risk trade-off; instead, these dimensions coexist simultaneously in the user's cognitive map.

Table 3. Perceived disadvantages scale: Factor loadings and factor structure

Factor dimensions/ items	Factor loading	Eigenvalue	Variance explained	Cronbach's alpha
Factor 1: Range and infrastructure constraints		3.815	27.25%	0.783
Q16.3. Long charging time	0.832			
Q16.4. Limited availability of charging stations	0.788			
Q16.2. Limited driving range	0.776			
Factor 2: Driving experience and sensory limitations		2.549	18.21%	0.770
Q16.10. Absence of a manual transmission	0.772			
Q16.9. Reduced driving enjoyment due to low engine noise	0.754			
Q16.8. Potential safety risks for pedestrians due to vehicle quietness	0.733			
Q16.11. Unconventional design and appearance	0.709			
Factor 3: Battery technology and safety		1.758	12.56%	0.848
Q16.13. Insufficient battery lifespan	0.915			
Q16.14. High battery replacement costs	0.896			
Q16.12. Safety concerns	0.715			
Factor 4: Economic and technological uncertainty		1.160	8.29%	0.638
Q16.6. Uncertainties associated with the use of new technology	0.734			
Q16.7. Acceleration-related concerns	0.642			
Q16.1. High purchase prices	0.604			
Q16.5. Limited service and spare parts support	0.512			
Total variance explained			66.30%	
KMO / Bartlett's test (sig.)			0.664 / 0.000	

To examine how these perceptual dimensions interact across the entire sample before performing market segmentation, a bivariate Pearson correlation analysis was conducted across the calculated factor scores (N=160). The resulting baseline correlation matrix is presented in Table 4.

Table 4. Pearson correlation matrix between perceived advantage and disadvantage factor scores

Factors	adv. factor 1	adv. factor 2	adv. factor 3	adv. factor 4	disadv. factor 1	disadv. factor 2	disadv. factor 3	disadv. factor 4
adv. factor 1	-							
adv. factor 2	0.000	-						
adv. factor 3	0.000	0.000	-					
adv. factor 4	0.000	0.000	0.000	-				
disadv. factor 1	0.071 (0.374)	-0.018 (0.817)	-0.078 (0.327)	0.141 (0.076)	-			
disadv. factor 2	0.070 (0.380)	-0.175* (0.027)	-0.073 (0.362)	0.297** (0.001)	0.000	-		
disadv. factor 3	-0.223** (0.005)	0.047 (0.553)	0.090 (0.256)	0.063 (0.432)	0.000	0.000	-	
disadv. factor 4	0.002 (0.982)	-0.564** (0.001)	-0.070 (0.377)	0.057 (0.477)	0.000	0.000	0.000	-

* Note: (i) p-values (Sig. 2-tailed) are provided in parentheses. (ii) ** p<0.01, * p<0.05

According to Table 4, the sample exhibits patterns consistent with a conventional inverse benefit-risk relationship between specific factors. A strong negative correlation is observed between Performance and Incentives (adv. factor 2) and Economic and Technological Uncertainty (disadv. factor 4), alongside a significant negative relationship between Structural and Design Advantages (adv. factor 1) and Battery Technology and Safety (disadv. factor 3). These correlations indicate that for the aggregated consumer baseline, higher perceived advantages systematically mask or suppress perceived risks, operating in line with the traditional affect heuristic framework. However, while this overarching baseline suggests a uniform inverse relationship, relying solely on sample-wide correlations carries the risk of masking localized consumer realities by implicitly assuming a homogeneous market structure. Therefore, these baseline correlation findings directly demonstrate the necessity of a cluster-based segmentation approach to uncover potential structural heterogeneity within the dataset, which is explored in the following section.

5.2 User segmentation: Cluster analysis results

To identify distinct consumer profiles based on the extracted perception dimensions, a hierarchical cluster analysis was performed. In line with established transport and consumer behavior literature, the segmentation was executed using the standardized factor scores derived from the exploratory factor analysis—a methodology widely formalized as the factor-cluster segmentation approach (Punj & Stewart, 1983; Wedel & Kamakura, 2000). Utilizing orthogonal, standardized factor scores rather than raw summated scales offers distinct methodological advantages; it effectively mitigates potential multicollinearity among multi-item scales, controls for individual response style biases, and ensures that the subsequent clustering algorithm operates on mutually independent dimensions. To establish the methodological framework for the optimal partition, the statistical progression within the agglomeration schedule coefficients was systematically evaluated (see Table B1 in Appendix B). Across the final stages of the hierarchical sequence (Ward's method), the agglomeration coefficients progressed from 972.808 at Stage 156 (4-cluster solution) to 1064.032 at Stage 157 (3-cluster solution, representing a 9.37% increase), and reached 1160.343 at Stage 158 (2-cluster solution, representing a 9.05% increase). This consistent variance structure indicates that a three-cluster solution (k = 3) provides the most appropriate stopping point for the dataset. Systematically testing an alternative two-cluster model forced the distinct micro-segments (n = 21 and n = 9) to artificially dissolve into the majority, reducing critical empirical granularity. Conversely, a four-cluster model merely fragmented the large pragmatic cluster (n = 130) into statistically redundant sub-groups with identical mean structures. Consequently, the three-cluster structure was retained as it statistically balances within-cluster homogeneity and between-cluster variance. The final cluster centers (Z-scores) resulting from this partition are presented in Table 5.

Table 5. Final cluster centers (z-scores) and segment definitions

Factor dimensions	Cluster 1 Comfort-oriented satisfied users (n = 21)	Cluster 2 Performance-oriented users with high perceived technical risk (n = 9)	Cluster 3 Cautious pragmatic users (n = 130)
Perceived advantages			
Structural and design advantages	-0.036	-2.224	0.159
Performance and incentives	-0.034	1.212	-0.078
Environmental sustainability and comfort	0.611	0.188	-0.111
Accessibility and charging convenience	-1.150	0.261	0.167
Perceived disadvantages			
Range and infrastructure constraints	-1.243	-0.256	0.218
Driving experience and sensory limitations	-0.944	-0.402	0.180
Battery technology and safety	0.295	1.286	-0.136
Economic and technological uncertainty	0.029	-1.639	0.108

While the cluster analysis was executed using standardized factor scores (Z-scores) to maintain methodological rigor and to minimize the distorting influence of outliers on the distance metrics (Punj & Stewart, 1983), the final segments were cross-examined against the original 5-point Likert scale metrics via post-hoc mean comparisons. To maximize interpretability and facilitate a direct evaluation in terms of the original scale levels, the mean scores for each finalized cluster across all individual items have been integrated into the master matrix provided in Appendix A (see Table A1). A baseline examination of these original metrics indicates that high overall sample means for primary advantages (such as low energy costs and environmental friendliness) coexist with equally elevated scores for systemic barriers (such as charging infrastructure limits and long charging times). Furthermore, this post-hoc profiling demonstrates that the micro-segments (Cluster 1 and Cluster 2) exhibit distinct, noteworthy leanings toward technical innovation and specific risk thresholds compared to the pragmatic majority in Cluster 3, thereby reflecting the baseline descriptive picture suggested by the aggregated data. When we examine Table 5, the first cluster, Comfort-oriented satisfied users (n=21), exhibits high positive scores for environmental sustainability and comfort while showing the lowest negative scores for range and infrastructure constraints. This profile reflects a high level of compatibility within Rogers' framework, where the technology is experienced as a seamless comfort space rather than a problem domain.

The second cluster, Performance-oriented users with high perceived technical risk (n=9), represents a crucial finding. Although numerically small, this group is distinguished by its internal homogeneity and qualitative significance. In line with Rogers' (2003) description of an "elite minority" of innovators, this group evaluates performance very positively while simultaneously exhibiting the highest levels of perceived risk regarding battery technology and safety. This finding directly challenges the affect heuristic assumption that benefits and risks are inversely related, suggesting that high technical awareness may intensify sensitivity to technological risks.

The third cluster, Cautious pragmatic users (n=130), constitutes the majority of the sample. Notably, this is the only group with positive scores for range and infrastructure constraints, indicating that despite high adoption, infrastructural limitations remain a salient and persistent barrier for the "silent majority" of active users.

When these cluster-specific structures are cross-examined against the aggregate baseline correlation results presented earlier in Table 4, the critical importance of uncovering market heterogeneity becomes empirically evident. Although the sample-wide correlation analysis indicated an inverse relationship between advantages and disadvantages, partitioning the data via cluster analysis reveals that consumer perceptions are not uniform. Specifically, Cluster 2 operates as a localized empirical exception that directly contradicts the aggregate pattern. While the broad sample evaluates EVs through an inverse lens where benefits suppress risks, this micro-segment of technical innovators exhibits a boundary condition where high technical awareness allows strong performance appreciation to coexist with acute technical risk sensitivities. Consequently, these findings confirm that generalizing a uniform 'high benefit equals low risk' heuristic across all users is conceptually inadequate; consumer profiles are structurally heterogeneous, and dedicated cluster-based segmentation is critical to capture the true granularity of emerging technology markets.

5.3 Demographic and socio-economic profiling

To examine the differences across segments, ANOVA and Chi-square tests were conducted (see Table 6).

Table 6. Profiling of clusters based on demographic and usage characteristics

Variables	Subcategories/ unit	Cluster 1 Comfort-oriented satisfied users	Cluster 2 Performance-oriented users with high perceived technical risk	Cluster 3 Cautious pragmatic users	Test statistic	p-value
Sample distribution	n (%)	21 (13.1%)	9 (5.6%)	130 (81.3%)		
Driving experience	Years (Mean)	4.14	4.11	4.85	F=4.740	0.010**
Annual mileage	Thousand km (Mean)	11.38	15.56	13.05	F=2.624	0.076*
Age	Years (Mean)	41.14	44.44	42.72	F=0.909	0.405
Education level	High school or below	14.3%	4.1%	81.6%		
	Associate / Bachelor's	26.6%	4.1%	85.1%	χ^2=29.381	0.001***
	Master's / PhD	44.4%	61.1%	94.5%		
Monthly income	Below 50,000 TL	25%	0%	75%	χ^2=34.240	0.000***
	50.001 – 100.000	11.6%	0%	88.4%		
	100,001 TL and above	16.2%	58.8%	54%		
Gender	Female	17.2%	0%	82.8%	χ^2=2.460	0.292
	Male	12.2%	6.9%	80.9%		

* Notes: (i) ***, **, and * indicate significance levels at 0.01, 0.05, and 0.10, respectively. (ii) Percentages represent the proportion of each category within the respective cluster. (iii) TL stands for Turkish Lira.

The results indicate that driving experience and socio-economic variables, rather than age or gender, are the primary drivers of perceptual differentiation. Cautious pragmatic users have the highest level of usage experience (mean = 4.85 years). This contradicts the common expectation that anxiety diminishes with experience, suggesting instead that prolonged use leads to a more realistic and cautious stance toward infrastructure gaps. Education and income emerged as the most powerful discriminators. The high-risk, performance-oriented cluster (Cluster 2) is characterized by significantly higher education and income levels. This demonstrates that higher socio-economic status and technical knowledge do not eliminate risk perceptions; rather, they may deepen the awareness of underlying technological uncertainties.

6 Discussion

The structuring of perceived advantages around performance, environmental sustainability, comfort, and structural/design-related attributes aligns directly with the concept of relative advantage, which occupies a central position in Diffusion of Innovations Theory (Rogers, 1962). The fact that EVs generate value not only through instrumental attributes such as lower energy costs but also through hedonic and symbolic features such as driving comfort and technological pioneering indicates that users evaluate the innovation in a multidimensional manner. Moreover, the inclusion of elements such as distinctive design and social visibility among perceived advantages strengthens the relevance of observability, referring to the extent to which an innovation's outcomes are visible within the social environment (Rogers, 2003). This interpretation is consistent with scholarship positioning EVs not merely as an individual transportation choice but also as a consumption practice connected to social identity and image (Heffner et al., 2007; Moore & Benbasat, 1991). In this sense, debates on EV adoption have highlighted the layered interaction between instrumental benefits and emotional and symbolic dimensions, and the present findings provide support for this framework at the critical "confirmation" stage of active use (Egbue & Long, 2012; Schuitema et al., 2013).

Prominent disadvantage perceptions, particularly those related to driving range, charging infrastructure, and uncertainties surrounding battery technology, can be interpreted through the theoretical dimensions of complexity and compatibility. Factors such as charging duration and infrastructure access increase perceived complexity by making the use of the innovation more demanding both practically and cognitively. The characterization of inadequate charging

infrastructure as one of the most influential barriers in the literature (Mesquita et al., 2025) supports the view that this perception reflects a structural constraint rather than one that is contingent solely on individual experience. Furthermore, evidence suggesting that users perceive driving range not only as a technical limit but as a resource to be actively managed (Franke et al., 2012) implies that range-related concerns may persist throughout the usage process. In addition, scholarship has argued that range anxiety can evolve into a discourse used to resist behavioral change, providing an explanation for why certain risk perceptions may remain durable despite increasing experience (Noel et al., 2019). Sensory limitations related to driving experience (e.g., the absence of engine noise) raise compatibility-related issues by highlighting the extent to which the innovation aligns with prior habits and established routines, indicating that features that diverge from familiar practices may challenge the continuity of adoption (Rogers, 2003). Taken together, these findings indicate that infrastructure- and range-related constraints remain salient even among active and experienced users and that such perceptions should not be treated as transient barriers limited to early adopters.

The perception-based segmentation results provide empirical support for the user heterogeneity anticipated by Diffusion of Innovations Theory. In particular, the cluster labeled "performance-oriented users with high perceived technical risk" exhibits both the highest perceived performance and the highest perceived technical risk, indicating that the assumption that risk perceptions decline as perceived benefits increase does not hold for users with relatively high levels of technical knowledge. The affect heuristic framework posits that benefit and risk evaluations may be inversely related, especially in pre-adoption contexts or under limited experience (Alhakami & Slovic, 1994; Finucane et al., 2000). By contrast, within the logic of Diffusion of Innovations Theory, increasing experience and knowledge may enable users to differentiate among distinct attributes of an innovation and to hold high perceived benefits and high perceived risks simultaneously. The higher income and education levels observed in the performance-oriented, high-risk cluster further suggest that socio-economic advantages do not eliminate risk perceptions; rather, they may deepen awareness of technological risks. Conversely, the presence of the cautious pragmatic profile, which constitutes the majority of the sample, indicates a silent majority within the user base that remains sensitive to infrastructural constraints. The more pronounced perception of range and infrastructure limitations within this cluster offers a clear explanation for why investments in charging infrastructure remain critical for scaling EV diffusion (Mesquita et al., 2025).

More broadly, the findings can be better understood when viewed alongside perspectives emphasizing that diffusion processes are shaped not only by individual evaluations but also by social environments and interpersonal interactions (Jansson et al., 2017; Rogers, 1976). The results indicate that benefit and risk perceptions among EV users do not operate as mutually neutralizing opposites; rather, they function as simultaneous and relatively independent perceptual dimensions. In this respect, the study provides original empirical evidence contributing to the literature on how Diffusion of Innovations Theory operates within the context of EVs. The findings suggest that adoption continuity depends not only on increasing perceived benefits but also on how risk and uncertainty perceptions are managed, and they indicate that perception- and experience-based segmentation offers a stronger explanatory lens for user behavior than demographic variables alone.

From a transport policy perspective, these findings suggest that the diffusion of EVs cannot be effectively supported through one-size-fits-all policy instruments. Instead, the presence of distinct perceptual segments highlights the need for differentiated and coordinated policy approaches. For example, while infrastructure expansion may address the needs of the pragmatic majority, technological risk perceptions among performance-oriented users may require targeted warranty mechanisms and more transparent technical communication. Overall, the results underscore the value of perception-based segmentation as an analytical lens for informing segment-specific mobility interventions, offering transferable insights for European urban contexts where increasing user heterogeneity and ongoing socio-technical transitions shape the dynamics of EV diffusion.

7 Conclusion

This study examined the multidimensional structure of perceived advantages and disadvantages among active EV users in Turkey's Marmara Region during the first half of 2025 and developed a user segmentation based on these perceptions. The findings demonstrate that EV users do not constitute a homogeneous group; rather, distinct user profiles emerge through meaningful differentiation based on simultaneous evaluations of perceived advantages and disadvantages. The findings suggest that EV adoption cannot be explained solely through technical adequacy or economic rationality. Instead, adoption is a complex, non-linear process shaped by the joint functioning of individual perceptions, usage experience, and the broader socio-technical context. By focusing on post-adoption users, the study highlights that perceptual dynamics continue to evolve beyond the initial adoption decision—specifically within the "confirmation" stage of Rogers' model—and play a critical role in sustained diffusion.

From a practical and policy perspective, the findings indicate that uniform, "one-size-fits-all" strategies are unlikely to effectively accelerate EV diffusion in contexts characterized by perceptual heterogeneity. The coexistence of high perceived benefits and high perceived risks, particularly evident among performance-oriented users who exhibit high levels of technical risk sensitivity, indicates that enhancing perceived advantages alone is insufficient for alleviating uncertainty and risk-related concerns. Accordingly, policymakers should consider that improvements in performance, incentives, or accessibility do not automatically reduce EV users' perceptions of disadvantages. Crucially, while aggregate baseline correlations across the entire sample point toward an inverse relationship between specific factors of benefits and risks, the subsequent consumer segmentation exposes critical boundary conditions. The presence of tech-oriented users who simultaneously hold intense performance satisfaction and risk sensitivities demonstrates that sample-wide averages can mask hidden consumer heterogeneities, underscoring the necessity of cluster-based granular approaches in emerging technology markets.

Based on the derived user segments, this study proposes a coordinated policy framework. While continued investment in charging infrastructure remains critical for addressing the persistent concerns of cautious pragmatic users, targeted measures such as transparent information provision, strengthened warranty and battery assurance mechanisms, and long-term reliability guarantees are necessary to mitigate technical risk perceptions among highly informed and socio-economically advantaged users. These results indicate that infrastructure expansion and uncertainty-reducing measures should be designed as complementary rather than substitute policy instruments. Strategies that enhance the social visibility (observability) and symbolic value of EVs (e.g., priority parking or access to low-emission zones) can reinforce adoption stability without assuming a trade-off with risk perceptions. Overall, the results underscore the importance of multi-component and segment-sensitive policy designs that acknowledge the non-mutually exclusive nature of benefit and risk perceptions.

While the empirical setting is Turkey's Marmara Region, the identified segmentation offers transferable insights for European urban contexts facing similar socio-technical transition challenges. As European regions move beyond the initial adoption phase toward a mass-market expansion, understanding the perceptual tensions of the 'silent majority' (cautious pragmatics) and the 'informed skeptics' (performance-oriented/high-risk) becomes essential for achieving long-term decarbonization targets. In this respect, the study contributes to the sustainable transport policy literature by demonstrating how perception-based segmentation can inform more targeted and behaviorally grounded electrification strategies necessary for a sustainable mobility transition.

This study has several limitations. Notably, its reliance on cross-sectional data represents a significant constraint, as it does not allow for the examination of changes in perceptions over time. In addition, although the three-cluster partition is methodologically justified by the agglomeration schedule progression, the relatively small sample sizes within Cluster 1 and Cluster 2 represent an additional inherent constraint. Although these highly homogeneous micro-segments provide noteworthy empirical granularity regarding technical innovators and specific consumer boundary

conditions, the low number of participants restricts the statistical generalizability and stability of the reported cluster centers. Future research should examine the evolution of perceptions through longitudinal designs with expanded sample sizes across diverse geographic contexts, focusing specifically on how these simultaneous evaluations stabilize over time as the market transitions from early technological adopters to the broader mass consumer market.

Funding

This research was supported by Bursa Uludağ University Scientific Research Projects Coordination Unit through a General Research Project (Project Code: SGA-2024-1513). The funder had no role in the design of the study, in the collection, analysis, or interpretation of data, or in the writing of the manuscript. Data collection was conducted by an independent survey company as a paid service, and all data analysis and interpretation were performed by the authors.

Data Access Statement

The data that support the findings of this study are not publicly available due to privacy and ethical restrictions involving human participants but are available from the corresponding author upon reasonable request.

Author and Contributor Statement

Ecem Ozkan: Conceptualization; Investigation; Writing – original draft; Data Curation; Formal Analysis; Methodology. Arda Gurus: Investigation; Writing – original draft.

Ethical approval

This study was conducted in accordance with ethical standards and was approved by the Social and Human Sciences Research and Publication Ethics Committee of Bursa Uludağ University (Decision No: 59, Session: 2023-04, Date: 28 April 2023).

Use of AI

During the preparation of this work, the authors did not use AI.

Conflict Of Interest (COI)

There is no conflict of interest.

References

Adnan, N., Nordin, S. M., & Rahman, I. (2017). Adoption of PHEV/EV in Malaysia: A critical review on predicting consumer behaviour. *Renewable and Sustainable Energy Reviews*, *72*, 849–862. https://doi.org/10.1016/j.rser.2017.01.121

Alhakami, A. S., & Slovic, P. (1994). A psychological study of the inverse relationship between perceived risk and perceived benefit. *Risk Analysis*, *14*(6), 1085–1096. https://doi.org/10.1111/j.1539-6924.1994.tb00080.x

Bektaş, B. C., & Akyıldız Alçura, G. (2024). Understanding electric vehicle adoption in Türkiye: Analyzing user motivations through the technology acceptance model. *Sustainability*, *16*(21), Article 9439. https://doi.org/10.3390/su16219439

Egbue, O., & Long, S. (2012). Barriers to widespread adoption of electric vehicles: An analysis of consumer attitudes and perceptions. *Energy Policy*, *48*, 717–729. https://doi.org/10.1016/j.enpol.2012.06.009

Finucane, M. L., Alhakami, A., Slovic, P., & Johnson, S. M. (2000). The affect heuristic in judgments of risks and benefits. *Journal of Behavioral Decision Making*, *13*(1), 1–17. https://doi.org/10.1002/(SICI)1099-0771(200001/03)13:1<1::AID-BDM333>3.0.CO;2-S

Franke, T., Neumann, I., Bühler, F., Cocron, P., & Krems, J. F. (2012). Experiencing Range in an electric vehicle: Understanding psychological barriers. *Applied Psychology*, *61*(3), 368–391. https://doi.org/10.1111/j.1464-0597.2011.00474.x

Hair, J. F., Jr., Black, W. C., Babin, B. J., & Anderson, R. E. (2019). *Multivariate data analysis* (8th ed.). Cengage Learning.

Heffner, R. R., Kurani, K. S., & Turrentine, T. S. (2007). Symbolism in California's early market for hybrid electric vehicles. *Transportation Research Part D: Transport and Environment*, *12*(6), 396–413. https://doi.org/10.1016/j.trd.2007.04.003

Jansson, J., Pettersson, T., Mannberg, A., Brännlund, R., & Lindgren, U. (2017). Adoption of alternative fuel vehicles: Influence from neighbors, family and coworkers. *Transportation Research Part D: Transport and Environment*, *54*, 61–73. https://doi.org/10.1016/j.trd.2017.04.012

Javanmardi, E., Hoque, M., Tauheed, A., & Umar, M. (2023). Evaluating the factors affecting electric vehicles adoption considering the sustainable development level. *World Electric Vehicle Journal*, *14*(5), Article 120. https://doi.org/10.3390/wevj14050120

Liao, F., Molin, E., & van Wee, B. (2017). Consumer preferences for electric vehicles: A literature review. *Transport Reviews*, *37*(3), 252–275. https://doi.org/10.1080/01441647.2016.1230794

Loewenstein, G. F., Weber, E. U., Hsee, C. K., & Welch, N. (2001). Risk as feelings. *Psychological Bulletin*, *127*(2), 267–286. https://doi.org/10.1037/0033-2909.127.2.267

Manjula. B. C, Shilpa. B. S, & Sundaresh. M. (2022). A study on barriers to adoption of electric vehicles. *East Asian Journal of Multidisciplinary Research*, *1*(7), 1303–1316. https://doi.org/10.55927/eajmr.v1i7.802

Mesquita, A. R., de Abreu, V. H. S., Poyares, C. N., & Santos, A. S. (2025). Barriers to electric vehicle adoption: A framework to accelerate the transition to sustainable mobility. *Sustainability*, *17*(18), Article 8318. https://doi.org/10.3390/su17188318

Moore, G. C., & Benbasat, I. (1991). Development of an instrument to measure the perceptions of adopting an information technology innovation. *Information Systems Research*, *2*(3), 192–222. https://doi.org/10.1287/isre.2.3.192

Noel, L., Zarazua de Rubens, G., Sovacool, B. K., & Kester, J. (2019). Fear and loathing of electric vehicles: The reactionary rhetoric of range anxiety. *Energy Research & Social Science*, *48*, 96–107. https://doi.org/10.1016/j.erss.2018.10.001

Ostlund, L. E. (1974). Perceived innovation attributes as predictors of innovativeness. *Journal of Consumer Research*, *1*(2), 23–29. https://www.jstor.org/stable/2489103

Petschnig, M., Heidenreich, S., & Spieth, P. (2014). Innovative alternatives take action – Investigating determinants of alternative fuel vehicle adoption. *Transportation Research Part A: Policy and Practice*, *61*, 68–83. https://doi.org/10.1016/j.tra.2014.01.001

Plötz, P., Schneider, U., Globisch, J., & Dütschke, E. (2014). Who will buy electric vehicles? Identifying early adopters in Germany. *Transportation Research Part A: Policy and Practice*, *67*, 96–109. https://doi.org/10.1016/j.tra.2014.06.006

Punj, G., & Stewart, D. W. (1983). Cluster analysis in marketing research: Review and suggestions for application. *Journal of Marketing Research,* *20*(2), 134–148. https://doi.org/10.1177/002224378302000204

Rezvani, Z., Jansson, J., & Bodin, J. (2015). Advances in consumer electric vehicle adoption research: A review and research agenda. *Transportation Research Part D: Transport and Environment*, *34*, 122–136. https://doi.org/10.1016/j.trd.2014.10.010

Rogers, E. M. (1962). *Diffusion of Innovations*. The Free Press.

Rogers, E. M. (1976). New product adoption and diffusion. *Journal of Consumer Research*, *2*(4), 290-301. https://doi.org/10.1086/208642

Rogers, E. M. (1995). *Diffusion of Innovations* (4th ed.). The Free Press.

Rogers, E. M. (2003). *Diffusion of Innovations* (5th ed.). The Free Press.

Sang, Y.-N., & Bekhet, H. A. (2015). Modelling electric vehicle usage intentions: An empirical study in Malaysia. *Journal of Cleaner Production*, *92*, 75–83. https://doi.org/10.1016/j.jclepro.2014.12.045

Schuitema, G., Anable, J., Skippon, S., & Kinnear, N. (2013). The role of instrumental, hedonic and symbolic attributes in the intention to adopt electric vehicles. *Transportation Research Part A: Policy and Practice*, *48*, 39–49. https://doi.org/10.1016/j.tra.2012.10.004

Sierzchula, W., Bakker, S., Maat, K., & van Wee, B. (2014). The influence of financial incentives and other socio-economic factors on electric vehicle adoption. *Energy Policy*, *68*, 183–194. https://doi.org/10.1016/j.enpol.2014.01.043

Singh, V., Singh, V., & Vaibhav, S. (2020). A review and simple meta-analysis of factors influencing adoption of electric vehicles. *Transportation Research Part D: Transport and Environment*, *86*, Article 102436. https://doi.org/10.1016/j.trd.2020.102436

Slovic, P., Finucane, M. L., Peters, E., & MacGregor, D. G. (2007). The affect heuristic. *European Journal of Operational Research*, *177*(3), 1333–1352. https://doi.org/10.1016/j.ejor.2005.04.006

Wang, F.-P., Yu, J.-L., Yang, P., Miao, L.-X., & Ye, B. (2017). Analysis of the barriers to widespread adoption of electric vehicles in Shenzhen China. *Sustainability*, *9*(4), Article 522. https://doi.org/10.3390/su9040522

Wedel, M., & Kamakura, W. A. (2000). Market segmentation: Conceptual and methodological foundations (2nd ed.). Springer. https://doi.org/10.1007/978-1-4615-4651-1

Appendix A

Table A1. Integrated individual item statistics and cluster profiles on the original Likert scale

Item No	Questionnaire item	Total sample mean	Total sample standard deviation	Cluster 1 mean (n=21)	Cluster 2 mean (n=9)	Cluster 3 mean (n=130)
Perceived Advantages (Q15)						
Q15.1.	Low energy costs	4.80	0.39	4.90	4.88	4.78
Q15.2.	Environmentally friendly	4.77	0.41	4.95	4.88	4.73
Q15.3.	Home charging capability	4.76	0.49	4.42	5.00	4.80
Q15.4.	Ease of parking	4.44	0.82	3.57	3.33	4.66
Q15.5.	Comfortable driving and reduced noise levels	4.78	0.42	4.90	4.66	4.76
Q15.6.	Availability of designated parking spaces	4.35	0.81	4.00	3.11	4.50
Q15.7.	Easy access to low-emission zones	4.03	0.95	3.71	3.33	4.13
Q15.8.	Absence of a gearbox	4.48	0.73	4.23	3.55	4.58
Q15.9	Being at the forefront of new technologies	4.60	0.50	4.42	5.00	4.60
Q15.10	Rapid acceleration	4.15	0.77	3.95	5.00	4.12
Q15.11	Compatibility with smartphones and mobile applications	4.43	0.66	4.42	3.66	4.49
Q15.12	Distinctive appearance	4.29	0.73	4.52	3.00	4.34
Q15.13	Absence of size/dimension-related problems	4.26	0.77	4.38	3.00	4.33
Q15.14	Low periodic maintenance costs	4.06	0.82	4.19	4.55	4.00
Q15.15	Tax incentives	3.92	0.85	4.09	3.11	3.95
Perceived disadvantages (Q16)						
Q16.1.	High purchase prices	3.85	0.97	3.47	2.66	3.99
Q16.2.	Limited driving range	4.29	0.69	3.76	4.22	4.38
Q16.3	Long charging time	4.66	0.61	3.85	4.33	4.81
Q16.4.	Limited availability of charging stations	4.58	0.72	3.71	4.44	4.73
Q16.5.	Limited service and spare parts support	4.21	0.78	3.71	3.77	4.32
Q16.6.	Uncertainties associated with the use of new technology	3.70	0.85	3.61	2.66	3.78
Q16.7.	Acceleration-related concerns	2.66	1.05	2.52	1.33	2.78
Q16.8.	Potential safety risks for pedestrians due to vehicle quietness	2.39	0.89	1.61	1.77	2.56
Q16.9.	Reduced driving enjoyment due to low engine noise	1.80	0.72	1.33	1.66	1.88
Q16.10	Absence of a manual transmission	2.03	0.94	1.33	1.66	2.17
Q16.11.	Unconventional design and appearance	1.91	0.86	1.42	2.44	1.96
Q16.12.	Safety concerns	2.37	0.87	2.09	3.00	2.37
Q16.13.	Insufficient battery lifespan	2.66	0.94	2.71	3.77	2.58
Q16.14.	High battery replacement costs	2.75	0.94	3.00	3.55	2.66

Appendix B

Table B1. Agglomeration schedule coefficients for the final merging stages

Stage	Cluster 1	Cluster 2	Coefficients
155 (5 Clusters)	4	20	892.28
156 (4 Clusters)	4	8	972.80
157 (3 Clusters)	1	4	1064.03
158 (2 Clusters)	1	2	1160.34
159 (1 Clusters)	1	27	1272.00

* Note: Detailed data and the full 159-stage agglomeration schedule are available from the authors upon request.