Consumer attitudes and preferences for plug-in hybrid electric vehicles: A case of Delhi and Kolkata, India

Case Studies on Transport Policy 17 (2024) 101259

Contents lists available at ScienceDirect

Case Studies on Transport Policy

journal homepage: www.elsevier.com/locate/cstp

Consumer attitudes and preferences for plug-in hybrid electric vehicles: A case of Delhi and Kolkata, India

Reema Bera Sharma [a,c,*], Deepjyoti Das [b], Bhargab Maitra [c]

[a] Division of Physical Resource Theory, Department of Space, Earth and Environment, Chalmers University of Technology, Gothenburg 41258, Sweden
[b] Division of Environmental Systems Analysis, Department of Technology Management and Economics, Chalmers University of Technology, Gothenburg 41258, Sweden
[c] Transportation Engineering Division, Department of Civil Engineering, Indian Institute of Technology Kharagpur, Kharagpur 721302, India

ARTICLE INFO

Keywords:
Sustainable mobility
Consumer segmentation
Environmental consciousness
Transport policy
E-mobility

ABSTRACT

In the push for passenger transportation electrification, Plug-in Hybrid Electric Vehicles (PHEVs) serve as a suitable bridge towards sustainable transportation, especially in settings marked by rapid urbanization and socio-economic variations, such as India. Compared to conventional vehicles, PHEVs can offer distinct advantages, but Battery Electric Vehicles (BEVs) often overshadow their potential. Addressing the dearth of PHEV-specific research, this study investigates consumer attitudes and preferences for PHEVs in two Indian megacities: Delhi and Kolkata. Using a three-step method on attitudinal and stated preference data from 415 (Delhi) and 500 (Kolkata) car-owners, the study segmented consumers employing factor and cluster analyses, revealing dominant groups such as the 'actively concerned', which merges consumers with technological enthusiasm and environmental awareness. Mixed logit models further unveil consumers' willingness-to-pay (WTP) for various PHEV attributes. Notably, Delhi consumers exhibited 56 % more WTP for Advanced Vehicle Technology (AVT) options compared to their Kolkata counterparts. While Delhi consumers prioritized battery range, battery warranty, and recharging time, Kolkata consumers emphasized emission reduction. Sensitivity analysis revealed price as a dominant adoption barrier, suggesting subsidies could enhance PHEV uptake. This research highlights diverse PHEV preferences across Indian cities, underscoring the need for city-specific policy interventions.

1. Introduction

The emphasis on environmental sustainability globally has underscored the role of electric vehicles (EVs) in mitigating climate change, especially in the transportation sector, which is responsible for about 25 % of global CO_2 emissions (Khurana et al., 2020; Das et al., 2021; Xiong et al., 2023). While much of the focus has been on Battery Electric Vehicles (BEVs), Plug-in Hybrid Electric Vehicles (PHEVs) have been understudied despite their potential benefits in various geographical and consumer contexts (Helveston et al., 2015; Huang et al., 2021; Visaria et al., 2022) (detailed discussion in Section 2). This is particularly significant in India, the world's third-largest passenger car market, which has set ambitious targets for EV market shares of 40 % by 2030 and 100 % by 2047 (Bera and Maitra, 2023; Khurana et al., 2020). Given the country's infrastructural and socio-economic challenges, expanding the focus to include PHEVs alongside BEVs is crucial (Bera and Maitra, 2021a; Das et al., 2022; Tarei et al., 2021).

PHEVs offer an upfront cost reduction of up to 20 % compared to BEVs, making them especially relevant in India, where over 60 % of the population falls within the low-to middle-income category (IEA, 2021; Kolluru et al., 2021; Slowik et al., 2022; Zoepf et al., 2013). Recent data suggest that the average electric range of PHEVs has remained consistent at 50 km, sufficient for urban commutes, and their supplemental gasoline engines alleviate range apprehensions, offering a more approachable introduction to electric mobility (IEA, 2021; Zoepf et al., 2013). The myriad advantages of PHEVs, ranging from energy diversity to adaptability with fluctuating fuel standards, render them particularly relevant in developing countries such as India, where fuel consistency and power supply may be unreliable. Despite these evident benefits, academic investigations into PHEVs in developing countries remain limited, with a specific lacuna in studies focusing on consumer attitudes, perceptions, and preferences (Jia and Chen, 2023; Kowalska-Pyzalska et al., 2022). This knowledge gap has led to policy formulations that inadequately address PHEVs and, consequently, limited public awareness.

* Corresponding author at: Division of Physical Resource Theory, Department of Space, Earth and Environment, Chalmers University of Technology, Gothenburg 41258, Sweden.
E-mail addresses: reemas@chalmers.se (R.B. Sharma), dasd@chalmers.se (D. Das), bhargab@civil.iitkgp.ac.in (B. Maitra).

https://doi.org/10.1016/j.cstp.2024.101259
Received 12 November 2023; Received in revised form 12 June 2024; Accepted 8 July 2024
Available online 11 July 2024

Therefore, the present study aims to fill this knowledge gap by exploring key research questions. These questions focused on consumer perspectives on PHEVs are essential for shaping future transport policies and initiatives:

- RQ1: What specific attitudes do consumers hold towards the environment and technology?
- RQ2: Can we categorize consumers based on their attitudinal differences?
- RQ3: What drives PHEV adoption decisions among these consumer groups?

The study's contributions are threefold. First, from a theoretical standpoint, this research is among the initial scholarly efforts to systematically analyze consumer attitudes and perceptions towards PHEVs in developing countries such as India. This adds a much-needed dimension to the existing literature by focusing on a context that has not been adequately explored. Second, the study employed a unique approach of combined factor and cluster analyses to segment consumer attitudes, which helped to identify critical areas for targeted interventions and added a layer of granularity to our understanding of asset utilization in sustainable transportation. Lastly, from a policy viewpoint, this study developed and validated Mixed Logit (MXL) models and performed sensitivity analysis of the model estimates to evaluate differences in the preferences among different consumer clusters toward PHEV attributes, which provided valuable insights. These insights can guide vehicle manufacturers and the government in crafting suitable strategies to encourage the adoption of PHEVs in the Indian context.

2. Literature review

Based on the identified research gaps in the context of studies investigating consumer preferences and attitudes towards EVs, the literature review is segmented into four sub-sections, namely PHEVs in EV landscape, the geographical disparity in EV studies, the interplay of preference and attitude, and interplay of attitude and technology. The review concludes by highlighting specific gaps that warrant attention for a thorough PHEV study. For further details on the reviewed literature and their findings, refer to Table A1 in Appendix A.

2.1. PHEVs in the EV landscape

Serving as a transitional solution between traditional vehicles and fully electric ones, PHEVs distinctively utilize a combination of both gasoline and electricity (Zoepf et al., 2013). This dual nature of fuel sources in PHEVs is expected to have varied impacts on consumer preferences as compared to other EVs due to alleviated range anxiety and the ability to access locations with limited charging infrastructure. However, in the existing studies on consumer preferences towards EVs (Jia and Chen, 2023; Mpoi et al., 2023; Kowalska-Pyzalska et al., 2022; Ji and Gan, 2022; Rommel and Sagebiel, 2021), PHEVs are often clustered along with other EV categories, obscuring the specific benefits, obstacles and user preferences unique to PHEVs (Slowik et al., 2022; Zoepf et al., 2013). There are only a few studies like those by Axsen and Kurani (2009) and Krupa et al. (2014) that exclusively focus on drivers and barriers to the adoption of PHEVs. In this regard, it is necessary to conduct more detailed studies on PHEVs to comprehensively understand consumer preferences and demand, such that focused improvement strategies could be recommended to enable their wider adoption.

2.2. Geographical disparity in EV studies

The review of EV literature indicates a noticeable geographical disparity in research emphasis, with the majority of the studies conducted in developed nations such as the United States (US) (Jia and Chen, 2023; Tanaka et al., 2014), Italy (Danielis et al., 2020; Giansoldati et al., 2020b), Greece (Mpoi et al., 2023), Denmark (Visaria et al., 2022), South Korea (Lashari et al., 2022), Poland (Kowalska-Pyzalska et al., 2022), Germany (Rommel and Sagebiel, 2021; Hackbarth and Madlener, 2016), Canada (Miele et al., 2020; Higgins et al., 2017), Spain (Rahmani and Loureiro, 2019), Netherlands (Hoen and Koetse, 2014) and countries where EVs have already been adopted as mainstream transportation such as China (Ji and Gan, 2022; Helveston et al., 2015), offering detailed insights into EV adoption factors like vehicle, infrastructure, policy, sociodemographic and trip-related attributes. Conversely, research within developing regions, such as India, appears less comprehensive concerning consumer choice preferences towards EVs in general and PHEVs in particular (Khurana et al., 2020; Navalgund and Nulkar, 2020; Tarei et al., 2021). This disparity emphasizes the importance of more region-specific research that accounts for unique socio-economic and cultural contexts.

2.3. Interplay of preference and attitude

Many studies, including those by Jia and Chen (2023), Visaria et al. (2022), Rommel and Sagebiel (2021), Danielis et al. (2020), Rahmani and Loureiro (2019), Hackbarth and Madlener (2016) have investigated consumer preferences towards EVs in terms of their willingness to pay for related attributes by developing Stated Preference (SP) survey-based discrete choice models such as Multinomial Logit (MNL), Mixed Logit (MXL), Multinomial Probit (MNP), Latent Class (LC) models, etc. On the other hand, studies done by Tarei et al. (2021), Khurana et al. (2020), Giansoldati et al. (2020a), Krupa et al. (2014), Schuitema et al. (2013) have used consumer rating responses to identify consumer attitude and purchase intention towards EVs by developing multivariate analysis techniques such as principal component analysis (PCA), cluster analysis, factor analysis, structural equation modeling (SEM), regression analysis, etc. However, limited studies in the literature integrate both attitudinal dimensions with attribute-based choice models to deepen the understanding of consumer mode choice decision-making for EVs in general and PHEVs in specific. Hence, it is important to consider a unified methodology that combines both attitudes and preferences, providing enhanced insights toward formulating more effective strategies to enhance PHEV adoption.

2.4. Interplay of attitude towards environment and technology

Among studies investigating consumer attitudes towards EVs, most studies included only attitudinal statements towards the environment to investigate their purchase intention towards EVs. For instance, Mpoi et al. (2023) have underscored the role of environmental awareness, financial incentives, and charging infrastructure as crucial determinants of EV purchase intentions. Parallel conclusions were drawn from a study done by Navalgund and Nulkar (2020) and Khurana et al. (2020), where pro-environmental behavior was found to sway EV buying decisions among Indian consumers significantly. However, very few studies, such as those by Lashari et al. (2022) in South Korea and Nie et al. (2018) in China have ventured into merging environmental and technological attitudes, discovering that affluent individuals with a strong sense of environmental responsibility and a receptiveness to innovation show a higher willingness to invest in enhanced EV attributes. This highlighted a gap in existing studies and emphasizes the critical need for future research to simultaneously include attitudinal questions towards both the environment and technology to improve our understanding of consumer choices towards PHEVs.

2.5. Specific research gaps

There are four specific research gaps identified in the context of the present study. First, despite the importance of PHEVs as a transitional solution between conventional and fully electric vehicles, research often blends other EV-type studies (Jia and Chen, 2023; Ji and Gan, 2022; Rommel and Sagebiel, 2021; Miele et al., 2020; Higgins et al., 2017). This consolidation potentially overlooks PHEV-specific considerations (such as availability of dual fuel sources, the difference in capital cost and charging infrastructure requirements compared to BEVs, etc.) needing dedicated studies that exclusively examine PHEV's unique challenges and advantages from consumers' perspectives. Second, most of the existing studies on EVs have been conducted in developed nations (Mpoi et al., 2023; Lashari et al., 2022; Visaria et al., 2022; Rommel and Sagebiel, 2021; Danielis et al., 2020; Miele et al., 2020; Rahmani and Loureiro, 2019), with limited research carried out in developing countries such as India. This disparity highlights the necessity for in-depth studies to explore consumer preferences toward PHEVs and related attributes in the Indian context. Such studies are essential to guide vehicle manufacturers and the government in formulating effective strategies to increase the attractiveness of PHEVs among Indian consumers. Third, the majority of the studies have either employed stated-preference data-based discrete choice models (Jia and Chen, 2023; Visaria et al., 2022; Miele et al., 2020) to investigate consumer preferences towards EVs or consumer perception data-based multivariate statistical techniques (Tarei et al., 2021; Higueras-Castillo et al. 2020; Krupa et al., 2014) to explore consumer attitudes towards EV purchase intentions. A notable gap exists in a joint investigation of consumer attitudes and preferences towards EVs in general and PHEVs in particular. Bridging this gap using attitudinal factors with preference modeling can offer a richer understanding of consumer decision-making processes for PHEVs. Lastly, although many studies have investigated the environmental attitude of consumers toward EVs (Mpoi et al., 2023; Khurana et al., 2020; Hackbarth and Madlener, 2016), there is a relative scarcity of research that concurrently focuses on both environmental and technological attitudes. Given that these dimensions are not mutually exclusive, it is important to investigate consumers' attitudes towards the environment and technology to obtain a holistic picture of consumer purchase intention towards PHEVs.

Based on specific research gaps, the present study aims to investigate consumer attitudes and preferences towards PHEVs in the Indian context. The study employed a rigorous methodology, utilizing factor analysis to identify consumers' latent attitudes toward the environment and technology, followed by cluster analysis to categorize respondents into specific groups based on attitudinal differences. These groups were subsequently analyzed through mixed logit (MXL) models to investigate consumer perceived benefit towards PHEV-related attributes in terms of Willingness to Pay (WTP) values. Finally, a sensitivity analysis of the model parameter was conducted to understand the sensitivity of the demand across various consumer segments with respect to improvement in PHEV attributes.

3. Study area: Delhi and Kolkata

For the demonstration of the proposed methodology, two case study cities-a) Delhi and b) Kolkata have been selected and necessary data collection has been conducted. Both cities represent typical Indian megacities, which hold the potential to adopt PHEVs significantly if appropriate actions are taken. For both study cities, socio-economic features are discussed below.

Globally, Delhi and Kolkata (as shown in Fig. 1) are identified as two megacities facing significant environmental pollution challenges. Both cities are frequently ranked among the world's most polluted urban regions, posing substantial health and economic challenges to their inhabitants (Dutta et al., 2021; Kolluru et al., 2021; Tiwari and Saxena, 2021).

Delhi, the capital of India, sprawls across an area of 1,483 km^2 and has a population of approximately 16.36 million (Government of India, 2011; Kolluru et al., 2021). The city has a notable count of 3 million passenger cars, the highest among Indian megacities, significantly contributing to its air pollution crisis (Bera and Maitra, 2021b; Kolluru et al., 2021; Tiwari and Saxena, 2021). In terms of ownership, Delhi has 157 cars per 1000 residents, significantly higher than the national average of 22 cars per

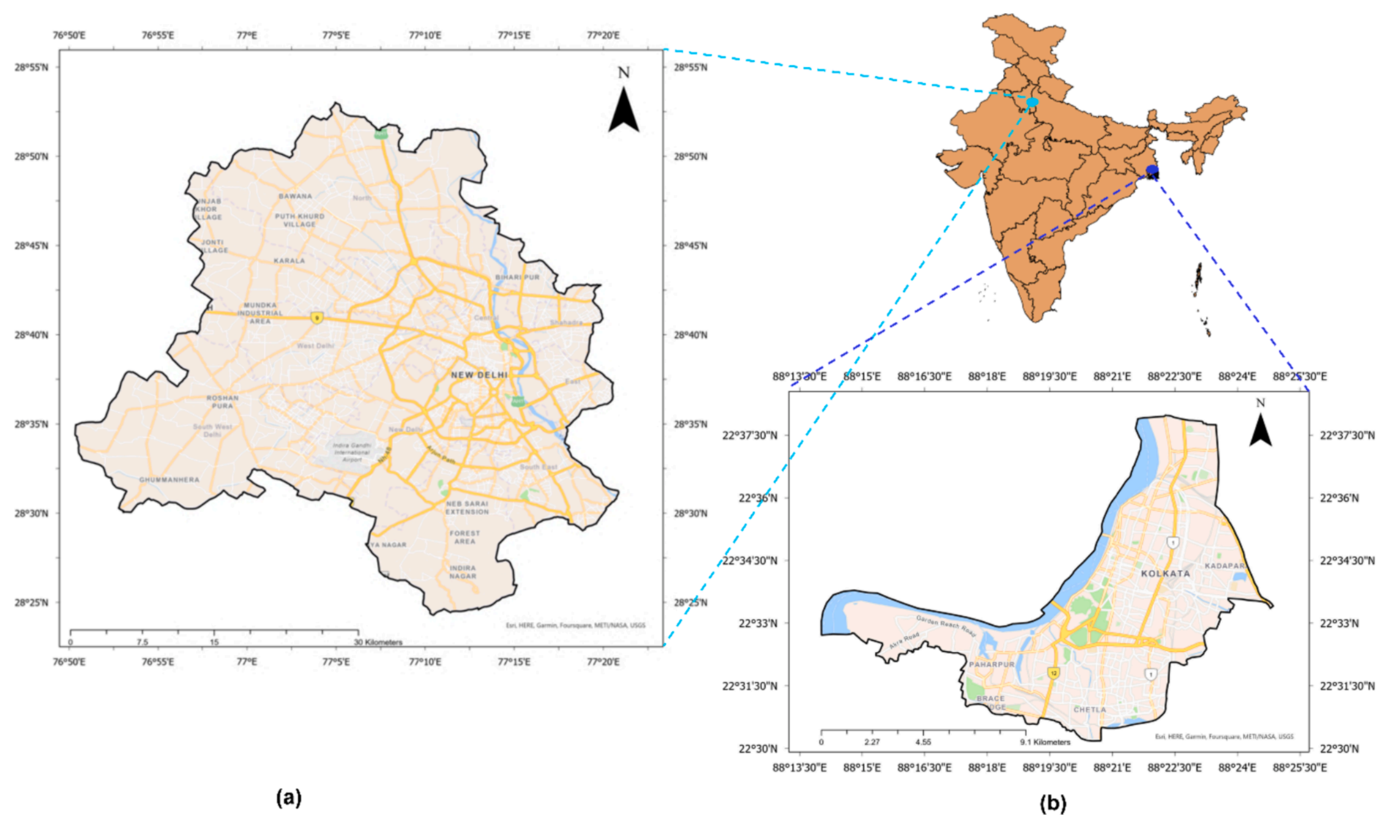

Fig. 1. Case study areas: cities of a) Delhi (left), b) Kolkata (bottom right), and the nation India (top right).

1000 residents. Further, cars in Delhi cover 26,085 million kilometers annually, making up 36 % of the city's total annual vehicle kilometers traveled (VKT) i.e., 73,350 million kilometers (Malik et al., 2019). The vast number of cars and their high share of annual VKT add to Delhi's severe pollution levels and is a crucial factor behind the city's release of 10,867.51 Gg/year of greenhouse gas (CO_2 equivalent) emissions (Ramachandra et al., 2015). Delhi has an annual average PM2.5 emission of 84.1 μg/m^3, which is about 8 times higher than WHO guidelines, where the permissible emission is 10 μg/m^3 (IQAir, 2020). Exposure to such harmful air pollutants is responsible for severe health concerns among Delhi residents such as respiratory problems, cardiovascular issues, premature deaths, etc. (Kolluru et al., 2021).

On the other hand, Kolkata, the cultural capital of India, despite its smaller area of 187 km^2, supports a sizable population of 4.49 million (Government of India, 2011; Haque and Singh, 2017). The city has a road space of only 6 % of its total area, which is substantially low compared to other Indian megacities (Dutta et al., 2021; Haque and Singh, 2017). However, Kolkata records 0.35 million passenger car ownership among its residents. In terms of car ownership, Kolkata has 42 cars per 1000 residents (MoRTH, 2020). Bansal et al. (2018) reported that the average annual car travel per household in Kolkata is around 7,230 km. Hence, restricted road space together with high car ownership is responsible for high pollution levels, with an estimated greenhouse gas (CO_2 equivalent) emission of 1886.6 Gg/year from road transport (Ramachandra et al., 2015). Kolkata has an annual average PM2.5 emission of 46.6 μg/m^3, which is about 5 times higher than WHO guidelines (IQAir, 2020). Hence, the deterioration of urban air quality has severe negative health implications such as exacerbation of asthma, allergy, and other respiratory diseases among city dwellers in Kolkata (Haque and Singh, 2017).

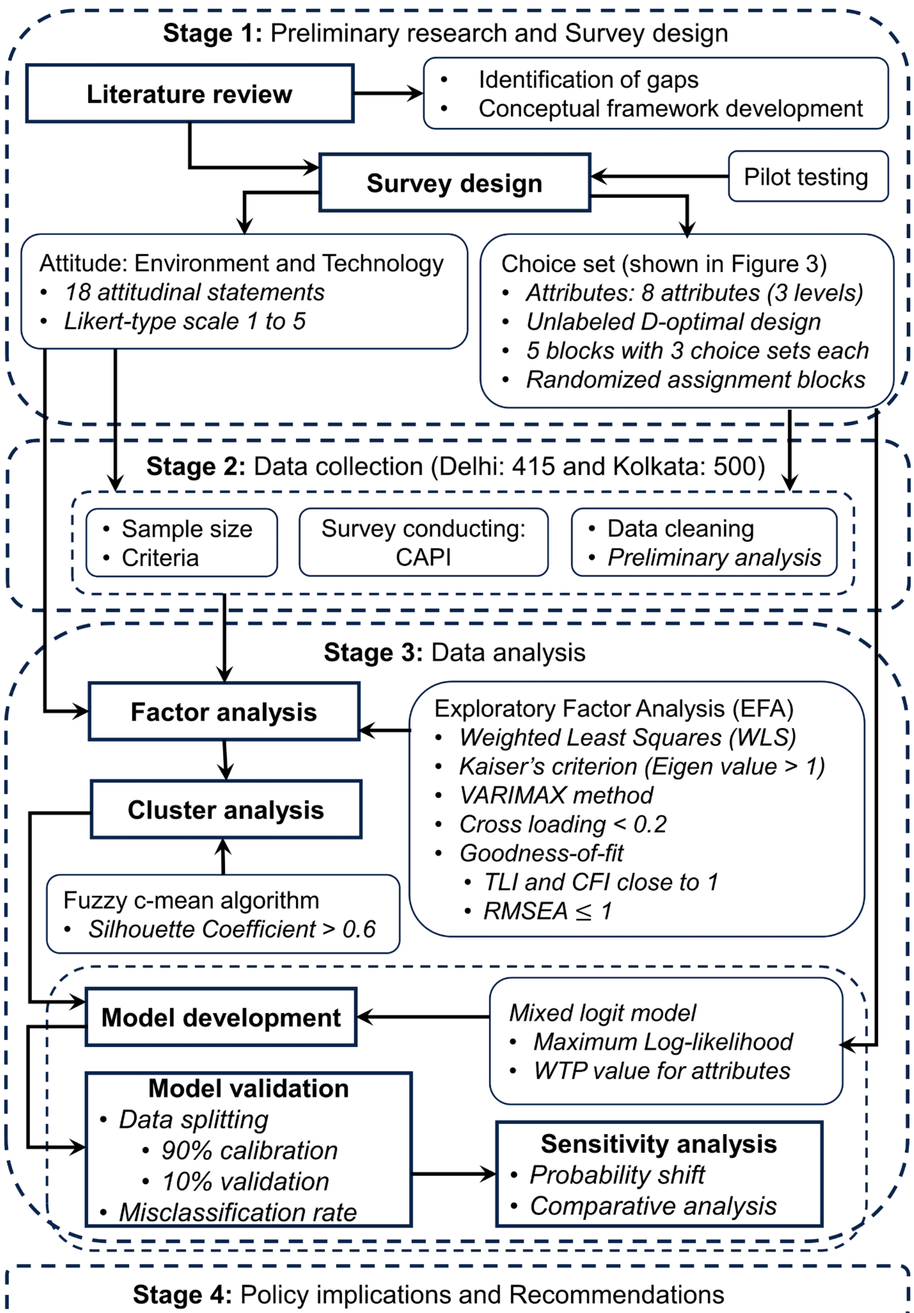

Fig. 2. Schematic representation of the study methodology.

4. Methodology and data

This section details the methodology employed in this study. The survey design is initially discussed, followed by the description of data collection and data organization. Subsequently, the analytical techniques used to interpret the data are explained. A schematic representation of the study methodology is provided in Fig. 2.

4.1. Survey design

The survey was divided into five primary sections. The first section gathered information on the respondents' degree of agreement with various statements assessing attitudes towards the environment and technology. The second section gathered information on respondents' existing and future car ownership plans, including driving habits such as daily fuel mileage, average trip length for work trips, trip frequency, etc. The third section provided respondents with a comprehensive explanation of the attributes of PHEV used in the choice experiment design (as shown in Fig. 3), describing each level using appropriate text and visuals. The fourth section recorded participants' stated choice responses for the given choice sets. Finally, the fifth section collected respondents' socio-demographic information, including gender, age, education, monthly family income, and whether respondents can access home-based parking with charging outlets.

Before the main survey, pilot tests were conducted from January to February 2019. The preliminary tests served to fine-tune the questionnaire in several ways. The tests evaluated the attributes' clarity, verified the adequacy of information provided, determined the ideal number of choice scenarios per questionnaire to avoid respondent fatigue, and assessed the average time needed for survey completion. Based on pilot study, involving 50 participants from case study cities, several modifications were made in the questionnaire to improve clarity and ensure higher-quality responses. The description of the 'AVT-option' was notably simplified for easier comprehension. The training sessions for survey enumerators and identification of optimal survey locations were also carried out during this phase.

4.1.1. Attitudinal statements

The attitudinal statements assessing consumers' environmental and technological attitudes are present in Table 2 and are adapted from past literature (Ewing and Sarigöllü, 2000; Helveston et al., 2015; Nie et al., 2018). This approach, similar to Ewing and Sarigöllü (2000), builds on the well-established relationship between attitudes, preferences, and behaviors to provide a more nuanced understanding of consumer choices. To gauge these attitudes, respondents were asked to indicate their level of agreement with specific statements, using the Likert scale from 1 (strongly disagree) to 5 (strongly agree). The approach aligns well with a broad range of contemporary research, further supported by advancements in the Theory of Planned Behavior (TPB), which now incorporates elements like moral norms and identity (Sparks and Shepherd, 2002). Numerous studies across different domains, such as health behaviors and environmental psychology, underscore the influential role of attitudes in shaping behaviors (Gifford and Nilsson, 2014; Klöckner, 2013; McEachan et al., 2011). Moreover, in consumer behavior, attitudes have been proven to impact the initial purchase and post-purchase activities like brand loyalty and advocacy (Buil et al., 2013; Casidy and Wymer, 2016).

4.1.2. Design of choice experiment

Drawing from Bera and Maitra (2021b), the design of the Stated Preference (SP) choice experiment was carefully planned. The SP experiment aimed to balance the number and types of attributes to avoid cognitive burden on respondents while providing a comprehensive view of alternatives (Hensher et al., 2015). A total of eight attributes were selected, each having three levels. These included factors such as purchase cost, travel cost reduction, advanced vehicle technology (AVT) options, battery range, availability of public charging station, recharging time, battery warranty, and tailpipe emissions (for attribute

Attributes	Levels
Purchase cost (compared to CVs)	25% higher 50% higher 75% higher
Travel cost reduction (compared to CVs)	20% 40% 60%
Advance vehicle technology (AVT) option	None TJA TJA+IEMS
Battery range	30 km 60 km 90 km
Public charging station (compared to CVs)	20% 60% 100%
Recharging time	7 h 3 h 1 h
Battery warranty	3 yrs./60,000 km 5 yrs./1,00,000 km 8 yrs./1,60,000 km
Tailpipe emission (compared to CVs)	75% 50% 25%

(a)

Choice set # A1

Suppose on your next purchase of a new car or replacement of an existing car you were offered only the following two alternative options of Plug-in Hybrid Vehicle with features shown below. Assuming that the two alternatives are otherwise identical, please select the one you would most likely purchase.

Attribute	**Alternative 1**	**Alternative 2**
Purchase cost (compared to reference[a])	15,62,500	21,87,500
Travel cost reduction (compared to CVs)	20%	60%
Advance Vehicle Technology (AVT) option	TJA[b] + IEMS[c]	None
Battery range	90 km	30 km
Public charging station (compared to CVs)	60%	100%
Recharging time	3 hr	1 hr
Battery warranty	5 yrs./1,00,000 km	8 yrs./1,60,000km
Tailpipe emission (compared to CVs)	50%	50%
I would choose	☐	☐

[a]Anticipated average purchase cost for the next car purchase is INR 12,50,000
[b]TJA = Traffic Jam Assist
[c]IEMS = Intelligent Energy Management System

(b)

Fig. 3. Illustration of PHEV attributes presented in the choice experiment design section: a) selected attributes and their levels and b) a sample choice set.

Table 1
Overview of respondent's data (Bera & Maitra, 2021b).

Demographics/ Attributes	Delhi Sample (N = 415)	Delhi Population (%)	Kolkata Sample (N = 500)	Kolkata Population (%)
Gender				
Male	349 (84 %)	54 %	405 (81 %)	52 %
Female	66 (16 %)	46 %	95 (19 %)	48 %
Age (Years)				
≤35	249 (60 %)	66 %	200 (40 %)	53 %
>35	166 (40 %)	34 %	300 (60 %)	47 %
Education Level				
Up to Higher Secondary	237 (57 %)	83 %	275 (55 %)	82 %
Graduate or Higher	178 (43 %)	17 %	225 (45 %)	18 %
Monthly Family Income (INR)				
≤1,50,000	241 (58 %)	–	365 (73 %)	–
>1,50,000	174 (42 %)	–	135 (27 %)	–
Car Ownership				
One Car	278 (67 %)	–	370 (74 %)	–
Two or More Cars	137 (33 %)	–	130 (26 %)	–
Garage Availability				
Available	195 (47 %)	–	365 (73 %)	–
Not Available	220 (53 %)	–	135 (27 %)	–
Average Trip Length (Journey to and from work in km)				
≤30	145 (35 %)	–	340 (68 %)	–
>30	270 (65 %)	–	160 (32 %)	–

Note: The conversion rate used is 1 INR = US $0.014 approx.

descriptions, refer to Bera and Maitra, 2021b). Among these, only the AVT option was qualitative, while the rest were quantitative. When presenting these attributes, it was essential to use a format easily understood by participants. The choice of presenting travel cost reduction, public charging station availability, and tailpipe emissions levels in percentages and other quantitative attributes in absolute terms aligns with previous research in the EV context (Hackbarth and Madlener, 2013; Tanaka et al., 2014) as well as WTP studies in other areas (Kurtuluş and Çetin, 2020; Parumog et al., 2006; Wang et al., 2018).

Generating hypothetical scenarios for respondents involved combining these attributes and their levels. Given the eight attributes with three levels each, a full factorial design would generate 6,561 combinations, an impractical number for a single survey. Therefore, fractional factorial, particularly efficient designs, were employed (Das et al., 2023; Hensher et al., 2015). These designs aimed to minimize data correlation and enhance parameter estimation accuracy, guided by D-error and D-optimality criteria (Hensher et al., 2015). Using JMP 14 statistical software, the final survey included 30 choice sets, subdivided into five blocks. Each block contained three choice sets, presenting the respondents with two hypothetical PHEV options. Attributes with their levels and a sample choice set are outlined in Fig. 3.

4.2. Data collection and organization

The survey data, previously utilized in the study by Bera and Maitra (2021b), was collected in Delhi and Kolkata from March to May 2019 using Computer Assisted Personal Interviews (CAPI). The participants were current car owners, 18 years or older, with valid driving licenses who were randomly sampled. The sample size was calculated in advance, aiming for a minimum of 384 responses based on the guidelines of Taherdoost (2017). The survey was conducted at various locations, such as residential areas, shopping malls, and educational institutions. Trained enumerators initially approached more than 1,500 individuals in each city; random sampling targeted 18- and older conventional vehicle (CV) owners with valid driving licenses in the two cities. However, only 500 in Delhi and 550 in Kolkata considered PHEV as a potential future vehicle option. Each survey took 10–15 min, and data was stored automatically. As a token of appreciation, respondents received a pen as a gift upon completing the survey. After data cleaning, 415 responses from Delhi and 500 from Kolkata were retained for further study.

Table 2
Factor analysis results on attitudinal statements.

Attitudinal Statements	Technology Enthusiast		Environmental Activist		Neutral		Uncommitted	
	Delhi	Kolkata	Delhi	Kolkata	Delhi	Kolkata	Delhi	Kolkata
I am excited by the possibilities offered by new technologies	0.800	0.830						
I love new technology	0.824	0.959						
Taking one new technology makes one trendy	0.531	0.741						
I am excited to learn to use new technologies	0.818	0.942						
Using new technology makes life easier	0.686	0.783						
I am willing to spend a bit more to buy a product that is more ecologically friendly to save the environment			0.734	0.501				
Now is the real time to worry about the effects of vehicular emission			0.716	0.613				
The highest priority should be given to protect the environment, even if it hurts the economy			0.674	0.495				
I would be willing to go door to door to discuss and distribute literature on the environment			0.784	0.669				
I am willing to join a group, club or organization that is concerned with environmental issues			0.828	0.770				
There is never enough time in a day to get everything done					0.738	0.822		
Change is rarely for the good, and I prefer things as they are					0.844	0.806		
Whatever we do, the world's destiny is predetermined					0.791	0.770		
Things have become so complicated in the world that it is really hard to understand what is going on					0.729	0.746		
The environmental crisis is greatly exaggerated							0.738	0.640
I rarely ever worry about the effect of pollution on me and my family							0.768	0.656
It is acceptable for a country like ours which is experiencing rapid urbanization to produce a certain degree of pollution							0.845	0.794
Humans have the right to modify the natural environment to suit their needs							0.854	0.833

Goodness of fit: Delhi- TLI = 0.993, CFI = 0.996, RMSEA = 0.027; Kolkata- TLI = 0.992, CFI = 0.996, RMSEA = 0.043.

The current study focuses on existing car owners in Delhi and Kolkata as the target population. However, it is essential to note that a direct comparison between the sample and the target population is not possible due to the lack of specific sociodemographic data from the Indian census manual (Government of India, 2011). Thus, we used broader demographic data from urban Delhi and Kolkata to compare with our sample data. According to the available data (Table 1), the sample has a few disparities compared to the general urban population in both cities. Specifically, the sample from Delhi consists of 84 % males and 16 % females, while in Kolkata, the sample comprises 81 % males and 19 % females, indicating an underrepresentation of females in both cities compared to general urban population. Furthermore, the sample disproportionately represents educated individuals, with 43 % in Delhi and 45 % in Kolkata having a graduate degree or higher, notably higher than the general urban population. Two potential explanations exist for these disparities. Firstly, the general population statistics cover all urban residents, whereas our sample is limited to current car owners. Secondly, during the data collection phase, a considerable number of females were less inclined to participate, which contributed to the gender skewness in the sample. Despite these deviations, the age distribution in the sample aligns well with the broader population data. In Delhi, 60 % of the sample is aged 35 or below; in Kolkata, this age group constitutes 40 %. Unfortunately, due to the limitations of available data, a comparison of income levels between the sample and the general population was not feasible.

Based on Bera and Maitra (2021b), different coding strategies were employed on the final database used in discrete choice modeling. Quantitative attributes such as purchase cost, travel cost reduction, battery range, public charging station, recharging time, battery warranty, and tailpipe emission were coded linearly, whereas the qualitative attribute of AVT option was dummy-coded (Hensher et al., 2015).

4.3. Factor and cluster analyses

This study employed Exploratory Factor Analysis (EFA) to identify the latent factors affecting consumer choices for PHEVs in India, using the M-plus statistical package for the analysis (Muthén and Muthén, 2015). By applying EFA to a selected set of attitudinal variables (refer to Table 2) and adhering to robustness criteria such as a minimum sample size of 300 and a sample-to-variable ratio between 3:1 and 20:1, the study ensured the reliability of the EFA model (Hair et al., 2014). The analysis utilized the Weighted Least Squares method for factor extraction, guided by Kaiser's criterion of retaining factors with eigenvalues greater than one and allowing cross-loadings below 0.2 (Sharma and Maitra, 2024; Das and Mandal, 2021). Factor rotation was performed using the VARIMAX method to define the factor structure, while the model's fit was assessed using goodness-of-fit indices including the Tucker-Lewis Index (TLI), Comparative Fit Index (CFI), and Root Mean Square Error of Approximation (RMSEA) (Hair et al., 2014). The extracted factors were subsequently interpreted and categorized based on the strength of variable loadings and alignment with the study's theoretical framework.

Following the EFA, we employed the factor scores to perform cluster analysis using the fuzzy c-means algorithm, implemented in MATLAB R2015b. This algorithm was selected based on its proven capability to produce stable and robust clusters, especially in situations involving outliers and overlapping data sets (Purnawansyah et al., 2018; Wiharto and Suryani, 2020).

The Fuzzy c-means (FCM) algorithm is a non-hierarchical clustering method that assigns each data point a degree of membership, indicative of its likelihood to belong to each cluster (Bezdek, 1981). The objective function of the FCM algorithm, denoted as Q_m, is as follows:

$$Q_m = \sum_{i=1}^{N}\sum_{j=1}^{C}(m_{ij})^m \|x_i - z_j\|^2, \quad 1 \le m < \infty \tag{1}$$

where m is the fuzzifier; m_{ij} is the degree of membership of the i^{th} data point x_i to the j^{th} *cluster*, z_j is the center of the j^{th} cluster, and N and C are the number of data points and clusters, respectively.

During each iteration, the membership m_{ij} and the cluster center z_j are updated as follows:

$$m_{ij} = \frac{1}{\sum_{k-1}^{c}\left(\frac{\|x_i - z_j\|}{\|x_i - z_k\|}\frac{2}{m-1}\right)} \tag{2}$$

$$z_j = \frac{\sum_{i=1}^{N} {m_{ij}}^m x_i}{\sum_{i=1}^{N} {m_{ij}}^m} \tag{3}$$

The algorithm iterates until the degree of membership achieves its largest value across all data points for each cluster.

To identify the optimal number of clusters, the silhouette coefficient was calculated to measure cluster quality (Annam et al., 2023). Silhouette values range between −1 and +1, with values closer to +1 suggesting a better cluster structure for the data sample. Guidelines for interpreting silhouette values and categorizing the clusters' strength and robustness are provided in Fletcher et al. (2014).

4.4. Model specification

This study employed Mixed Logit (MXL) models to delve deeper into the stated preferences related to PHEVs within various clusters of respondents. MXL models provide a robust and flexible framework that accommodates individual taste variations and overcomes the limitations of Multinomial Logit (MNL) models, including the independence of irrelevant alternatives (IIA) and homogeneity assumptions across respondents (Brownstone, 1999; McFadden and Train, 2000).

The utility U_{ni}, derived by individual n for selecting alternative i can be formulated as:

$$U_{ni} = (W_{ni}\beta) + \varepsilon_{ni} \tag{4}$$

where W_{ni} represents the observed component of utility and is a function of both the attributes x_{ni} of the alternatives and the characteristics s_n of the individuals. The parameter vector β is to be estimated based on the available choice data.

$$W_{ni} = W(x_{ni}, s_n) \tag{5}$$

The unobserved portion ε_{ni} serves as the error term. The choice probability $Q_n(i)$ for individual n selecting alternative i is expressed as:

$$Q_n(i) = \int\left(\sum_j \frac{e^{W_{nj}\beta}}{e^{W_{ni}\beta}}\right)h(\beta|\omega)d\beta \tag{6}$$

where $h(\beta|\omega)$ is the density function of β given parameters ω. The log-likelihood function L is formulated as:

$$L(\omega) = \sum_{n=1}^{N}\ln(Q_n(i)\,) \tag{7}$$

Due to the integral form, analytical solutions are unattainable, necessitating simulation techniques. This study employed a simulated maximum log-likelihood estimator with 100 Halton draws (Bhat, 2001; Hensher and Greene, 2003). Additionally, for model estimation, it is necessary to make assumptions concerning the distributions of each random variable. In this context, the present study assumed that all random variables follow a constrained triangular distribution, as per the guidelines set by Hensher et al. (2015). The constrained triangular distribution is beneficial when aiming to value attributes or estimate WTP. It ensures consistent parameter estimate signs across the sample, allows quicker convergence due to lesser computational time, and simplifies WTP estimation due to a smaller standard deviation assumption. Thus, WTP estimates can be easily obtained by dividing the average coefficient of the desired attribute by that of the cost attribute, avoiding complications from standard deviation seen in other distributions (Train, 2009).

The model's adequacy was assessed using ρ^2_{adj} values (Sharma et al., 2024; Das et al., 2023; Hensher et al., 2015). The outcomes were evaluated for both their statistical significance and practical relevance. The computed WTP values help elucidate the relative importance of different attributes across respondent clusters. Therefore, by capitalizing on the capabilities of MXL models, the present study aims to furnish a nuanced understanding of PHEV preferences among the respondent groups. These insights will contribute to the design of more targeted and effective policy interventions.

5. Results and discussion

5.1. Factor analysis

The EFA results in Table 2 show a robust model fit, with TLI and CFI values approaching 1 for both Delhi and Kolkata. Specifically, the TLI values are 0.993 for Delhi and 0.992 for Kolkata, while the CFI values are 0.996 for both cities. Additionally, the RMSEA of 0.027 for Delhi and 0.043 for Kolkata are well below the threshold of 0.08, further indicating a good fit (Hair et al., 2014).

The analysis identified four distinct latent factors, each capturing a different aspect of consumers' attitudes toward the environment and technology. The first factor, 'Technology enthusiast', is highly pronounced in Delhi and Kolkata, with factor loadings ranging from 0.531 to 0.959. Particularly noteworthy is an inclination towards the "I love new technology" and "I am excited to learn to use new technology", with loadings of 0.824 and 0.818 in Delhi and 0.959 and 0.942 in Kolkata, respectively. These results suggest that a significant segment of the population is open to and excited about technological innovations. These insights could be leveraged in marketing PHEVs as state-of-the-art technology for sustainable urban mobility. This aligns with research based on technology adoption theories and models that finds technology adoption rates higher among those with positive attitudes toward new technology (Khan and Qudrat-Ullah, 2021). The second factor is 'Environmental activist', which focuses on environmental activism, with loadings ranging from 0.495 to 0.828. The willingness to join environmental groups is particularly strong in both cities, at 0.828 in Delhi and 0.770 in Kolkata. These results could inform targeted marketing strategies for PHEVs that emphasize their environmental benefits, as this segment is willing to take extra steps for environmental causes. Previous research has shown that pro-environmental attitudes are strongly associated with pro-social engagement behaviors (Čapienė et al., 2021). The third factor is 'Neutral', where factor loadings for variables range from 0.729 to 0.844; this indicates that this group holds somewhat neutral attitudes towards technological advances and environmental issues. Tailoring messages to this group may require different strategies, perhaps focusing on the practical benefits of PHEV ownership, such as cost savings over time (Bera and Maitra, 2021b; Björnsson and Karlsson, 2017). The fourth factor is 'Uncommitted', which seems skeptical of technological and environmental claims, with high loadings on statements like "Humans have the right to modify the natural environment to suit their needs" (0.854 in Delhi, 0.833 in Kolkata). This group could be the most challenging to sway but may respond to messages framed around national or economic benefits supported by hedonic values (Steg et al., 2014).

The results also show regional variations, with differences in factor loadings between Delhi and Kolkata. This points to the necessity of location-specific marketing and policy interventions, as discussed in the literature (Chen et al., 2020). Overall, the EFA results offer a nuanced understanding of consumer attitudes toward the environment and technology in the selected cities, providing a foundation for targeted marketing and policy initiatives.

The identified latent factors align well with previous research on consumer behavior and environmental attitudes towards EVs (Ewing and Sarigöllü, 2000; Helveston et al., 2015; Nie et al., 2018), adding credibility to these findings.

5.2. Cluster analysis

While EFA offers valuable insights into the underlying dimensions of consumer attitudes, it lacks the resolution to differentiate between the diverse respondent pools in Delhi and Kolkata. Here, cluster analysis bridges this gap, grouping respondents into more homogenized clusters based on their environmental concerns and technological attitudes. Factor scores derived for the latent variables, identified using EFA were utilized in the Fuzzy c-mean clustering algorithm to group respondents into more homogenized clusters. The silhouette plots in Fig. 4 support the decision for a three-cluster solution, confirming the robustness of this approach.

For Delhi, the three-cluster solution yielded a silhouette value of 0.65. The largest cluster, 'Actively concerned,' accounted for 186 or 45 % of the consumers. This group scored highest in their environmental concern and displayed significant enthusiasm for new technology. Notably, this cluster embodies the convergence of environmental activism and technological enthusiasm, highlighting a suitable target group for policy interventions promoting PHEVs. Targeted policy interventions such as subsidies for PHEV technology or privileged access to low-emission zones could be most effective for this group. In contrast, the 'Passively concerned' cluster in Delhi comprised 55 or 13 % of consumers. Although environmentally conscious, these individuals showed less willingness to act on these concerns. This cluster may respond well to awareness campaigns that convert latent concerns into active behaviors. Policy measures could include educational programs that bridge the gap between concern and action (Nie et al., 2018). Lastly, the 'Unconcerned' cluster represented 174 or 42 % of the sample, indicating a significant number of consumers who are skeptical about the environmental crisis. For this segment, a different set of incentives focusing on economic gains may be more effective, such as demonstrating the long-term cost benefits of PHEV ownership (Bera and Maitra, 2021b). On the other, Kolkata presented a slightly different picture from Delhi in terms of consumer grouping considering attitude towards the environment and technology, with a silhouette value 0.61 for three-cluster structure. The 'Actively concerned' cluster comprised 204 or 41 % of the respondents. Just like their Delhi counterparts, they not only scored high on environmental concerns but were also enthusiastic about new technologies. The 'Passively Concerned' group was notably larger in Kolkata, capturing 203 or 40 % of the consumers. Meanwhile, the 'Unconcerned' category was smaller, with 93 or 19 % of the sample.

5.3. Mixed logit model for PHEV preferences

Past studies have shown that consumers who are actively concerned about the environment or those with high environmental consciousness are more willing to purchase EVs as compared to others (Ewing and Sarigöllü, 2000; Hackbarth and Madlener, 2013; Helveston et al., 2015; Nie et al., 2018). Hence, to investigate if higher environmental awareness has any impact on consumer perceived benefit associated with PHEV-related attributes, separate MXL models were developed for consumers, who are 'actively concerned' and a combined group of consumers, who are 'passively and unconcerned'. For 'actively concerned' and 'combined passively and unconcerned' consumers in Delhi and Kolkata, separate MXL models were developed i) for complete dataset without considering taste heterogeneity to estimate consumer perceived benefit associated with PHEV-related attributes in terms of WTP values and ii) for complete dataset considering taste heterogeneity to estimate variation in consumer preference for PHEV with respect to different sociodemographic variables. The obtained model fit values range from 0.18 to 0.30, which is an acceptable fit for consumer choice models in the transportation domain (Das et al., 2023; Bera and Maitra,

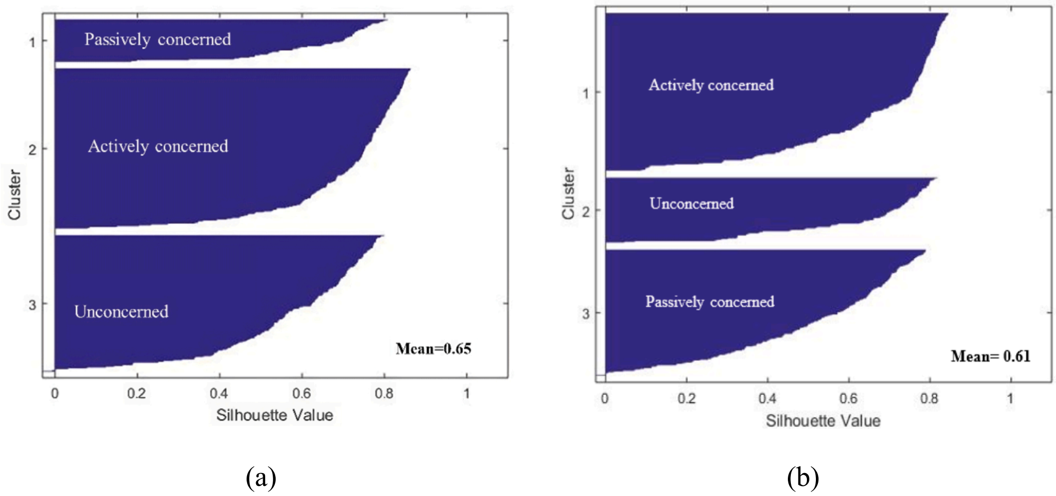

Fig. 4. Silhouette plot for a) Delhi sample data and b) Kolkata sample data.

2022; Hensher et al., 2015).

5.3.1. *Model estimation and WTP results of complete dataset without considering taste heterogeneity*

The model estimation results of separate MXL models for complete dataset of actively concerned and combined passive and unconcerned consumers in Delhi without considering taste heterogeneity are shown in Tables 3 and 4 respectively.

The 'Actively concerned' consumers, as delineated in Table 3, exhibit a pronounced WTP for a unit improvement in specific attributes of PHEVs, reflecting their environmental consciousness and technological inclination. On the other hand, the 'Combined passive and unconcerned' consumers, represented in Table 4, also show specific preferences, although with a lower WTP, indicating varied motivational factors driving their PHEV adoption. Table 3 shows that the actively concerned consumers are willing to pay INR 2,647 to reduce travel costs, but it is not their primary concern. On the other hand, Table 4 shows that the combined group of passive and unconcerned consumers are willing to pay more, INR 3,659, to cut down travel costs, which is a 38.2 % increase compared to what actively concerned consumers are willing to pay. This difference indicates that the combined group of passive and unconcerned consumers is more worried about saving money, while the actively concerned consumers care more about being eco-friendly. Technological features such as Traffic Jam Assist (TJA) and Intelligent Energy Management System (IEMS) hold significant appeal across both consumer segments but to varying degrees. The WTP for TJA + IEMS among actively concerned consumers is INR 4,40,324, considerably higher than the WTP of INR 1,95,773 among the combined passive and

Table 3
Estimation results of MXL model for complete dataset of actively concerned consumers in Delhi without taste heterogeneity.

	Coefficient	T-statistics	Average WTP	Confidence interval of WTP
Random parameter in utility function				
Travel Cost reduction (as compared to CVs)	0.0090*	1.68	2,647	1,169–5,774
AVT option: TJA + IEMS	1.4971***	5.83	4,40,324	2,80,796–6,12,317
AVT option: TJA	1.2667***	4.16	3,72,560	1,84,929–5,60,053
Battery Range	0.0139***	4.35	3,941	2,365–5,720
Public Charging Station (as compared to CVs)	0.0084***	3.57	2,470	1,034–4,040
Recharging Time	−0.1979***	−5.52	58,235	38,315–80,613
Battery Warranty	0.2828***	4.20	83,176	47,800–1,19,359
Tailpipe Emission	−0.0215***	−4.06	6,324	3,249–9,612
Non-random parameter in utility function				
Purchase Cost#	−0.0034***	−7.19		
Model fit				
N	558			
Log-likelihood	−270.812			
ρ^2_{adj}	0.277			

Note:#Purchase cost in INR 1,000; CV: Conventional vehicle; TJA: Traffic Jam Assist; IEMS: Intelligent Energy Management System; *10 % level of significance; ***1 % level of significance.

Table 4
Estimation results of MXL model for complete dataset of combined passive and unconcerned consumers in Delhi without taste heterogeneity.

	Coefficient	T-statistics	Average WTP	Confidence interval of WTP
Random parameter in utility function				
Travel Cost reduction (as compared to CVs)	0.0161***	3.61	3,659	1,704–5,645
AVT option: TJA + IEMS	0.8614***	4.39	1,95,773	1,10,479–2,82,701
AVT option: TJA	0.8502***	3.48	1,93,227	85,710–3,02,365
Battery Range	0.0113***	4.42	2,568	1,545–3,611
Public Charging Station (as compared to CVs)	0.0067***	3.64	1,523	662–2,385
Recharging Time	−0.2328***	−7.56	52,909	40,524–65,748
Battery Warranty	0.1569***	3.27	35,840	15,195–56,440
Tailpipe Emission	−0.0083*	−1.95	1,886	921–3,806
Non-random parameter in utility function				
Purchase Cost#	−0.0044***	−9.54		
Model fit				
N	687			
Log-likelihood	−356.159			
ρ^2_{adj}	0.233			

Note: #Purchase cost in INR 1,000; CV: Conventional vehicle; TJA: Traffic Jam Assist; IEMS: Intelligent Energy Management System; *10 % level of significance; ***1 % level of significance.

unconcerned consumers, indicating a 124.8 % higher WTP. Similarly, for the TJA option alone, the WTP is INR 3,72,560 among actively concerned consumers and INR 1,93,227 among the combined passive and unconcerned consumers, denoting a 93 % higher WTP among the former. This substantial difference in WTP for advanced vehicle technologies between these groups underscores the stronger technological affinity or willingness to invest in eco-friendly technologies among the actively concerned consumers. The results on battery range and charging infrastructure highlight the different preferences among consumer groups. Actively concerned consumers are ready to pay INR 3,941 for a better battery range and INR 2,470 for improved charging station accessibility, while the figures for the combined group of passive and unconcerned consumers are lower, at INR 2,568 and INR 1,523 respectively. This shows a 53.5 % and 62.2 % higher WTP for better battery range and charging station accessibility, respectively, among the actively concerned consumers. The results suggest that individuals interested in environmental activism and technology value a better battery range. This trend aligns with the idea that such environmentally and technologically inclined individuals will likely be among the early adopters of PHEVs.

Similar to Delhi, the comparative analysis of the MXL model estimation results for complete dataset of actively concerned consumers (Table 5) and the combined group of passive and unconcerned consumers (Table 6) in Kolkata without considering taste heterogeneity unveils a detailed narrative on their preferences and valuation concerning difference attributes related to PHEVs. A notable difference is observed initially in the valuation of travel cost reduction, where actively concerned consumers show a higher average WTP of INR 5,992 than INR 1,940 for the combined group. This discrepancy in valuation may stem from actively concerned consumers' better understanding or engagement with the technological and environmental benefits of reduced travel costs. They might be more acquainted with the financial burdens of conventional vehicle use, hence willing to pay more for technologies with lower travel cost. Additionally, their environmental concerns might link reduced travel costs to lower fuel consumption.

Table 5
Estimation results of MXL model for complete dataset of actively concerned consumers in Kolkata without taste heterogeneity.

	Coefficient	T-statistics	Average WTP	Confidence interval of WTP
Random parameter in utility function				
Travel Cost reduction (as compared to CVs)	0.0215**	4.12	5,992	3,424–8,740
AVT option: TJA + IEMS	1.0140***	4.85	2,81,694	1,59,380–4,12,643
AVT option: TJA	0.6701***	2.68	1,86,278	45,910–3,32,340
Battery Range	0.0093***	3.47	2,583	1,233–3,982
Public Charging Station (as compared to CVs)	0.0050**	2.52	1,361	267–2,513
Recharging Time	−0.1020***	−3.55	28,333	13,377–44,171
Battery Warranty	0.1848***	3.27	51,333	23,175–81,047
Tailpipe Emission	−0.0372***	−6.86	10,333	7,147–13,593
Non-random parameter in utility function				
Purchase Cost#	−0.0036***	−7.19		
Model fit				
N	612			
Log-likelihood	−320.083			
ρ^2_{adj}	0.224			

Note: #Purchase cost in INR 1,000; CV: Conventional vehicle; TJA: Traffic Jam Assist; IEMS: Intelligent Energy Management System; **5 % level of significance; ***1 % level of significance.

Table 6
Estimation results of MXL model for complete dataset of combined passive and unconcerned consumers in Kolkata without taste heterogeneity.

	Coefficient	T-statistics	Average WTP	Confidence interval of WTP
Random parameter in utility function				
Travel Cost reduction (as compared to CVs)	0.0096**	2.52	1,940	501–3,343
AVT option: TJA + IEMS	0.8719***	5.09	1,70,960	1,03,859–2,35,856
AVT option: TJA	0.7288***	3.44	1,42,900	60,670–2,23,287
Battery Range	0.0051***	2.58	1,080	306–1,826
Public Charging Station (as compared to CVs)	0.0070***	4.23	1,380	712–2,047
Recharging Time	−0.0784***	−3.83	15,380	7,521–23,046
Battery Warranty	0.1434***	3.67	28,120	13,618–42,121
Tailpipe Emission	−0.0074**	−2.14	1,460	174–2,716
Non-random parameter in utility function				
Purchase Cost#	−0.0051***	−10.97		
Model fit				
N	888			
Log-likelihood	−492.186			
ρ^2_{adj}	0.186			

Note: #Purchase cost in INR 1,000; CV: Conventional vehicle; TJA: Traffic Jam Assist; IEMS: Intelligent Energy Management System; **5 % level of significance; ***1 % level of significance.

Furthermore, for AVT options, actively concerned consumers demonstrate a higher average WTP for both TJA + IEMS (INR 2,81,694 vs. INR 1,70,960) and TJA (INR 1,86,278 vs. INR 1,42,900) options as compared to combined passively and unconcerned consumers. The significant difference in WTP could indicate a stronger inclination among actively concerned consumers towards advanced vehicle technologies, perhaps spurred by environmental considerations or a liking for modern, technologically sophisticated solutions. When examining battery-related features, the actively concerned consumers again exhibit a higher average WTP for battery range (INR 2,583 vs. INR 1,080) and battery warranty (INR 51,333 vs. INR 28,120), reflecting a greater concern for long-term vehicle reliability and a willingness to invest upfront for potential long-term benefits such as cost savings on battery replacements. In the context of public charging facilities, the WTP is comparable between the two groups. The environmental consciousness among consumers comes to light under the tailpipe emission parameter, where actively concerned consumers exhibit a stronger disutility with an average WTP of INR 10,222 compared to INR 1,460 by the combined group for emission reduction. This significant difference underlines a stronger environmental consciousness and possibly a higher willingness among actively concerned consumers to pay for reducing tailpipe emissions. For recharging time, both groups show a negative coefficient reflecting a common disutility associated with longer recharging times. However, the disutility is more pronounced among actively concerned consumers, with an average WTP of INR 28,333 versus INR 15,380 by the combined group, hinting at a potential lifestyle or time-value difference that makes recharging time a more critical concern for the actively concerned group.

5.3.2. Model estimation results of complete dataset considering taste heterogeneity for sociodemographic variables

In this section, taste heterogeneity considering sociodemographic variables such as age, gender, education, monthly family income, car ownership, garage availability, and average trip length is detailed for the complete dataset of actively concerned and combined passive and unconcerned consumers in Delhi and Kolkata. The primary aim of the heterogeneity study was to explore how these aforementioned variables impact preferences for PHEVs. The results of MXL model considering taste heterogeneity, for both actively concerned and combined passive and unconcerned consumers in Delhi and Kolkata, are outlined in Tables 7 and 8 respectively.

It is important to note that Tables 7 and 8 present an inclusive model only for those combinations of variables with statistically significant coefficient estimates and taste variations. Sociodemographic variables were integrated into the model as separate dummy variables, as explained in the footnotes of Tables 7 and 8. A statistically significant interaction effect of a particular sociodemographic variable with a random parameter signifies the presence of taste heterogeneity, and vice versa. For instance, in Table 7, with respect to gender (male or female), a statistically significant decomposition effect is observed around the mean estimates of travel cost reduction and battery range for actively concerned consumers in Delhi. The results indicate that in Delhi, gender substantially influences actively concerned consumers' preference for PHEV in terms of their electric range and fuel cost savings characteristics. Furthermore, the insignificant interaction effect with other attributes signifies that actively concerned consumers belonging to different genders do not perceive them as statistically significantly distinct. Similar interpretations can be made for all the other sociodemographic variables and their respective interaction effects.

5.3.3. Comparison of Delhi and Kolkata

This sub-section compares the consumer preferences across Delhi and Kolkata (as obtained in Section 5.3.1), focusing on sociodemographic and trip-related characteristics indicated in Table 1.

Travel cost reduction: Delhi's 'Actively concerned' consumers signal a WTP of INR 2,647 towards travel cost reduction. Meanwhile, Kolkata's 'Actively Concerned' segment demonstrates a WTP of INR 5,992 — a significant surge of 126.5 %. Kolkata has a higher representation of individuals with monthly incomes of INR 1,50,000 or less (73 %) than Delhi (58 %). This predominance of a relatively lower-income demographic in Kolkata could drive this heightened WTP towards travel cost reduction, indicating their greater value-for-money-saving attributes.

AVT option: Regarding the appreciation of AVT options, consumers in both cities indicate substantially higher WTP for such advanced features in the car. However, unlike Kolkata, Delhi consumers indicate a higher valuation for AVT options. For instance, 'Actively Concerned' consumers of Delhi show a WTP of INR 4,40,324 for TJA + IEMS, towering over Kolkata's figure of INR 2,81,694—a 56.4 % difference. The reason could be attributed to a higher percentage of individuals in Delhi (42 %) with a monthly income of more than INR 1,50,000 compared to their Kolkata counterparts (27 %). This suggests that in urban settings, monthly income strongly correlates with a proclivity towards innovative vehicle technologies.

Battery range and battery warranty: Battery range and battery warranty emerge as a significant factor in Delhi, with both consumer segments willing to pay relatively higher than Kolkata consumers. For instance, for battery range improvement, 'Actively concerned' consumers in Delhi are willing to pay INR 3,941, overshadowing Kolkata's WTP of INR 2,583—a 52.6 % increase. Similarly, battery warranty is considerably more valued among 'Actively concerned' consumers in Delhi, with a WTP of INR 83,176, 62.6 % more than Kolkata's WTP of INR 51,333. Given the descriptive statistics, Delhi, with a city size of 1,483 km^2, exhibits an average trip length of more than 30 km for 65 % of its sample, possibly emphasizing the need for a robust battery range and higher warranty coverage, compared to Kolkata's smaller city size of 187 km^2, and the resulting average trip length of 30 km and less for 68 % of its commuters.

Public charging station and recharging time: For an increase in density of public charging facilities and a reduction in battery recharging time, both consumer groups in Delhi show higher WTP values

Table 7
Estimation results of MXL model with taste heterogeneity for actively concerned and combined passive and unconcerned consumers in Delhi.

Consumer category	Actively concerned	Combined passive and unconcerned
Attributes		
Random parameters		
Travel Cost Reduction (as compared to CVs)	0.0199*(1.73)	0.0200***(2.93)
AVT option: TJA + IEMS	1.1418**(2.13)	0.5618*(1.93)
AVT option: TJA	1.1380* (1.79)	0.7203*(1.93)
Battery Range	0.0264***(3.71)	0.0102***(2.63)
Public Charging Station (as compared to CVs)	0.0084*(1.75)	0.0090***(3.14)
Recharging Time	−0.4545*** (−4.29)	−0.2627***(−5.44)
Battery Warranty	0.2110* (1.72)	0.1317* (1.75)
Tailpipe Emission	−0.0245** (−2.06)	−0.0117*(−1.82)
Non-random parameter in utility function		
Purchase Cost[#]	−0.0048*** (−6.60)	−0.0052***(−9.49)
Heterogeneity around the mean of random parameter		
Travel Cost Reduction: Gender[a]	−0.0329** (−2.01)	–
Travel Cost Reduction: Monthly Family Income[b]	–	–
Travel Cost Reduction: Garage Availability[c]	–	–
TJA + IEMS: Gender	–	–
TJA + IEMS: Monthly Family Income	1.0605**(2.02)	1.0348**(2.32)
TJA + IEMS: Garage Availability	–	–
TJA: Gender	–	–
TJA: Monthly Family Income	1.0991*(1.65)	1.5629***(2.64)
TJA: Garage Availability	–	–
Battery Range: Gender	−0.0172* (−1.93)	−0.0324**(−2.41)
Battery Range: Monthly Family Income	0.0147**(1.97)	0.0188***(3.05)
Battery Range: Garage Availability	−0.0185** (−2.50)	–
Public Charging Station: Gender	–	–
Public Charging Station: Monthly Family Income	0.0169***(2.96)	–
Public Charging Station: Garage Availability	–	–
Recharging Time: Gender	–	
Recharging Time: Monthly Family Income	–	−0.2405***(−3.21)
Recharging Time: Garage Availability	0.2665***(2.87)	0.1168**(2.06)
Battery Warranty: Gender	–	–
Battery Warranty: Monthly Family Income	0.6589***(4.12)	0.3991***(3.28)
Battery Warranty: Garage Availability	–	–
Tailpipe Emission: Gender	–	–
Tailpipe Emission: Monthly Family Income	–	–
Tailpipe Emission: Garage Availability	–	–
Model fit		
N	558	687
Log-likelihood function	−236.124	−329.039
ρ^2_{adj}	0.304	0.240

Note: Cells with dash indicate statistically insignificant heterogeneity around the mean of random parameters.
T-statistics are mentioned in the parenthesis.
[#] Purchase cost in INR 1,000; CV: Conventional vehicle; TJA: Traffic Jam Assist; IEMS: Intelligent Energy Management System; *10 % level of significance; ***1 % level of significance.

[a] Gender was divided into two categories to investigate heterogeneity: Male consumers were coded as '0' and female consumers were coded as '1'.
[b] Monthly Family Income was divided into two categories to investigate heterogeneity: Consumers with income $\leq$ 1,50,000 were coded as '0' and those with income > 1,50,000 were coded as '1'.
[c] Garage Availability was divided into two categories to investigate heterogeneity: Consumers without the availability of a garage were coded as '0' and those with garage availability were coded as '1'.

relative to Kolkata consumers. For instance, Delhi's 'Actively concerned' consumers show a WTP of INR 2,470 for charging station accessibility, which is 81.48 % higher than Kolkata counterpart, with WTP of INR 1,361. Similarly, for a reduced recharging time, Delhi's 'Actively concerned' consumers demonstrate a stronger aversion with a WTP of INR 58,235 compared to Kolkata's INR 28,333. With 53 % of Delhi's sample having no garage to park/charge a vehicle at home, this might hint at Delhi consumers' higher valuation for access to public charging infrastructure and fast charging rates.

Tailpipe emissions: Environmental considerations come to the forefront with Kolkata's 'Actively concerned' consumers' WTP of INR 10,222 to reduce tailpipe emissions, surpassing Delhi's INR 6,324. This marked discrepancy underscores the environmental concerns in Kolkata, potentially exacerbated by the environmental consciousness of the population.

5.4. Model validation

To ensure the reliability and generalizability of the findings from the developed MXL models, model validation was carried out through market simulation. Initially, the dataset was randomly partitioned, to use 90 % of the dataset for model development, and the remaining 10 % of the dataset as a holdout sample. The dataset was split to check the ability of the calibrated model i.e., the model developed using 90 % of the dataset, to accurately predict the market share and consumer choices for the remaining dataset i.e., 10 % holdout sample. The efficacy of the model validation process was assessed by analyzing the rate of misclassification. This measure indicates the discrepancy between the actual choices made by consumers in the holdout sample and the choice probability predicted by the calibrated model. A lower misclassification rate signifies higher predictive accuracy, as it demonstrates the model's ability to closely replicate actual consumer behavior. The model validation results are presented in Table 9. It may be seen from Table 9 that for all four MXL models corresponding to different consumer segments and cities, predictive accuracy lies between 70.79 % to 74.17 %, which indicates a lower misclassification rate between the simulated estimates of calibration model and actual choices of holdout sample and hence high predictive accuracy (Das et al., 2023). The model validation results affirm the model's robustness in capturing consumer preferences for PHEVs across different consumer segments and cities. Hence, the developed MXL models are deemed reliable for policy formulation and designing market strategies to increase the attractiveness of PHEVs in Delhi and Kolkata.

5.5. Sensitivity analysis

A comparison of sensitivity outcomes across various consumer groups and cities in Fig. 5 reveals some interesting trends. Sensitivity tests were conducted using MXL models for two user groups in Delhi and Kolkata. These tests focused on seven main attributes: travel cost reduction, battery range, public charging stations, recharging time, battery warranty, tailpipe emission, and purchase cost. For improvement in one attribute at a time, keeping all other attributes fixed to their base value, the percentage shift in probabilities was evaluated for alternative scenarios relative to the base scenario. For the car's purchase price, the base level was 25 % more than what the average actively concerned consumers and combined passive and unconcerned

Table 8
Estimation results of MXL model with taste heterogeneity for actively concerned and combined passive and unconcerned consumers in Kolkata.

Consumer category	Actively concerned	Combined passive and unconcerned
Attributes		
Random parameters		
Travel Cost Reduction (as compared to CVs)	0.0175**(2.14)	0.0095**(2.06)
AVT option: TJA + IEMS	1.6487***(4.53)	0.8232***(3.87)
AVT option: TJA	1.0718***(2.63)	0.7149***(2.70)
Battery Range	0.0074* (1.75)	0.0044*(1.72)
Public Charging Station (as compared to CVs)	0.0075**(2.33)	0.0074***(3.55)
Recharging Time	−0.1337*** (−2.73)	−0.0827***(−3.33)
Battery Warranty	0.2503***(2.74)	0.1399***(3.01)
Tailpipe Emission	−0.0271*** (−3.43)	−0.0074*(−1.74)
Non-random parameter in utility function		
Purchase Cost[#]	−0.0040*** (−7.30)	−0.0055***(−10.90)
Heterogeneity around the mean of random parameter		
Travel Cost Reduction: Gender[a]	–	–
Travel Cost Reduction: Monthly Family Income[b]	0.0216**(2.09)	0.0215*(1.72)
Travel Cost Reduction: [c]Average Trip Length	–	–
TJA + IEMS:Gender	–	−1.0430**(−2.02)
TJA + IEMS: Monthly Family Income	–	1.0465**(2.06)
TJA + IEMS: [c]Average Trip Length	–	–
TJA: Gender	–	–
TJA: Monthly Family Income	–	–
TJA: Average Trip Length	–	–
Battery Range: Gender	−0.0111* (−1.70)	–
Battery Range: Monthly Family Income	–	–
Battery Range: Average Trip Length	0.0122**(1.99)	0.0109**(2.03)
Public Charging Station: Gender	–	−0.0098**(−1.99)
Public Charging Station: Monthly Family Income	–	–
Public Charging Station: Average Trip Length	–	0.0083*(1.75)
Recharging Time: Gender	–	–
Recharging Time: Monthly Family Income	–	–
Recharging Time: Average Trip Length	–	–
Battery Warranty: Gender	−0.3584*** (−2.72)	–
Battery Warranty: Monthly Family Income	–	–
Battery Warranty: Average Trip Length	–	–
Tailpipe Emission: Gender	−0.0213* (−1.79)	–
Tailpipe Emission: Monthly Family Income	−0.0245** (−2.34)	−0.0191*(−1.75)
Tailpipe Emission: Average Trip Length	–	–
Model fit		
N	612	888
Log-likelihood function	−297.510	−470.490
ρ^2_{adj}	0.221	0.182

Note: Cells with dash indicate statistically insignificant heterogeneity around the mean of random parameters.
T-statistics are mentioned in the parenthesis.

[#] Purchase cost in INR 1,000; CV: Conventional vehicle; TJA: Traffic Jam Assist; IEMS: Intelligent Energy Management System; *10 % level of significance; ***1 % level of significance.

[a] Gender was divided into two categories to investigate heterogeneity: Male consumers were coded as '0' and female consumers were coded as '1'.

[b] Monthly family income was divided into two categories to investigate heterogeneity: Consumers with income ≤ 1,50,000 were coded as '0' and those with income > 1,50,000 were coded as '1'.

[c] Average trip length was divided into two categories to investigate heterogeneity: Consumers with average trip length ≤ 30 km were coded as '0' and those with average trip length > 30 km were coded as '1'.

Table 9
Model validation with market simulation.

Model	Model Accuracy
Model 1: Actively concerned consumers in Delhi	74.14 %
Model 2: Combined passive and unconcerned consumers in Delhi	73.91 %
Model 3: Actively concerned consumers in Kolkata	73.77 %
Model 4: Combined passive and unconcerned consumers in Kolkata	70.79 %

consumers in Delhi and Kolkata would spend to buy the next car. Choice probability changes were determined based on variations in attributes from 0 % to 100 % at 10 % steps. However, the measurement only exceeded 90 % for recharging time and tailpipe emissions.

Travel cost reduction: For a 50 % surge in travel cost savings, the choice probability of actively concerned consumers in Kolkata boosts by 10.74 %, while that of combined passive and unconcerned consumers increases by 4.85 % compared to the base case. The results indicate that future PHEV designs with improvement in travel cost savings would enhance the appeal of PHEV as a mode among all consumer groups in Kolkata. Similar trends were noted among Delhi participants. This finding aligns with previous research, which highlighted that better fuel efficiency significantly influences the selection of EVs (Danielis et al., 2020; Helveston et al., 2015; Rommel and Sagebiel, 2021).

Battery range: Overall, the sensitivity analysis indicates that an increase in battery range would encourage the selection of PHEVs among both user groups in both cities, aligning with previous research (Beak et al., 2020; Kowalska-Pyzalska et al., 2022; Tarei et al., 2021). Moreover, the WTP analysis and sensitivity assessment demonstrate that Delhi consumers are more sensitive to battery range enhancement than Kolkata consumers.

Public charging stations: For a 50 % increase in public charging station availability, the PHEV choice probability in Delhi rises by 4.20 % for those actively concerned and 3.35 % for the combined passive and unconcerned individuals compared to the base scenario. Similarly, in Kolkata, the choice probability rises by 2.45 % for the actively concerned group and 3.45 % for the combined passive and unconcerned group relative to the base case. The sensitivity results indicate that a

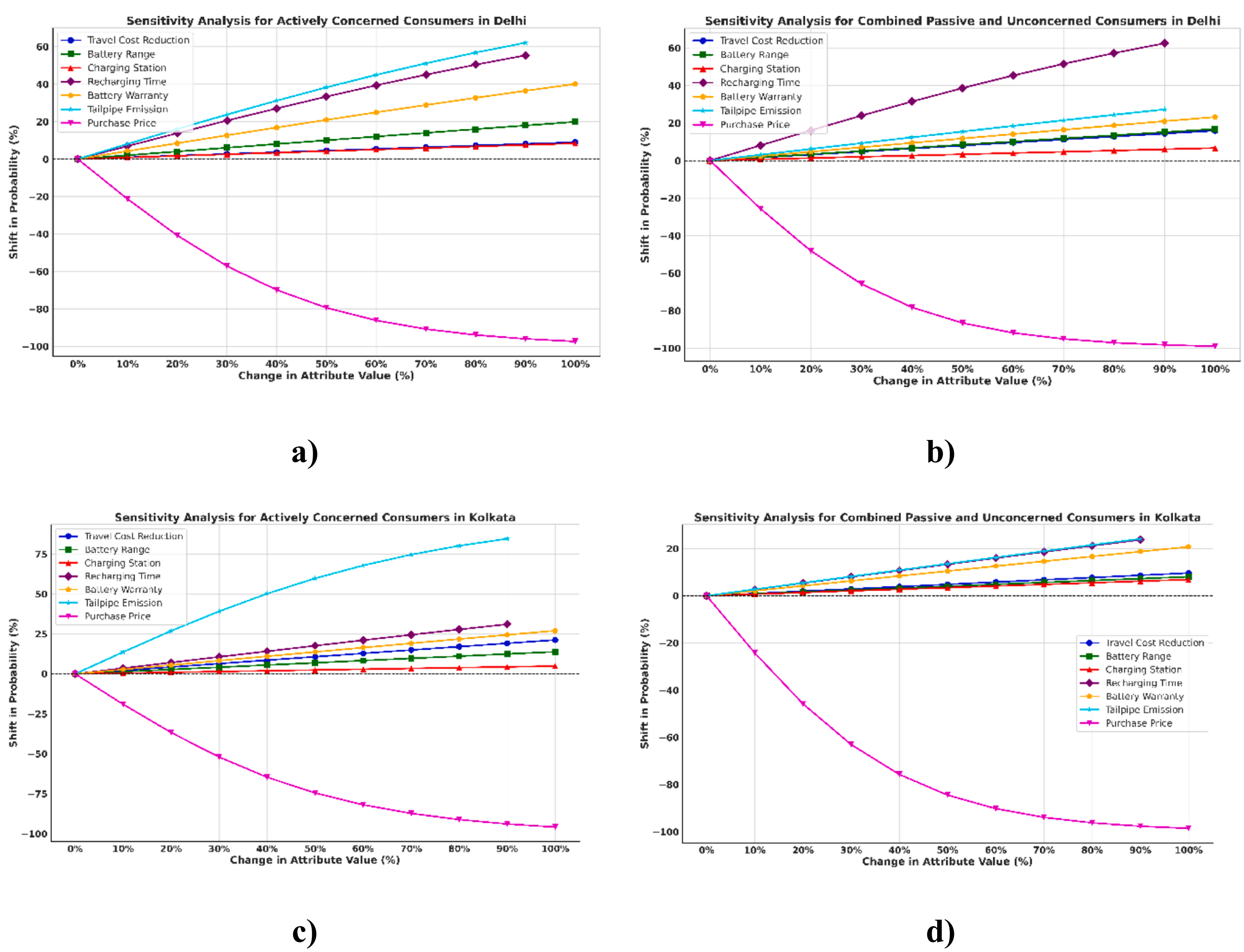

Fig. 5. Sensitivity results across different consumer groups in Delhi and Kolkata: a) Actively concerned consumers in Delhi, b) Combined passive and unconcerned consumers in Delhi, c) Actively concerned consumers in Kolkata, and d) Combined passive and unconcerned consumers in Kolkata.

higher density of charging facilities would encourage both consumer groups in both cities towards PHEV choice. This supports earlier research which points out that a lack of charging facilities is a significant obstacle to the broader adoption of EVs (Giansoldati et al., 2020b; Jia and Chen, 2023; Rommel and Sagebiel, 2021).

Recharging time: For a 50 % reduction in battery recharging time, in Delhi, the probability of choosing PHEV increased by 33.33 % and 38.63 % among actively concerned and combined passive and unconcerned consumers, respectively, relative to the base scenario. The results indicate that improving battery recharging time for future PHEV models would strongly motivate both actively concerned and others in Delhi to choose PHEV. Kolkata also showed similar trends. Previous studies have also found that reduced charging times significantly boost people's interest in EVs (Hoen and Koetse, 2014; Lashari et al., 2022; Mpoi et al., 2023). Further, from the results, it may be observed that the estimates obtained for Delhi consumers are about 1.8–2.9 times higher than Kolkata consumers. Sensitivity analysis clearly reflects that Delhi consumers are more influenced by recharging time when considering PHEV adoption than those in Kolkata.

Battery warranty: Overall, the sensitivity results show that enhancing battery coverage would strongly motivate PHEV choice among consumers in both Delhi and Kolkata. This observation aligns with previous research (Higgins et al., 2017). Furthermore, when examining WTP values and sensitivity analysis outcomes, it is evident that actively concerned consumers in Delhi are marginally more sensitive to battery warranty improvements than their counterparts in Kolkata.

Tailpipe emission: For a 50 % decrease in tailpipe emission, the choice probability of PHEVs in Delhi rises by 38.26 % for those actively concerned about the environment and 15.44 % for the combined group of passive and not concerned consumers, compared to the base scenario. Similarly, in Kolkata, the positive probability shifts are 59.80 % among actively concerned groups and 13.60 % among combined passive and unconcerned groups, with a 50 % emission reduction. The observations suggest that tailpipe emission reduction would strongly motivate all consumers in both cities toward PHEV choice. Previous research supports these findings, emphasizing that reduction in vehicular emissions is crucial in persuading consumers to prefer EVs over conventional vehicles (Higgins et al., 2017; Rahmani and Loureiro, 2019; Tanaka et al., 2014). Nevertheless, actively concerned consumers in each city will likely be the first to embrace PHEVs with a further decrease in tailpipe emissions.

Purchase cost: The purchase price is the most influential attribute across all consumer groups and cities, displaying the most dramatic negative shifts in choice probability. However, in line with the WTP results, the price sensitivity is relatively higher among both cities' combined passive and unconcerned consumers than actively concerned consumers. For instance, in Delhi, when the purchase cost rises by 50 %, the probability of choosing a PHEV decreases by 79.40 % for those who are actively concerned. On the other hand, among combined passive and unconcerned consumers, the drop in choice probability is observed to be 86.56 % relative to the base case. Similarly, in Kolkata, a 50 % price hike results in a 74.51 % decrease in PHEV choice for actively concerned individuals, while the combined passive and unconcerned group sees a decrease of 84.49 %. The purchase cost factor is a significant hurdle for consumers when considering PHEVs. These patterns align with the results of past research (Jia and Chen, 2023; Lashari et al., 2022; Miele et al., 2020). Government support, such as purchase incentives, could be crucial to boost the adoption of PHEVs in India.

5.6. Policy implications of the results and recommendations

This section offers structured policy guidelines derived from the study's insights into consumer preferences for PHEVs in Delhi and Kolkata. These recommendations aim to guide policymakers in fostering PHEV adoption effectively by considering supporting examples from developed countries.

- **Addressing cost sensitivities:** Cost emerged as a decisive factor for PHEV adoption across all consumer segments. The data suggest that as the purchase cost of PHEVs rises, their attractiveness is substantially decreased, particularly among the more passive or unconcerned consumer group. Policymakers should consider introducing financial incentives for PHEV buyers. For instance, drawing inspiration from countries like Norway and the US, which have successfully promoted the adoption of electrified light-duty vehicles through comprehensive incentive programs (IEA, 2021). This could range from direct subsidies, inclusive push for PHEVs under the Faster Adoption and Manufacturing of Electric Vehicles (FAME) scheme with Goods and Services Tax (GST) exemptions, to road tax exemptions or rebates. Such incentives can help counteract the higher upfront costs of these vehicles, making them more financially accessible to a broader consumer base.
- **Promoting environmental awareness:** The environmental benefits, notably reduced tailpipe emissions, were seen as a significant motivator, especially amongst the actively concerned group in both cities. The government should conduct targeted educational campaigns emphasizing the environmental advantages of PHEVs. For example, a city-based campaign illustrating the direct connection between PHEVs and reduced smog levels could be impactful. Drawing parallels with cities like Los Angeles, which once had severe smog issues but witnessed substantial improvement due to regulatory measures and PHEV adoption, underscores the importance of environmental awareness (California Air Resources Board, 2022).
- **Enhancing charging infrastructure:** The data highlighted the availability and accessibility of charging stations as pivotal factors influencing adoption. With fewer households having garages (refer to Table 1), Delhi relies more on public charging infrastructure. An infrastructure-driven policy approach, like many developed nations, with its extensive network of public charging stations, could serve as a blueprint. Collaborative efforts between the government, real estate developers, and private companies can accelerate the establishment of charging points in commercial hubs, residential areas, and highways.
- **Improving battery technology:** Battery-related attributes, such as range and warranty, significantly influenced consumer preferences. The government should provide research grants and incentives to companies investing in advanced battery technologies. Lessons can be learned from countries like South Korea, which have focused plans to leap into battery technologies such as solid-state batteries due to vital government-backed Research and Development (R&D) initiatives (Crider, 2021).
- **Reducing recharging time:** Consumers value their time, evident in their preferences for faster battery recharging times. Hence, it is important to prioritize and incentivize the development and deployment of fast-charging stations. Using the Tesla Supercharger network as a model, India should focus on developing a similar rapid-charging infrastructure, ensuring that long waits at charging stations are minimized.
- **Encouraging technological adoption:** Technologically advanced features of PHEVs attracted a significant segment of consumers, especially in Delhi. Organize city-specific tech expos and conventions where automakers can demonstrate the latest PHEV technologies. For instance, cities like Frankfurt and Tokyo, with their renowned auto shows (Automotive Stage, 2022), offer platforms for manufacturers to showcase innovations, influencing both consumers and industry stakeholders.

Therefore, for PHEVs to gain mainstream adoption in cities like Delhi and Kolkata, technological advancements, financial incentives, infrastructure development, and consumer awareness campaigns tailored to each city's specific needs and characteristics are imperative.

5.7. Limitations and future scope of research

This study provides insights into consumer attitudes and preferences for PHEVs in Delhi and Kolkata and highlights avenues for further exploration and refinement:

- The study captured diverse responses; the sample disproportionately represents educated individuals and has a lower representation of females, as highlighted in sub-Section 4.2. While not diminishing the study's findings, this aspect suggests that future research should aim for a more balanced and inclusive sample. A broader representation would provide a more comprehensive understanding of consumer perspectives.
- This study explored how various traits, including socio-demographic characteristics, socio-psychological characteristics and trip-related factors, impact consumer preferences towards PHEV-related attributes. Future studies should investigate the effects of innovativeness, symbolic perceptions, peer influences, and prior experience with PHEVs on choice preferences for related attributes.
- The study's focus on Delhi and Kolkata was intentional, aiming to provide deep, localized insights. This geographical concentration is valuable for policymakers and stakeholders in these cities. However, extending this research to other urban and rural areas would offer a more comprehensive picture, enabling broader policy recommendations.
- The use of data in this study offers a snapshot of current consumer preferences, serving as a valuable baseline for policymakers. Future research could adopt a time-series data approach to capture the evolving dynamics of consumer behavior, particularly as new technologies and policies emerge.
- The study's emphasis on existing technologies like TJA and IEMS provides a realistic view of current market offerings. As the automotive landscape evolves, there will be ample opportunities to update this research to include newer technologies, keeping the insights fresh and relevant.
- Although an interesting observation of the differences in consumer attitudes towards the environment and technology is found between Delhi and Kolkata, it was not possible to state conclusively the intrinsic causes of differences between the two cities, with the available data in the present work. It would be interesting and necessary to investigate the intrinsic causes of differences between the two cities as a scope of future research.
- Estimation of consumers' WTP values for PHEV attributes using hypothetical choices of SP experiment offers an initial understanding of consumer preference towards PHEVs and related attributes. Incorporating real-world purchasing data (as and when available) in future studies could enhance the predictive accuracy of these insights, making them even more actionable for manufacturers and policymakers.
- Another future scope of the present study lies in applying the Integrated Choice and Latent Variable (ICLV) model to analyze the prospective users' perception towards choosing PHEVs.

6. Conclusions

The global shift towards a greener environment has emphasized the importance of EVs in reducing climate change impacts. In this context, this study explored consumer attitudes and preferences for PHEVs in Delhi and Kolkata. Some significant observations from the present study are as follows:

- This study identified two primary consumer segments. The 'Actively concerned,' who prioritize environmental and technological aspects, are significantly different from the 'Combined passive and unconcerned,' whose motivations are more economically driven.
- Actively concerned consumers in Delhi showed a WTP of INR 2,647 for travel cost reduction, compared to a higher WTP of INR 5,992 in Kolkata. This indicates that Kolkata consumers value travel savings more than Delhi.
- Delhi's actively concerned consumers indicated a WTP of INR 3,941 for the battery range, 52.6 % higher than Kolkata's INR 2,583. This suggests that battery range is a crucial deciding factor, particularly in Delhi.
- In Delhi, 'Actively Concerned' consumers exhibit a 56.4 % higher WTP for advanced vehicle technologies like TJA + IEMS than their Kolkata counterparts.
- Emphasis on reduced emissions is evident in Kolkata, where the WTP to reduce tailpipe emissions is INR 10,222 among actively concerned consumers, outpacing Delhi's INR 6,324.
- The study also highlights the impact of sociodemographic variables such as gender, monthly family income, garage availability, and average trip length (journey to and from work) on PHEV adoption in the Indian context.
- In Delhi, a 50 % reduction in recharging time leads to a 33.33 % increased choice probability of PHEV selection among actively concerned consumers. This underlines the importance of faster charging capabilities.
- The WTP study and sensitivity analysis indicate that improvements in battery warranty play an important role in PHEV adoption across all consumer segments and cities. This insight underscores the importance of robust warranty offerings by manufacturers to boost consumer confidence and PHEV adoption rates.
- Sensitivity analysis identifies purchase price as a major barrier towards PHEV adoption, with a substantial increase in disutility observed among all consumer groups and cities, with a 50 % increase in the purchase price. The government interventions in terms of purchase subsidies can play a key role in encouraging wider adoption of PHEVs in the Indian context.

Therefore, while environmental concerns and economic factors are pivotal for PHEV adoption, their importance differs based on consumer type and city. For successful market penetration, strategies should be tailored considering these distinctions and the quantified preferences of consumers in each segment. The study primarily offers three main contributions. First, in theory, this study adds necessary knowledge about PHEVs, especially in developing countries such as India, where this area has not been explored much. It introduces new ideas about how people in Delhi and Kolkata feel about PHEVs. Second, in practice, work is one of the few that looks at different types of consumers in these cities. The study results help to understand where efforts should be focused to promote PHEVs. This is particularly relevant for countries such as India, grappling with asset utilization challenges due to resource constraints. Lastly, although the present study findings are specific to Delhi and Kolkata, the demonstrated methodological framework is generic and can be used by vehicle manufacturers and policymakers in other developed and developing countries, to better plan for the future of sustainable urban transportation in their respective cities.

CRediT authorship contribution statement

Reema Bera Sharma: Writing – original draft, Writing – review & editing, Visualization, Validation, Software, Methodology, Investigation, Formal analysis, Data curation. **Deepjyoti Das:** Writing – original draft, Visualization, Methodology, Investigation. **Bhargab Maitra:** Writing – review & editing, Supervision, Resources, Project administration, Methodology, Funding acquisition, Conceptualization.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence

the work reported in this paper.

Acknowledgment

This study is a part of project initiated and funded by Ministry of Human Resource Development (Government of India), Tata Motors Limited, and Ministry of Heavy Industries & Public Enterprises (Government of India). Authors are thankful to the supporting organizations for giving the opportunity to undertake the present study. Reema Bera Sharma acknowledges the Indian Institute of Technology (IIT) Kharagpur and Chalmers University of Technology for providing all necessary support to complete this part of the study.

Appendix A:. Existing consumer-based studies on EVs

Table A1. Past studies on consumer attitudes and preferences toward EVs.

Study (year)	Study region	Data type	Vehicle type(s)	Attributes used	Target group	Method	Focus	Key findings
Jia and Chen (2023)	Virginia, U. S.	Stated Preference (SP)	ICEV, HEV, PHEV, BEV	Battery range, fuel economy, annual tailpipe CO_2 emission, charging station availability, purchase price, annual fuel/ charging cost, annual maintenance cost, federal tax credit, state rebates	837 residents	Mixed logit (MXL), Latent class (LC), and Latent class-mixed logit (LC-MXL)	• WTP for attributes of PHEVs • Comparison of different modeling techniques	• Lowering purchase costs and expanding public charging stations is more critical than extending the battery range for PHEV adoption. • No model is unanimously superior to other models.
Mpoi et al. (2023)	Greece	SP	EVs	Environmental awareness, trip characteristics, fuel price, government policies, charging time, charging stations every 10–15 km, socio-demographic attributes	350 citizens	Ordinal regression	• Factors affecting consumer intention to purchase EVs	• Financial incentives increase willingness to purchase EVs • Environmental awareness, charging time, and charging infrastructure affect EV purchase intent
Lashari et al. (2022)	South Korea	SP	ICEV, BEV, and HFCV	Approach time to charging/refueling stations (minutes), driving range, charging/refueling time, purchase price, sociodemographic attributes and attitudinal perception	1500 potential car buyers	MNL and MXL model	▪ Sensitivity analysis of attributes on vehicle choice	▪ Vehicle attributes such as price, range, charging time, and attitudinal perceptions such as perceived environmental and economic benefit significantly influence AFV choice.
Kowalska-Pyzalska et al. (2022)	Poland	Conjoint	BEV, PHEV and HEV	Car type, functionality level, access to service, monthly price, purchase price, access to charging, electric range, safety level	500 residents	Conjoint analysis	▪ Factors influencing consumer preference for AFVs	▪ Safety is identified as the most critical attribute for AFV purchase, followed by price, range, and car type.
Visaria et al. 2022)	Denmark	SP	EVs	Detour time, charger availability, charging speed, charging cost, additional facilities	558 EV owners	MXL	• WTP for charging-related attributes	• Detour respondents are willing to drive to obtain lower charging costs, a higher probability of charger availability, and additional facilities at the charging location.
Ji and Gan (2022)	China	SP	ICEV, BEV, PHEV	Gender, education level, car ownership, commuting distance, desired car purchase price, total cost of ownership	163 residents under 40 years of age	Rank-ordered logit	• Effect of providing total cost of ownership information on consumer preference towards BEVs and PHEVs	• Total cost of ownership information has a positive influence on consumer choice for BEVs and PHEVs • Gender and education have a significant influence on EV purchase intent.
Tarei et al. (2021)	India	Rating	BEV	Technical barrier, infrastructural barrier, financial barrier, behavioral barrier, external barrier	10 experts	Structural Equation Modeling (SEM)	• Ranking and prioritization of EV barriers • Identifying the strength of the relationship among	• Performance, range, total cost of ownership, charging infrastructure, and consumer awareness significantly drive EV adoption

(continued on next page)

(*continued*)

Study (year)	Study region	Data type	Vehicle type(s)	Attributes used	Target group	Method	Focus	Key findings
							barriers to EV adoption	
Rommel and Sagebiel (2021)	Germany	SP	ICEV, HEV, PHEV, BEV	Price, power, running cost, range, availability of petrol/ charging stations	405 car owners	LC	• WTP for attributes of AFVs	• Consumers interested in PHEV and BEV show higher WTP for increased charging station availability and lower running costs.
Danielis et al. (2020)	Italy	SP	ICEV, EV	Charging time, distance between charging stations, driving range, fuel economy, purchase price	996 license holders	MNL and MXL	• WTP for EV attributes • Scenario analysis to compare the impact of government policies vs technological improvement	• Improvement in fuel efficiency and electric range strongly influence driver preference for EVs • Government incentives impact EV purchases more than technology advancement.
Khurana et al. (2020)	India	Rating	BEV	Economic benefit, environmental concern, social influence, self-image, attitude	214 car owners	SEM	• Examining factors influencing BEV adoption	• Consumer attitude emerged as the primary factor affecting BEV adoption
Navalgund and Nulkar (2020)	Karnataka, India	Rating	BEV	Ecosystem for EV, awareness, performance, pro-environmental behavior and financial advantage and cost of EVs	384 residents	SEM	• Factors affecting purchase intention toward BEV	• Pro-environmental behavior plays a crucial role in the purchase intention of EVs • Financial advantage and cost have no significant relation with EV purchase intention.
Miele et al. (2020)	Canada	SP	ICEV, BEV, PHEV, HEV	Purchase price, purchase incentive, fuel cost, range, home charging, workplace charging, public charging	1884 new vehicle buyers	Latent Class (LC)	• WTP for EV-related attributes	• Charging infrastructure availability has a limited impact on EV choice • High purchase prices and low awareness are significant barriers to EV adoption.
Beak et al. (2020)	South Korea	Conjoint	EV, ICEV	Driving range, charging technology, charging time, autonomous driving function, CO_2 emission reduction, purchase price	1008 residents	MXL	• WTP for EV attributes	• CO_2 emission reduction is not an influencing factor for consumer purchase decisions towards EVs • Price and battery technology are identified as crucial features for EV uptake.
Giansoldati, et al., (2020a)	Italy	Rating	EVs		807 Italian drivers	PCA and Cluster analysis	• Purchase intention of EVs	• A lower density of charging infrastructure, lack of charging stations on highways, and purchase price are primary barriers to EV adoption.
Higueras-Castillo et al. (2020)	Spain	Rating	EVs	Socio-demographic, psychological, and EV attributes	404 potential consumers	PCA and Cluster analysis	• Intention to adopt EVs	• Price identified as a key barrier for potential adopters • Young women with high incomes could be early adopters of EVs
Rahmani and Loureiro (2019)	Spain	SP	HEV	Price, fuel consumption, CO_2 emission. Socio-demographic variables	875 Spanish drivers	LC	• WTP for HEV-related attributes	• HEV-oriented and aware drivers indicate the highest WTP for fuel savings and CO_2 emission reduction. • Individuals with high incomes are less sensitive to price and fuel costs.
Nie et al. (2018)	Shanghai, China	SP	EVs	Driving range, pollution, maximum speed, fuel costs, charging time, price, socio-demographic and socio-psychological attributes	760 potential car buyers	MNL and MXL	• WTP for EV attributes	• Potential EV purchasers show higher WTP for improvement in EV attributes compared to unlikely EV purchasers. • Potential EV purchasers include individuals with high income, high environmental awareness, and high

(*continued on next page*)

(*continued*)

Study (year)	Study region	Data type	Vehicle type(s)	Attributes used	Target group	Method	Focus	Key findings
								acceptance of new technology.
Higgins et al. (2017)	Canada	SP	ICEV, HEV, PHEV, BEV	Fuel/charging availability, battery warranty, charging time, battery range, gasoline range, acceleration, tailpipe emission, fuel/ charging cost, maintenance cost, purchase price	15,392 households	Multinomial Probit (MNP)	• Effect of consumers' vehicle body type preference on the utility of EVs • Sensitivity analysis of attributes	• Consumer preference for EVs and their attributes vary substantially based on vehicle body type choice. • Irrespective of preferred next vehicle body type, consumers favoring PHEV and BEV show high sensitivity towards fuel economy, emission reduction, battery range, and battery warranty.
Hackbarth and Madlener (2016)	Germany	SP	ICEV, HEV, PHEV, BEV	Battery recharging time, refueling time, fuel availability, driving range, CO_2 emission, fuel cost per 100 km, purchase price, policy incentives, sociodemographic attributes	711 respondents	MNL and LC	• WTP for AFV attributes	• WTP for vehicle attributes vary considerably across different consumer segments • Young, less educated, highly environmentally aware consumers with high daily mileage are more likely to choose AFVs
Helveston et al. (2015)	China/US	SP	ICEV, HEV, PHEV, BEV	Acceleration time, operating cost, fast charging capability, purchase price, brand, vehicle type	415 US, 572 China	MNL and MXL	• WTP for AFVs	• Chinese respondents have a higher choice preference towards mid-range PHEVs and BEVs as compared to American respondents. • Chinese respondents show higher WTP for acceleration time and operating cost than American counterparts.
Tanaka et al. (2014)	US (California, Texas, Michigan, and New York)/Japan	SP	ICEV, PHEV, BEV	Driving range, emission reduction (compared to CVs), alternative fuel availability (% of existing gas stations), home plug-in construction fee, purchase price	4202 US, 4000 Japan	MNL and MXL	• WTP for AFV attributes	• Consumers in both the US and Japan place higher value on fuel cost reduction, alternative fuel station availability, and emission reduction. However, WTP for fuel cost reduction and alternative fuel station availability is higher among average US consumers than Japanese consumers. • Variations in gasoline price and annual mileage across four cities in the US substantially influence consumers' WTP for fuel cost reduction of EVs.
Hoen and Koetse (2014)	Netherlands	SP	HEV, PHEV, BEV, fuel-cell, flexifuel	Car type, brand, additional detour time, driving range, monthly cost, policy incentives, trip length, trip frequency	1903 residents	MXL	• WTP for AFVs	• Short driving range, long charging times, and limited recharging infrastructure are identified as primary barriers to the widespread adoption of EVs • Commuters with lower mileage have a lower preference for driving range and are more likely to purchase EVs
Schuitema et al. (2013)	United Kingdom (UK)	Rating	ICEV, PHEV, BEV,	Instrumental, hedonic, symbolic, pro-environmental, car-authority identify	2728 car owners	Regression analysis	• Intention to adopt EVs	• The importance of instrumental attributes is linked to hedonic and symbolic aspects of owning and using EVs • Individuals who align their self-image with pro-environmental identity

(*continued on next page*)

(*continued*)

Study (year)	Study region	Data type	Vehicle type(s)	Attributes used	Target group	Method	Focus	Key findings
								show a higher willingness to choose EVs
Krupa et al. (2014)	US	Rating	PHEV	Environmental concern, fuel/financial savings, PHEV technology, image/ social influences, vehicle class	1000 US residents	Logistic regression	• Factors influencing PHEV adoption	• Price, mileage, and performance are identified as important attributes for PHEV purchase. • Environmentally sensitive consumers are identified as early adopters of PHEVs

Note: ICEV = Internal Combustion Engine Vehicle, HEV = Hybrid Electric Vehicle, PHEV = Plug-in Hybrid Electric Vehicle, BEV = Battery Electric Vehicle, AFV = Alternative Fuel Vehicles, EV = Electric Vehicle, HFCV = Hydrogen Fuel Cell Vehicle.

Appendix B:. Abbreviation and notation list

AFVs: Alternative Fuel Vehicles
AVT: Advanced Vehicle Technology
BEV: Battery Electric Vehicle
CAPI: Computer Assisted Personal Interviews
CFI: Comparative Fit Index
CO_2: Carbon Dioxide
CV: Conventional Vehicle
EFA: Exploratory Factor Analysis
EV: Electric Vehicle
FAME: Faster Adoption and Manufacturing of Electric Vehicles
FCM: Fuzzy c-means
Gg: Gigagram
GST: Goods and Services Tax
h(β|ω): Density function of β given parameters ω
HEV: Hybrid Electric Vehicle
HFCV Hydrogen Fuel Cell Vehicle
ICE: Internal Combustion Engine
ICEV: Internal Combustion Engine Vehicle
IEMS: Intelligent Energy Management System
IIA: Independence of Irrelevant Alternatives
INR: Indian Rupee
JMP: JMP Statistical Software
km: Kilometer
L(ω): Log-likelihood function
LC: Latent Class
LC-MXL: Latent Class-Mixed Logit
MNL: Multinomial Logit
MNP: Multinomial Probit
MXL: Mixed Logit
PHEV: Plug-in Hybrid Electric Vehicle
Q_n (i): Choice probability for individual n selecting alternative i
R&D: Research and Development
RMSEA: Root Mean Square Error Approximation
s_n: Characteristics of individual n
SEM: Structural Equation Modeling
SP: Stated Preference
TJA: Traffic Jam Assist
TLI: Tucker-Lewis Index
TPB: Theory of Planned Behavior
U_ni: Utility derived by individual n for selecting alternative i
VKT Vehicle Kilometer Traveled
W_ni: Observed component of utility
WLS: Weighted Least Squares
WTP: Willingness-to-Pay
x_ni: Attributes of the alternatives for individual n
β: Parameter vector to be estimated
ε_ni: Error term
ρ^2_adj: Adjusted Rho-squared values

References

Annam, S., Cheranchery, M.F., Chakraborty, A., Maitra, S., 2023. Areas of intervention for enhancing the knowledge of safe driving: an experience in West Bengal, India. Case Stud. Transp. Policy 13 (November 2022), 101065. https://doi.org/10.1016/j.cstp.2023.101065.

Automotive Stage, 2022. List of 2022 Auto Shows: Enjoy the Auto World First hand. Automotive Stage. https://automotivestage.com/list-of-2022-auto-shows/.

Axsen, J., Kurani, K.S., 2009. Early US market for plug-in hybrid electric vehicles: anticipating consumer recharge potential and design priorities. Transp. Res. Rec. 2139 (1), 64–72. https://doi.org/10.3141/2139-08.

Bansal, P., Kockelman, K.M., Schievelbein, W., Schauer-West, S., 2018. Indian vehicle ownership and travel behavior: a case study of Bengaluru, Delhi and Kolkata. Res. Transp. Econ. 71 (February), 2–8. https://doi.org/10.1016/j.retrec.2018.07.025.

Beak, Y., Kim, K., Maeng, K., Cho, Y., 2020. Is the environment-friendly factor attractive to customers when purchasing electric vehicles? Evidence from South Korea. Bus. Strateg. Environ. 29 (3), 996–1006. https://doi.org/10.1002/bse.2412.

Bera, R., Maitra, B., 2021a. Analyzing prospective owners' choice decision towards plug-in hybrid electric vehicles in urban India: a stated preference discrete choice experiment. Sustainability (Switzerland) 13 (14). https://doi.org/10.3390/su13147725.

Bera, R., Maitra, B., 2021b. Assessing consumer preferences for Plug-in Hybrid Electric Vehicle (PHEV): an Indian perspective. Res. Transp. Econ. 90 (May), 101161 https://doi.org/10.1016/j.retrec.2021.101161.

Bera, R., Maitra, B., 2022. Commuters' willingness-to-pay for the attributes of plug-in hybrid electric vehicle: a case study in Kolkata, India. Transp. Develop. Econ. 8 (1), 5. https://doi.org/10.1007/s40890-021-00142-3.

Bera, R., Maitra, B., 2023. Identification of priority areas of improvement for small passenger car segment in Indian market. Vision 27 (2), 225–242. https://doi.org/10.1177/09722629211004057.

Bezdek, J.C., 1981. Pattern recognition with fuzzy objective function algorithms. In: Pattern Recognition with Fuzzy Objective Function Algorithms. https://doi.org/10.1007/978-1-4757-0450-1.

Bhat, C.R., 2001. Quasi-random maximum simulated likelihood estimation of the mixed multinomial logit model. Transp. Res. B Methodol. 35 (7), 677–693. https://doi.org/10.1016/S0191-2615(00)00014-X.

Björnsson, L.H., Karlsson, S., 2017. Electrification of the two-car household: PHEV or BEV? Transp. Res. Part C: Emerg. Technol. 85 (September), 363–376. https://doi.org/10.1016/j.trc.2017.09.021.

Brownstone, D., 1999. Forecasting new product penetration with flexible substitution patterns. J. Econ. 89, 109–129.

Buil, I., de Chernatony, L., Martínez, E., 2013. Examining the role of advertising and sales promotions in brand equity creation. J. Bus. Res. 66 (1), 115–122. https://doi.org/10.1016/j.jbusres.2011.07.030.

California Air Resources Board, 2022. *California moves to accelerate to 100% new zero-emission vehicle sales by 2035*. https://ww2.arb.ca.gov/news/california-moves-accelerate-100-new-zero-emission-vehicle-sales-2035.

Čapienė, A., Rūtelionė, A., Tvaronavičienė, M., 2021. Pro-environmental and pro-social engagement in sustainable consumption: exploratory study. Sustainability (Switzerland) 13 (4), 1–20. https://doi.org/10.3390/su13041601.

Casidy, R., Wymer, W., 2016. A risk worth taking: perceived risk as moderator of satisfaction, loyalty, and willingness-to-pay premium price. J. Retail. Consum. Serv. 32, 189–197. https://doi.org/10.1016/j.jretconser.2016.06.014.

Chen, H., Lai, K., He, L., Yu, R., 2020. Where you are is who you are? The geographical account of psychological phenomena. Front. Psychol. 11 (March), 1–11. https://doi.org/10.3389/fpsyg.2020.00536.
Crider, J., 2021. *South Korea Has $ 41 Billion EV Battery Plan*. CleanTechnica. https://cleantechnica.com/2021/07/14/south-korea-has-41-billion-ev-battery-plan/.
Danielis, R., Rotaris, L., Giansoldati, M., Scorrano, M., 2020. Drivers' preferences for electric cars in Italy. evidence from a country with limited but growing electric car uptake. Transp. Res. A Policy Pract. 137 (May), 79–94. https://doi.org/10.1016/j.tra.2020.04.004.
Das, D., Kalbar, P.P., Velaga, N.R., 2021. Pathways to decarbonize passenger transportation: implications to India' s climate budget. J. Clean. Prod. 295, 126321 https://doi.org/10.1016/j.jclepro.2021.126321.
Das, D., Mandal, P., 2021. Comparative evaluation of commuters' preferences and expectations for sharing auto-rickshaw. Case Stud. Transport Policy 9 (4), 1567–1581. https://doi.org/10.1016/j.cstp.2021.08.006.
Das, D., Kalbar, P.P., Velaga, N.R., 2022. Role of non-motorized transportation and buses in meeting climate targets of urban regions. Sustain. Cities Soc. 86 (August), 104116 https://doi.org/10.1016/j.scs.2022.104116.
Das, D., Bhaduri, E., Velaga, N.R., 2023. Modeling commuters' preference towards sharing paratransit services. Transp. Policy. https://doi.org/10.1016/j.tranpol.2023.09.008.
Dutta, S., Ghosh, S., Dinda, S., 2021. Urban air-quality assessment and inferring the association between different factors: a comparative study among Delhi, Kolkata and Chennai Megacity of India. Aerosol Sci. Eng. 5 (1), 93–111. https://doi.org/10.1007/s41810-020-00087-x.
Ewing, G., Sarigöllü, E., 2000. Assessing consumer preferences for clean-fuel vehicles: a discrete choice experiment. J. Public Policy Mark. 19 (1), 106–118. https://doi.org/10.1509/jppm.19.1.106.16946.
Fletcher, R.S., Showler, A.T., Funk, P.A., 2014. Employing broadband spectra and cluster analysis to assess thermal defoliation of cotton. Comput. Electron. Agric. 105, 103–110. https://doi.org/10.1016/j.compag.2014.04.003.
Giansoldati, M., Monte, A., Scorrano, M., 2020a. Barriers to the adoption of electric cars: evidence from an Italian survey. Energy Policy 146 (June), 111812. https://doi.org/10.1016/j.enpol.2020.111812.
Giansoldati, M., Rotaris, L., Scorrano, M., Danielis, R., 2020b. Does electric car knowledge influence car choice? Evidence from a hybrid choice model. Res. Transp. Econ. 80 (March) https://doi.org/10.1016/j.retrec.2020.100826.
Gifford, R., Nilsson, A., 2014. Personal and social factors that influence pro-environmental concern and behaviour: a review. Int. J. Psychol. 49 (3) https://doi.org/10.1002/ijop.12034 n/a-n/a.
Government of India, 2011. Census of India 2011. Ministry of Home Affairs, New Delhi.
Hackbarth, A., Madlener, R., 2013. Consumer preferences for alternative fuel vehicles: a discrete choice analysis. Transp. Res. Part D: Transp. Environ. 25, 5–17. https://doi.org/10.1016/j.trd.2013.07.002.
Hackbarth, A., Madlener, R., 2016. Willingness-to-pay for alternative fuel vehicle characteristics: a stated choice study for Germany. Transp. Res. A Policy Pract. 85, 89–111. https://doi.org/10.1016/j.tra.2015.12.005.
Hair, J.F., Black, W.C., Babin, B.J., Anderson, R.E., 2014. Multivariat data analysis. In: Exploratory Data Analysis in Business and Economics. https://doi.org/10.1007/978-3-319-01517-0_3.
Haque, M., Singh, R., 2017. Air pollution and human health in Kolkata, India: a case study. Climate 5 (4), 77. https://doi.org/10.3390/cli5040077.
Helveston, J.P., Liu, Y., Feit, E.M.D., Fuchs, E., Klampfl, E., Michalek, J.J., 2015. Will subsidies drive electric vehicle adoption? Measuring consumer preferences in the U. S. and China. Transp. Res. A Policy Pract. 73, 96–112. https://doi.org/10.1016/j.tra.2015.01.002.
Hensher, D.A., Greene, W.H., 2003. The mixed logit model: The state of practice. Transportation 30 (2), 133–176. https://doi.org/10.1023/A:1022558715350.
Hensher, D.A., Rose, J.M., Greene, W.H., 2015. Applied choice analysis. In: Applied Choice Analysis. https://doi.org/10.1007/9781316136232.
Higgins, C.D., Mohamed, M., Ferguson, M.R., 2017. Size matters: How vehicle body type affects consumer preferences for electric vehicles. Transp. Res. A Policy Pract. 100, 182–201. https://doi.org/10.1016/j.tra.2017.04.014.
Higueras-Castillo, E., Molinillo, S., Coca-Stefaniak, J.A., Liébana-Cabanillas, F., 2020. Potential early adopters of hybrid and electric vehicles in Spain-Towards a customer profile. Sustainability (Switzerland) 12 (11). https://doi.org/10.3390/su12114345.
Hoen, A., Koetse, M.J., 2014. A choice experiment on alternative fuel vehicle preferences of private car owners in the Netherlands. Transp. Res. A Policy Pract. 61, 199–215. https://doi.org/10.1016/j.tra.2014.01.008.
Huang, Y., Qian, L., Tyfield, D., Soopramanien, D., 2020. On the heterogeneity in consumer preferences for electric vehicles across generations and cities in China. Technol. Forecast. Soc. Chang. 167 (July 20201), 5–10. https://doi.org/10.1016/j.techfore.2021.120687.
IEA, 2021. Global EV Outlook 2021 – Accelerating ambitions despite the pandemic. *Global EV Outlook 2021*, 101. https://iea.blob.core.windows.net/assets/ed5f4484-f556-4110-8c5c-4ede8bcba637/GlobalEVOutlook2021.pdf.
IQAir, 2020. World air quality report region and city PM2.5 ranking. https://www.iqair.com/world-most-polluted-cities/world-air-quality-report-2020-en.pdf.
Ji, D., Gan, H., 2022. Effects of providing total cost of ownership information on below-40 young consumers' intent to purchase an electric vehicle: a case study in China. Energy Policy 165 (March), 112954. https://doi.org/10.1016/j.enpol.2022.112954.
Jia, W., Chen, T.D., 2023. Investigating heterogeneous preferences for plug-in electric vehicles: policy implications from different choice models. Transp. Res. A Policy Pract. 173 (February), 103693 https://doi.org/10.1016/j.tra.2023.103693.
Khan, R.A., Qudrat-Ullah, H., 2021. Technology adoption theories and models. In: Advances in Science, Technology and Innovation (IEREK Inte, pp. 27–48). Springer. https://doi.org/10.1007/978-3-030-50112-9_5.
Khurana, A., Kumar, V.V.R., Sidhpuria, M., 2020. A study on the adoption of electric vehicles in india: the mediating role of attitude. Vision 24 (1), 23–34. https://doi.org/10.1177/0972262919875548.
Klöckner, C.A., 2013. A comprehensive model of the psychology of environmental behaviour—a meta-analysis. Glob. Environ. Chang. 23 (5), 1028–1038. https://doi.org/10.1016/j.gloenvcha.2013.05.014.
Kolluru, S.S.R., Patra, A.K., Nazneen, Shiva Nagendra, S.M., 2021. Association of air pollution and meteorological variables with COVID-19 incidence: evidence from five megacities in India. Environ. Res. 195 (February), 110854 https://doi.org/10.1016/j.envres.2021.110854.
Kowalska-Pyzalska, A., Michalski, R., Kott, M., Skowrońska-Szmer, A., Kott, J., 2022. Consumer preferences towards alternative fuel vehicles. results from the conjoint analysis. Renew. Sustain. Energy Rev. 155 https://doi.org/10.1016/j.rser.2021.111776.
Krupa, J.S., Rizzo, D.M., Eppstein, M.J., Brad Lanute, D., Gaalema, D.E., Lakkaraju, K., Warrender, C.E., 2014. Analysis of a consumer survey on plug-in hybrid electric vehicles. Transp. Res. A Policy Pract. 64, 14–31. https://doi.org/10.1016/j.tra.2014.02.019.
Kurtuluş, E., Çetin, İ.B., 2020. Analysis of modal shift potential towards intermodal transportation in short-distance inland container transport. Transport Policy 89 (August 2019), 24–37. https://doi.org/10.1016/j.tranpol.2020.01.017.
Lashari, Z.A., Ko, J., Jung, S., Choi, S., 2022. Choices of potential car buyers regarding alternative fuel vehicles in south Korea: a discrete choice modeling approach. Sustainability (Switzerland) 14 (9), 1–17. https://doi.org/10.3390/su14095360.
Malik, L., Tiwari, G., Thakur, S., Kumar, A., 2019. Assessment of freight vehicle characteristics and impact of future policy interventions on their emissions in Delhi. Transp. Res. Part D: Transp. Environ. 67, 610–627. https://doi.org/10.1016/j.trd.2019.01.007.
McEachan, R.R.C., Conner, M., Taylor, N.J., Lawton, R.J., 2011. Prospective prediction of health-related behaviours with the Theory of Planned Behaviour: a meta-analysis. Health Psychol. Rev. 5 (2), 97–144. https://doi.org/10.1080/17437199.2010.521684.
McFadden, D., Train, K., 2000. Mixed MNL models for discrete response. J. Appl. Economet. 15 (5), 447–470. https://doi.org/10.1002/1099-1255(200009/10)15:5<447::AID-JAE570>3.3.CO;2-T.
Miele, A., Axsen, J., Wolinetz, M., Maine, E., Long, Z., 2020. The role of charging and refuelling infrastructure in supporting zero-emission vehicle sales. Transp. Res. Part D: Transp. Environ. 81 (February), 102275 https://doi.org/10.1016/j.trd.2020.102275.
Ministry of Road Transport & Highways. (2020). Road Accidents in India 2019. *Goverment of India, Ministry of Road Transport & Highways, Transportation Research Wing*, 1–121.
Mpoi, G., Milioti, C., Mitropoulos, L., 2023. Factors and incentives that affect electric vehicle adoption in Greece. Int. J. Transp. Sci. Technol. xxxx, 1–16. https://doi.org/10.1016/j.ijtst.2023.01.002.
Muthén, L., Muthén, B., 2015. Mplus user's guide: Seventh Edition (Statistical Analysis With Latent Variables). In *Los Angeles, CA: Muthén & Muthén*. https://doi.org/10.1111/j.1532-5415.2004.52225.x.
Navalgund, N., Nulkar, G., 2020. Factors influencing purchase intention towards E-vehicles among the Potential Indian consumers – a study on Karnataka region. J. Soc. Sci. 48 (3), 3621–3628. https://doi.org/10.13140/RG.2.2.28103.11686.
Nie, Y., Wang, E., Guo, Q., Shen, J., 2018. Examining Shanghai consumer preferences for electric vehicles and their attributes. Sustainability 10 (6), 1–16. https://doi.org/10.3390/su10062036.
Parumog, M., Mizokami, S., Kakimoto, R., 2006. Value of traffic externalities from attribute-based stated choice: route choice experiment. Transp. Res. Record: J. Transp. Res. Board 1954 (1954), 52–60. https://doi.org/10.3141/1954-08.
Purnawansyah, Haviluddin, Gafar, A.F.O., Tahyudin, I., 2018. Comparison between K-means and fuzzy C-means clustering in network traffic activities. In: Proceedings of the Eleventh International Conference on Management Science and Engineering Management, April 2018, 300–310. https://doi.org/10.1007/978-3-319-59280-0_24.
Rahmani, D., Loureiro, M.L., 2019. Assessing drivers' preferences for hybrid electric vehicles (HEV) in Spain. Res. Transp. Econ. 73 (October 2018), 89–97. https://doi.org/10.1016/j.retrec.2018.10.006.
Ramachandra, T.V., Aithal, B.H., Sreejith, K., 2015. GHG footprint of major cities in India. Renew. Sustain. Energy Rev. 44, 473–495. https://doi.org/10.1016/j.rser.2014.12.036.
Rommel, K., Sagebiel, J., 2021. Are consumer preferences for attributes of alternative vehicles sufficiently accounted for in current policies? Transp. Res. Interdiscip. Perspect. 10 (April), 100385 https://doi.org/10.1016/j.trip.2021.100385.
Schuitema, G., Anable, J., Skippon, S., Kinnear, N., 2013. The role of instrumental, hedonic and symbolic attributes in the intention to adopt electric vehicles. Transp. Res. A Policy Pract. 48, 39–49. https://doi.org/10.1016/j.tra.2012.10.004.
Sharma, R.B., Maitra, B., 2024. Methodological approach to obtain key attributes affecting the adoption of plug-in hybrid electric vehicle. Case Stud. Transport Policy, 101165. https://doi.org/10.1016/j.cstp.2024.101165.
Sharma, R.B., Majumdar, B.B., Maitra, B., 2024. Commuter and non-commuter preferences for plug-in hybrid electric vehicle: A case study of Delhi and Kolkata, India. Res. Transp. Econ. 103, 101415 https://doi.org/10.1016/j.retrec.2024.101415.
Slowik, P., Isenstadt, A., Pierce, L., Searle, S., 2022. Assessment of light-duty electric vehicle costs and consumer benefits in the United States in the 2022–2035 time

frame. International Council on Clean Transportation: Washington, DC, USA. https://theicct.org/wp-content/uploads/2022/10/ev-cost-benefits-2035-oct22.pdf.
Sparks, P., Shepherd, R., 2002. The role of moral judgments within expectancy-value-based attitude-behavior models. Ethics Behav. 12 (4), 299–321. https://doi.org/10.1207/S15327019EB1204_01.
Steg, L., Perlaviciute, G., van der Werff, E., Lurvink, J., 2014. The significance of hedonic values for environmentally relevant attitudes, preferences, and actions. Environ. Behav. 46 (2), 163–192. https://doi.org/10.1177/0013916512454730.
Taherdoost, H., 2017. Determining sample size; how to calculate survey sample size by Hamed Taherdoost: SSRN. Int. J. Econ. Manage. Syst. 2 (February 2017), 237–239. https://papers.ssrn.com/sol3/papers.cfm?abstract_id=3224205.
Tanaka, M., Ida, T., Murakami, K., Friedman, L., 2014. Consumers' willingness to pay for alternative fuel vehicles: a comparative discrete choice analysis between the US and Japan. Transp. Res. A Policy Pract. 70 (2014), 194–209. https://doi.org/10.1016/j.tra.2014.10.019.
Tarei, P.K., Chand, P., Gupta, H., 2021. Barriers to the adoption of electric vehicles: evidence from India. J. Clean. Prod. 291, 125847 https://doi.org/10.1016/j.jclepro.2021.125847.
Tiwari, S., Saxena, P., 2021. Air Pollution and its Complications: From the Regional to the Global Scale. Springer Atmospheric Sciences.
Train, K.E., 2009. Discrete Choice Methods with Simulation. In *Cambridge University Press*. https://doi.org/10.1080/07474938.2014.975634.
Visaria, A.A., Jensen, A.F., Thorhauge, M., Mabit, S.E., 2022. User preferences for EV charging, pricing schemes, and charging infrastructure. Transp. Res. A Policy Pract. 165 (September), 120–143. https://doi.org/10.1016/j.tra.2022.08.013.
Wang, C., Sun, J., Russell, R., Daziano, R.A., 2018. Analyzing willingness to improve the resilience of New York City's transportation system. Transp. Policy 69 (May), 10–19. https://doi.org/10.1016/j.tranpol.2018.05.010.
Wiharto, W., Suryani, E., 2020. The comparison of clustering algorithms K-means and fuzzy C-means for segmentation retinal blood vessels. Acta Informatica Medica 28 (1), 42–47. https://doi.org/10.5455/AIM.2020.28.42-47.
Xiong, S., Yuan, Y., Yao, J., Bai, B., Ma, X., 2023. Exploring consumer preferences for electric vehicles based on the random coefficient logit model. Energy 263 (PA), 125504. https://doi.org/10.1016/j.energy.2022.125504.
Zoepf, S., MacKenzie, D., Keith, D., Chernicoff, W., 2013. Charging choices and fuel displacement in a large-scale demonstration of plug-in hybrid electric vehicles. Transp. Res. Rec. 2385 (1), 1–10. https://doi.org/10.3141/2385-01.