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Research paper

Commuter and non-commuter preferences for plug-in hybrid electric vehicle: A case study of Delhi and Kolkata, India

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ABSTRACT

This paper investigates the commuter and non-commuter preferences for Plug-in Hybrid Electric Vehicles in two Indian metro cities namely Delhi and Kolkata based on a stated preference (SP) framework. The SP data collected from the car-owning population in each city were analyzed using Mixed Logit (ML) models to obtain the commuter and non-commuter respondents' perceived benefit associated with PHEV operation-specific attributes in terms of willingness to pay (WTP). Thereafter, a sensitivity analysis was carried out to understand the impact of improvement in related attributes on consumer preferences towards PHEVs. The findings suggest an added focus by car manufacturers on fuel cost savings, battery recharging time, battery range, tailpipe emission, and battery warranty to attract commuters. This study also highlights that high purchase cost and lack of public charging stations are key barriers towards PHEV adoption. Based on study results, policy actions such as higher subsidy, increased public charging stations, and public educational and awareness campaigns by Government could play a major role towards wider diffusion of PHEVs in Indian context.

1. Background and motivation

Climate change is one of the major concerns confronting the global community (Han & Ahn, 2020). Emissions of greenhouse gases (GHGs) due to human activities are mainly responsible for global warming and climate change (Cook et al., 2013; Bera & Maitra, 2021a). Due to higher dependency on fossil fuels, the transportation sector has been regarded as one of the major emitters of GHGs (especially CO_2) (Achtnicht, 2012; Bera & Maitra, 2022). According to International Energy Agency (IEA), 24% of the global energy-related CO_2 emission are produced by the transportation sector, where three-quarters of these emissions are generated by road transport (IEA, 2020). Economic development in a growing nation like India has led to rapid urbanization, primarily due to high rates of rural-to-urban migration for better job opportunities and improved quality of life (Bera & Maitra, 2023). The increasing urban population combined with their higher disposable income has led to the rising trends of passenger car ownership in metro cities (Miglani, 2019; Bera & Maitra, 2021b). The growing passenger car ownership and usage is a major concern as car emits 604 mg of CO, 139 mg of HC, 178 mg of NOx, 144 g of CO_2, and 4 mg of PM2.5 (Sharma & Chandel, 2020) per km travel. The toxic exhaust emissions released into the atmosphere substantially deteriorate the urban air quality and are subsequently accountable for health concerns among urban residents (Verma et al., 2021). For more details on passenger car growth in India and externalities refer to Appendix A1. Apart from the negative environmental implications, importing crude oil to fuel the growing fleet of passenger cars poses a significant threat to economic development and future energy security (Upadhyayula et al., 2019). Therefore, to address the issues related to rising air pollution and future energy security, there is a need to replace the use of conventional cars with innovative and low-carbon emitting alternatives such as electric vehicles to create a sustainable urban ecosystem (Dhar et al., 2017).

In the global market, three types of EVs are available, namely, hybrid electric vehicles (HEVs), plug-in hybrid electric vehicles (PHEVs), and battery electric vehicles (BEVs). These vehicles have their own sets of advantages and disadvantages as compared to CVs (Wahid et al., 2021). This study has concentrated on understanding the consumers' perspective towards PHEVs. A PHEV uses battery pack to power an electric motor, and simultaneously uses conventional fuel, such as gasoline, to power an internal combustion engine (ICE) for vehicle propulsion

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(Markel & Simpson, 2007). The vehicle typically runs on electric power until the battery is nearly depleted, providing high fuel economy to consumers (Axsen & Kurani, 2010). PHEV produces zero emission at the tailpipe when run in all-electric mode (Markel & Simpson, 2007). Elgowainy et al. (2009) suggested that PHEV, by using grid electricity, displaces about 40–60 % of petroleum, leading to a considerable decrease in oil consumption compared to CVs. Hence, recognizing the benefit to the consumers and environment, and the potential to address the country's energy crisis, there is a need to promote less polluting and energy-efficient PHEVs to replace the existing CVs without disrupting the general travel pattern of Indian consumers for a sustainable future.

1.1. Need for the study

Although the Indian Government has taken several policy initiatives to stimulate EV adoption (for details refer to appendix A2), the market share of EVs still remains low. As per the report of Global EV outlook 2019, only 3300 electric four-wheelers were sold in India in 2018, accounting for less than 1% share of the Indian four-wheeler market (IEA, Global EV Outlook, 2019). The low market penetration indicates that consumers have a low sense of confidence towards EVs in general and PHEVs in particular and the related attributes (Jin & Slowik, 2017). Moreover, consumers' general lack of awareness, knowledge, and familiarity with new alternative modes such as PHEVs may also result in their reluctance to choose the new vehicle technology, leading to subsequent rejection (Axsen et al., 2017; Rajper & Albrecht, 2020). Therefore, the effectiveness of all the government initiatives to promote EVs is heavily reliant on consumer preferences for this new vehicle technology. It is, therefore, necessary to understand how consumers perceive PHEV-related attributes, and what are the possible drivers and barriers associated with PHEV adoption. Such studies would make a significant contribution towards guiding vehicle manufacturers and the government in the formulation of effective policies to increase the market penetration of PHEVs. In this regard, it is important to note that consumers' predominant trip purpose i.e., whether the intended PHEV usage is for commuting or non-commuting trips in nature significantly influences their choice of mode in general, and PHEV in particular (Musti and Kochelmen, 2011; Ziegler, 2012). Trip purpose is one of the crucial transport mode choice determinants (Limtanakool et al., 2006; Yum, 2020; Patil et al., 2020). For a relatively new mode of transport such as PHEV, it is necessary to understand how PHEV ownership and the perceived benefit associated with several PHEV operation-specific attributes would be influenced by consumers' socio-demographic determinants such as trip purpose. It is equally important to understand how consumers' probability to choose PHEVs change with improvement in the related operation-specific attributes with respect to intended predominant trip purpose. This is particularly important in the context of a developing country such as India, where there is low awareness regarding the benefits of PHEV and associated operation-specific attributes. Further, it is crucial to analyze the role of city characteristics on prospective users' perception towards PHEV attributes. City characteristics such as city size, population density, infrastructure readiness, residential conditions, urban regulations, and incentives, etc. could substantially influence consumers' choice decision for EVs (Wang and Zhao, 2017; Yang & Chen, 2021; Huang et al., 2021). Presently, the studies investigating city-specific influence on EV choice are majorly limited to China, where EVs are already a popular mode of transport. Understanding how city characteristics influence consumer choice of PHEVs is pivotal. Such information can help policymakers, planners, and vehicle manufacturers in devising tailored strategies to promote and facilitate wider adoption of PHEVs in specific urban settings. Hence, this study analyzes the city-specific influence on consumer preference towards PHEVs in India and is identified as one of the major study contributions. Against this background, the present study proposes a comprehensive methodology for investigating commuter and non-commuter preference for PHEVs in the context of Indian metro cities.

In the realm of transportation studies, user benefit is defined as reduction in disutility of travel and is evaluated in terms of Willingness to Pay (WTP) for improvement in each non-monetary attributes that defines an alternative (Hensher et al., 2015). Travel behavior models developed by analyzing stated preference (SP) data are integral for assessing attribute valuation and WTP estimation, especially for situations where alternatives/technologies do not currently exist (Cartenì, 2020; Rommel & Sagebiel, 2021; Shin et al., 2015). The WTP estimates linked to various attributes offer guidance to researchers and policymakers, aiding in the selection of targeted improvement strategies (Hensher et al., 2015). In this regard, three basic research questions are addressed in the present study. First, how does the predominant trip purpose (commuting/non-commuting trips) influence consumers' perceived benefit associated with improvement in PHEV operation-specific attributes? Second, is there any city-specific influence on consumers' perceived benefit for PHEV operation-specific attributes with respect to trip purpose? Third, how does consumers' PHEV choice probability change for different improvement scenarios with respect to trip purpose?

2. Review of literature

For review of research articles, we used several online search engines and databases such as Google Scholar, Web of Science, ScienceDirect, and Scopus. The search involved specific keywords such as "electric vehicles," "plug-in hybrid electric vehicles," paired with terms like "consumer preference," "commuters," "choice model." We focused on articles published between 2005 and 2023, filtering results from the search engines. Peer-reviewed articles were selected based on their direct relevance to the research questions addressed in this study. Further, to supplement the database search, we also manually reviewed reference lists of relevant articles to identify any additional studies pertinent to the present study context.

An overview of the literature on travel behavior analysis of consumers toward EVs is provided in this section. Due to the lack of sufficient revealed preference (RP) data from the actual sales of EVs, previous literature on EVs have focused on Stated Preference (SP) methods for analyzing consumer preferences towards EVs. Table 1 summarizes the existing SP studies on EVs. Among such studies, Potoglou and Kanaroglou (2007) evaluated consumers' WTP associated with clean vehicle attributes in Hamilton, Canada. Based on a Nested Logit (NL) model, the study concludes that reduced monetary costs, lower emission rates, and incentives such as purchase tax relieves are valued significantly higher than other attributes for clean vehicle adoption. Investigation on the influence of trip purpose reveals that individuals who are frequent long-distance commuters are more hesitant to choose clean vehicles due to limited fuel availability. Ziegler (2012) developed Multinomial Probit (MNP) model to investigate potential car buyers' preferences towards EVs in Germany. The study concludes that improvement in vehicle attributes such as motor power and service station availability, and reduction in purchase price, fuel costs, and CO_2 emission have positive impact on potential consumers' preference towards EVs. With respect to trip purpose, the study concludes that those who drive the vehicle for journey to work have higher preference towards gas vehicles. Another study by Hoen and Koetse (2014) considered a set of key vehicle attributes and developed Mixed Logit (ML) models to investigate Dutch private car owners' WTP for alternative fuel vehicle characteristics. The results indicate that short driving ranges, long charging times, and limited recharging infrastructure are the primary barriers to the widespread adoption of EVs. For trip purposes, commuters with low annual mileage indicate a lower preference for driving range and are more likely to purchase EVs. Mpoi et al. (2023) developed ordinal logistic regression model to identify the factors influencing the adoption of EV among consumers in Greece. The results reveal that government policies in terms of financial incentives would

Table 1
Existing SP studies on EVs.

Study	Country	Model(s) used	Attribute used in the analysis
Potoglou and Kanaroglou (2007)	Canada	Nested Logit	Annual fuel cost, acceleration, annual maintenance cost, pollution level, fuel availability, purchase price, incentives
Hidrue et al. (2011)	United States	Latent Class	Fuel cost, charging time, acceleration, pollution, driving range, price
Ziegler (2012)	Germany	Multinomial Probit	Purchase price, motor power, fuel costs, CO_2 emission, service station availability
Hackbarth and Madlener (2013)	Germany	Multinomial Logit and Mixed Logit	Fuel cost per 100 km, CO_2 emissions, driving range, fuel availability, refueling time, battery recharging time, purchase price, policy incentives
Hoen and Koetse (2014)	The Netherlands	Mixed Logit	Driving range, monthly costs, recharge time, additional detour time, purchase price, policy measures
Tanaka et al. (2014)	US (California, Texas, Michigan and New York)/ Japan	Mixed Logit	Purchase premium, fuel cost, driving range, emission reduction, alternative fuel availability, home plug-in construction fee
Helveston et al. (2015)	US/China	Multinomial Logit and Mixed Logit	Operating cost, acceleration time, fast charging capability, brand, vehicle type, purchase price
Nie et al. (2018)	China	Multinomial Logit and Mixed Logit	Driving range, pollution, charging time, maximum speed, fuel cost and purchase price
Danielis et al. (2020)	Italy	Multinomial Logit and Mixed Logit	Fuel economy, fast charging time, max. distance between charging stations, driving range, purchase price, free parking in urban areas
Gong et al. (2020)	Australia	Latent Class	Vehicle property: Vehicle body type, recharge time, set up cost, cost per km, driving range, electric vehicle price; support scheme: access to bus lane, rebate on upfront cost, rebate on parking fees
Rommel and Sagebiel (2021)	Germany	Latent Class	Range, running costs, availability of petrol/charging stations, price, bonus
Yang and Chen (2021)	China	Multinomial Logit and Mixed Logit	Purchasing costs, usage costs, driving range, charging infrastructure, reliability, air pollution reduction, CO_2 emissions reduction, incentives, battery quality, reaction to plug-in electric vehicle uptake
Huang et al. (2021)	China	Nested Logit	Purchase price, annual running cost, driving range, coverage of public fast charging stations, coverage of workplace/public slow charging posts, charging speed, government subsidy
Li et al. (2022)	China	Hybrid Choice	Vehicle attribute: Price, cruising range, fuel cost, battery warranty, quick charging time; policy attributes: tax exemption, access to HOV lanes, tradable driving credit (TDC) and personal carbon trading (PCT)
Mpoi et al. (2023)	Greece	Ordinal Logistic Regression	Fuel price, charging time, charging station every 10–15 km, government policies
Jia and Chen (2023)	US	Mixed Logit, Latent Class and Latent Class-Mixed Logit	Battery range, fuel economy, annual tailpipe CO_2 emission, DC fast-charging stations spacing along interstate highways, local charging station at workplace/school, local public charging stations at other destinations (restaurants, shopping centers, etc.), purchase price, annual fuel/charging cost, annual maintenance cost, annual use fee, federal tax credit, state rebates

play a major role towards EV uptake in Greece, followed by the availability of well-designed charging infrastructure network. With respect to travel characteristics, the study results indicate that those who regularly use their car to commute to work are more likely to purchase EVs.

Tanaka et al. (2014) conducted comparative discrete choice analysis across US and Japan, and across four states in US (California, Texas, Michigan, New York) to estimate consumers' WTP for plug-in vehicle (BEV and PHEV) attributes by developing ML models. The results indicate that relative to Japanese consumers, average US consumers indicate higher WTP for fuel economy and fuel availability. Also, among the four US states, consumers in California are found to place much higher value on fuel economy due to higher gasoline prices and higher average annual driving mileage. By developing MNL and ML models, Yang and Chen (2021) investigate the influence of several vehicle, environmental, socio-psychological, and policy attributes on consumer preference of plug-in electric vehicles across two different cities in China namely Hangzhou and Linyi. The results show high WTP among consumer of both cities for reliability, driving range, and battery quality. Interestingly, social influence and innovativeness are found to affect consumer preference and WTP differently in these two cities. Huang et al. (2021) investigated heterogeneity in consumer preference for EV attributes such as purchase price, annual running cost, driving range, coverage of charging stations, charging speed, and government subsidies across generations and different city sizes in China by developing NL models. The study concluded that young consumers in smaller cities show stronger preference for EVs as compared to others. For details on other studies mentioned in Table 1 and their findings, Appendix B may be referred to.

The review of literature including Appendix B shows that the consumer preference for EVs depends on vehicle attributes (e.g., fuel cost, battery recharging time, driving range, emission, battery warranty, purchase price), infrastructure attributes (e.g., number of charging stations, distance between charging stations, additional detour time), policy attributes (e.g., rebate on upfront costs, purchase tax rebate/ exemption, access to HOV/bus lane, free parking), sociodemographic attributes (e.g., gender, age, education, income, body-type choice), socio-psychological (e.g., social influence, innovativeness, environmental awareness/consciousness) and trip-related attributes (e.g., trip length, trip frequency, trip purpose). For data analysis, the literature review indicates the use of different econometric models such as Latent Class (LC), Nested Logit (NL), Multinomial Probit (MNP), Multinomial Logit (MNL), Mixed Logit (ML), Hybrid Choice (HC), Ordinal Logistic Regression (OLR), LC-ML models for investigating consumers' perceived benefit for EV-related attributes. Among these models, the two econometric models that are employed most frequently for valuing EV-related attributes are found to be MNL and ML models. The review of literature also reveals that the attributes influencing consumers' choice decision towards EVs vary substantially both across and within countries and that country-specific research is necessary. Past studies on EVs are majorly carried out in developed countries (e.g. Canada, United States, Germany, The Netherlands, Japan, South Korea, Italy, Australia, Greece) and countries where EVs have already been accepted as mainstream transportation (e.g. China). In the Indian context, there is a lack of empirical evidence regarding consumer preference towards EVs in general and PHEVs in particular. Hence, there is a need to conduct in-depth research on consumer preference towards PHEV operation-specific attributes, and also simultaneously examine the influence of intended predominant trip purpose and city characteristics on future PHEV demand. Such studies are important to guide vehicle manufacturers and the government for the formulation of suitable improvement policies to increase the attractiveness of PHEVs among different categories of consumers in the Indian context.

This paper investigates the preference of commuters and non-commuters towards PHEVs by conducting a Stated Preference (SP) survey on conventional four-wheelers users or the car-owning population in the Indian context. For econometric analysis of survey responses, ML model was selected, as it not only relaxes the assumption of independent and identically distributed (IID) (across alternatives) error structure of MNL model but also allows for random taste variation across individuals (McFadden & Train, 2000). Then, for commuters and non-commuters, separate ML models were developed to estimate user perceived benefit associated with PHEV operation-specific attributes in terms of willingness-to-pay (WTP) values. Finally, the sensitivity analysis of the model parameter was carried out by evaluating several hypothetical scenarios to understand the sensitivity of the demand with respect to improvement in PHEV operation-specific attributes.

3. Study location

3.1. Delhi

Delhi is India's capital city, and one of the largest cities in the world, with an area of 1483 km^2. Delhi has a population of over 16.7 million (Ministry of Home Affairs (MHA), 2011). The total number of registered passenger cars in Delhi is about 3 million, which is higher than the combined number of registered cars in Chennai, Kolkata, and Mumbai (MoRTH, 2019). In terms of ownership, Delhi has 157 cars per 1000 population as compared to the national average of 22 cars per 1000 population. Hence, the huge passenger car ownership adds significantly to the air pollution issues in Delhi (Dholakia & Garg, 2018). As a result, Delhi is recognized globally for its extreme pollution levels (Chowdhury et al., 2017). The annual average PM2.5 concentration in Delhi (84.1 μg/m3) is reported around 8 times greater than the WHO guidelines (10 μg/m3) (IQAir, 2020). In Delhi, exposure to PM alone is responsible for around 7350–16,200 premature deaths, and several million asthma attacks every year (Choudhary et al., 2021).

3.2. Kolkata

Kolkata is the capital city of the Indian state of West Bengal, and is located in eastern India on the east bank of river Hooghly. It is one of the world's most densely inhabited cities, with a population of around 4.49 million people and a city size of 187 km^2 (MHA, 2011). The total number of registered passenger cars in Kolkata is about 0.35 million (MoRTH, 2019). In Kolkata, land available for road transport is less than 7%. Low road space together with higher use of private cars for travel has resulted in higher air pollution in Kolkata (Chakrabartty & Gupta, 2014). As a consequence, Kolkata is listed as one of the world's most polluted cities and is India's second most polluted metro city, behind Delhi (Dutta et al., 2021). The annual average PM2.5 concentration in Kolkata (46.6 μg/m3) is reported nearly five times higher than the permissible limit set by WHO (10 μg/m3) (IQAir, 2020). Due to air pollution, seven out of 10 people in Kolkata are associated with some form of respiratory ailment (Citizens Report, 2011).

4. Method

This section demonstrates a sequential approach to investigate commuter and non-commuter preference for PHEV. The methodology comprises of three major steps-design of survey instrument, data collection and organization of the database, and development of suitable econometric models for valuation of PHEV operation-specific attributes in terms of willingness-to-pay (WTP) estimates.

4.1. Design of survey instrument

Design of survey instrument includes type of data and preference elicitation technique, attributes and attribute levels, and questionnaire design for data collection.

4.1.1. Type of data and preference elicitation technique

In this study, a Stated Preference (SP) survey-based discrete choice experiment (DCE) has been carried out to investigate commuter and non-commuter preference towards PHEVs and related attributes. In DCE, preferences are elicited by asking respondents to choose one alternative from the presented alternatives (Louviere et al., 2003). Choice situations in DCE resemble real-world situations and reduce task complexity significantly as compared to other techniques such as conjoint ranking and rating. Hence, this study adopted DCE as the preference elicitation technique for designing SP survey.

4.1.2. Attributes and attribute levels

The selection of attributes was based on review of literature, and consultation with subject experts, with the motive of selecting a limited set of attributes to control for cognitive effort and fatigue of respondents while answering the choice questions (Caussade et al., 2005). Hence, this study included six PHEV operation-specific attributes namely fuel cost savings (Potoglou & Kanaroglou, 2007; Danielis et al., 2020; Hackbarth & Madlener, 2013; Hidrue et al., 2011; Li et al., 2022; Nie et al., 2018; Rommel & Sagebiel, 2021; Tanaka et al., 2014; Ziegler, 2012), battery range (Hoen & Koetse, 2014; Danielis et al., 2020; Jia & Chen, 2023; Li et al., 2022), public charging availability (Potoglou & Kanaroglou, 2007; Danielis et al., 2020; Hackbarth & Madlener, 2013; Hidrue et al., 2011; Rommel & Sagebiel, 2021; Tanaka et al., 2014; Ziegler, 2012), battery recharging time (Potoglou & Kanaroglou, 2007; Danielis et al., 2020; Gong et al., 2020; Hackbarth & Madlener, 2013; Helveston et al., 2015; Hoen & Koetse, 2014; Mpoi et al., 2023; Nie et al., 2018), battery warranty (Higgins et al., 2017; Li et al., 2022) and tailpipe emission (Potoglou & Kanaroglou, 2007; Hackbarth & Madlener, 2013; Hidrue et al., 2011; Jia & Chen, 2023; Nie et al., 2018; Tanaka et al., 2014; Ziegler, 2012) along with purchase price (Potoglou & Kanaroglou, 2007; Danielis et al., 2020; Gong et al., 2020; Hackbarth & Madlener, 2013; Hidrue et al., 2011; Ziegler, 2012; Hoen & Koetse, 2014; Jia & Chen, 2023; Rommel and Sagebiel, 2021) in the SP experiment design for analyzing commuter and non-commuter preference towards PHEV in terms of WTP for these attributes. For each of the seven attributes, it was decided to consider three levels, keeping in mind the impact of increasing number of levels upon the choice set generation and finally the resource requirement for field data collection (Hensher et al., 2015). Moreover, more than two levels per attribute allow an analyst to capture the interrelationship between the levels of an attribute, even for the estimation of non-linearities, if expected (Train, 2009). The level range, extreme points, and the way levels are to be presented in SP experiment design were decided based on actual market scenario, literature review, and interaction with key experts and car manufacturers. Table 2 presents the attributes and attribute levels. It is important to mention that to create a more realistic choice task, pivoting design technique was used to individualize the purchase price for each respondent (Hensher et al., 2015). Using pivoting design technique, the values of the purchase price were fixed per respondent, based on their intended price range for the next car purchase, which was obtained prior to the SP experiment (Achtnicht, 2012; Hensher et al., 2015).

4.1.3. Questionnaire design

For SP survey, the hypothetical alternatives and choice sets are generated by using the selected attributes and attribute levels. Combining all attributes and levels (as indicated in Table 2) would produce 2187 ($=3^7$) potential combinations. Nevertheless, it is very challenging for the respondents to assess all the probable combinations. Hence, to overcome this barrier while maintaining statistical efficiency,

Table 2
Attributes and Attribute Levels used in DCE.

Attribute	Explanation	Attribute level
1. Fuel cost savings	Reduction in fuel cost as compared to conventional vehicles (CVs)	1. 20% 2. 40% 3. 60%
2. Battery recharging time	Time taken to fully recharge the battery	1. 7 h. 2. 3 h 3. 1 h
3. Battery range	Maximum distance a car can travel on full battery	1. 30 km 2. 60 km 3. 90 km
4.Tailpipe emission	Pollutants discharged from the tailpipe (e.g., CO_2, NO_x, SO_2, etc.) as compared to CVs	1. 25% 2. 50% 3. 75%
5. Public charging availability	Availability of public charging stations compared to fuel stations	1. 20% 2. 60% 3. 100%
6. Battery warranty	A battery warranty with duration and mileage typically refers to a guarantee that a manufacturer makes promising to replace the battery within a specific period and/or mileage limit, if it does not function as originally described or intended. For instance, if the battery warranty is specified as 8 yrs/1,60,000 km it means that if any defect or issue arises within the 8-year duration or before reaching the mileage limit of 1,60,000 km, the warranty would apply.	1. 3yrs./60,000 km 2. 5yrs./ 1,00,000 km 3. 8yrs./ 1,60,000 km
7. Purchase price	Price that the buyer must spend as compared to the average price range stated for next car purchase	1. 25% higher 2. 50% higher 3. 75% higher

this study employed D-optimal or D-efficient design (Rose et al., 2008) using JMP tool (SAS Institute 2018). In this study, an unlabeled SP experiment is designed for further analysis (Louviere et al., 2000; Hensher et al., 2015). As one of the primary goals of this study is to estimate consumers' WTP for PHEV operation-specific attributes, designing an unlabeled experiment is considered more appropriate.

An unlabeled experiment design yielded 30 choice alternatives. The choice alternatives were then split into five blocks at random, providing each respondent with one random block containing three choice tasks. During pilot study, three choice task per respondent proved to be a manageable amount without inducing cognitive complexity. In each task, respondents had the option to choose between two hypothetical alternatives of PHEV (alternative 1 and alternative 2). The respondents were instructed to assume that other than the characteristics listed, the PHEVs were identical. Table 3 presents an example of DCE choice task.

The questionnaire used in this study has four main parts: i) questions pertaining to car ownership (current and prospective), and trip-related information such as trip length, trip frequency, predominant trip purpose, etc. ii) introduction on PHEV as a mode, followed by attributes and attribute level description using proper text (shown in Table 2) and pictorial illustration iii) questions on respondents' stated preference among two alternative options of PHEV (shown in Table 3) in three different choice sets and iv) questions on respondent's sociodemographic characteristics such as age, gender, education, income, etc. An overview of survey items is presented in Table 4.

Table 3
Sample DCE choice task.

Attribute	Alternative 1	Alternative 2
Fuel cost savings (compared to CVs)	40%	20%
Battery recharging time	3 h	7 h
Battery range	30 km	60 km
Tailpipe emission (compared to CVs)	75%	25%
Public charging availability (compared to fuel stations)	60%	100%
Battery warranty	3 yrs/60,000 km	8 yrs/1,60,000 km
Purchase price (compared to reference[a])	₹22,75,000 (US $31,853.82)	₹19,50,000 (US $27,303.28)
I would choose	◻	◻

[a] Average price of ₹ 13,00,000 (US$18202.18) stated for future vehicle purchase.

Before fielding the questionnaire, a pilot survey was conducted to i) fix the number of choice tasks to be presented per respondent considering cognitive complexity, ii) estimate the time prerequisite to complete the questionnaire, iii) ensure that the questions were not difficult to understand and iv) provide training to the enumerators. A sample of 50 responses was collected from each city, which is considered as adequate sample size for conducting pilot survey (Sim & Lewis, 2012). According to the pilot survey, a respondent requires at least 10 min to answer the questionnaire earnestly. Also, in the pilot survey, respondents indicated problems and recommended a number of modifications, which helped to improve the overall performance of the questionnaire.

4.2. Survey administration

The questionnaire survey was fielded during February to April 2019. The data was collected by a team of five enumerators (including the author). Initially, the questionnaire survey was thoroughly explained to the enumerators in the research lab. Thereafter, during pilot survey, the enumerators underwent extensive training so that they could collect the data effectively and independently during the main survey. Using computer assisted personal interviewing (CAPI), the trained enumerators collected data from survey respondents in Delhi and Kolkata (Sainsbury et al., 1993). Important trip generators such as shopping malls, residential complexes, offices, universities, colleges, and schools were identified across the two cities. Among them, 10 major trip generators distributed across various zones in each city were selected as target locations to perform the interview. Firstly, the respondents were intercepted randomly and asked about their car ownership. The respondents who owned cars were interviewed further, i.e., the target population for the study was the car-owning population. Then, the car owners were asked three questions i) if they possessed a valid driving license, ii) if they plan on purchasing a new car within the next five years and iii) if they were somewhat aware or educated about new vehicle technologies such as PHEVs, and see it as a potential alternative for conventional cars. The respondents who fulfilled all the criteria i.e. had a valid driving license, plan to purchase a new car in the next five years, and see PHEV as a potential alternative for conventional cars were surveyed using the designed questionnaire. Hence, the data collected could be biased with responses from consumers with comparatively

Table 4
Overview of survey items.

Information Collected	Survey Items	Levels
Current and planned car ownership	Number of cars in your household	1 ≥2
	Price range (in INR) you are willing to pay for new car	Open-ended response
Trip characteristics	Frequency of commuting/revenue generating trips within a city (in a week)	Less than 3 trips 3 to 4 trips 5 to 6 trips More than 6 trips
	Frequency of non-commuting/non-revenue generating trips within a city (in a week)	Less than 3 trips 3 to 4 trips 5 to 6 trips More than 6 trips
	Predominant trip purpose	Commuting/revenue generating Non commuting/non-revenue generating
	On an average within a city, approximate distance (in km) traveled for commuting/revenue generating trips using your car (in a week)	Open-ended response
	On an average within a city, approximate distance (in km) traveled for non-commuting/non-revenue generating trips using your car (in a week)	Open-ended response
Sociodemographic characteristics	Gender	Male Female
	Age	<35 years ≥35 years
	Educational level	Upto higher secondary Graduate or higher
	Monthly family income	<1,50,000 ₹/month ≥1,50,000 ₹/month
	Garage availability at home	Yes No

Table 5
Sample profile.

Characteristics	Delhi		Kolkata	
	Commuters, n (%)	Non-commuters, n (%)	Commuters, n (%)	Non-commuters, n (%)
Total number of respondents	203	212	279	221
Age				
<35 years	98 (48%)	149 (70%)	102 (37%)	98 (44%)
≥35 years	105 (52%)	63 (30%)	177 (63%)	123 (56%)
Gender				
Male	167 (82%)	182 (86%)	208 (75%)	197 (89%)
Female	36 (18%)	30 (14%)	71 (25%)	24 (11%)
Education level				
Upto higher secondary	98 (48%)	131 (62%)	149 (53%)	134 (61%)
Graduate or higher	105 (52%)	81 (38%)	130 (47%)	87 (39%)
Monthly household income				
<1,50,000 ₹/month (US$2100.25)	107 (53%)	138 (65%)	185 (66%)	186 (84%)
≥1,50,000 ₹/month (US$2100.25)	96 (47%)	74 (35%)	94 (34%)	35 (16%)
Car ownership				
1	122 (60%)	158 (75%)	174 (62%)	186 (84%)
≥2	81 (40%)	54 (25%)	105 (38%)	35 (16%)
Garage availability				
Yes	99 (49%)	96 (45%)	247 (89%)	164 (74%)
No	104 (51%)	116 (55%)	32 (11%)	57 (26%)
Trip length (round trip)				
<30 km	87 (43%)	119 (56%)	185 (66%)	176 (80%)
≥30 km	116 (57%)	93 (44%)	94 (34%)	45 (20%)

stronger opinion towards PHEVs. Initially, 1200 respondents were intercepted in each city, and only 505 (42.08%) and 524 (43.67%) of them in Delhi and Kolkata respectively fulfilled the selection criteria for participation and were provided with the questionnaire survey. The trained enumerators guided the respondents through the survey questions asked in CAPI. During extensive cleaning and filtering, a percentage of respondents were eliminated, if i) incomplete responses were received for stated choice questions ii) incomplete or inconsistent responses were obtained for sociodemographic information and iii) respondent complete the survey in less than 10 min. After necessary data refining, the available dataset of the filled questionnaire (Delhi: 415, Kolkata: 500) was used for further analysis. However, the retained sample satisfied the minimum sample size requirements (384) to perform data analysis, assuming 95% confidence level (Taherdoost, 2017).

In this study, the target population included the car-owning population in Delhi and Kolkata. Indian census manual (MHA, 2011) do not provide any details regarding sociodemographic profile of car-owning population. Hence, the sample representativeness could not be checked directly. Instead, a broad level comparison between the sample data and the sociodemographic profile of Delhi and Kolkata urban population statistics was carried out. The sample data for Delhi under-represents female (male: 84%, female: 16%), when compared to population statistics (male: 54%, female 46%) as per the Indian census manual. The sample statistics for Kolkata is also found to under-represent female (male: 81%, female 19%) when compared to the entire urban population of Kolkata (male: 52% and female: 48%). With respect to education, the sample statistics for Delhi is found to over-represent educated individuals (up to higher secondary: 55%, graduate or higher: 45%) when compared to population statistics (up to higher secondary: 83%, graduate or higher: 17%). In Kolkata, the sample data is also found to over-represent educated individuals (up to higher secondary: 57%, graduate or higher: 43%) when compared to the urban population statistics (up to higher secondary: 82%, graduate or higher: 18%). Such observations could be attributed to two reasons. Firstly, the urban population do not include only car-owning population, rather consists of all the urban residents. Secondly, during data collection, female respondents made up a sizable portion of non-responsive samples since they were relatively less willing to participate in the questionnaire survey as compared to males. As a result, the sample obtained from both cities indicates a notable skewness towards male respondents. With respect to age distribution, sample statistics in Delhi (<35 years: 60%, ≥35 years: 40%) almost perfectly reflect the urban population statistics (<35 years: 66%, ≥35 years: 34%). For Kolkata, the age distribution of sample data (<35 years: 40%, ≥35 years: 60%) is found to be roughly close to the population statistics (<35 years: 53%, ≥35 years: 47%). Comparison of income distribution could not be carried out due to the absence of data in the Indian census manual.

The sample profile is presented in Table 5. The sample was further subdivided into two groups for each city: a) Commuters (respondents whose intended predominant trip purpose for PHEV usage is commuting/revenue-generating trips) and b) Non-commuters (respondents whose intended predominant trip purpose for PHEV usage is non-commuting/non-revenue generating trips). During final database preparation, the attributes considered in this study, namely fuel cost savings, battery recharging time, battery range, tailpipe emission, public charging availability, battery warranty, and purchase price, which are quantitative/numeric in nature, were coded in cardinal linear form for model development and data analysis (Train, 2009).

4.3. Econometric model development

In the present study, Mixed Logit (ML) models were developed to investigate commuter and non-commuter preferences for PHEVs. The discrete choice modeling approach employed in this study is based on the concepts presented in Train (2009). Interested readers are suggested to refer Train (2009) for a detailed theoretical basis of the econometric models. For the developed ML models, the choice probabilities are estimated using maximum simulated likelihood estimator with standard Halton sequence, which is the most common form of intelligence draw used in the model estimation (Bhat, 2000). Specifically, this study employed 500 Halton random draws for simulation. Further, the assumption regarding the distribution of random parameters is an important component of ML model estimation. This study assumes all the random parameters to have constrained triangular distribution, where the mean parameter is constrained to equal its standard deviation (Hensher & Greene, 2003). Hence, for the developed ML models, the estimates of standard deviation are not separately reported. When valuation of attributes or WTP estimation is one of the primary objectives, the constrained triangular distribution provides several unique advantages. First, it maintains the same sign of the parameter estimate for the entire sample. Second, unlike, normal or lognormal distribution, the confined nature of this distribution leads to early convergence owing to low computing time. Lastly, and most notably, the calculation of WTP estimates is simpler due to constraint assumption of reduced standard deviation. As a result, WTP estimates can be obtained by dividing the mean coefficient of the attribute of interest by the mean coefficient of the cost attribute, unlike other cases, where standard deviation has a substantial influence on WTP estimation (Train, 2009).

Table 6
Summary of ML model estimates with city heterogeneity for commuters and non-commuters.

Attributes	ML model with city heterogeneity for commuters	ML model with city heterogeneity for non-commuters
Random parameters		
Fuel cost savings	0.0289*** (7.23)	0.0064*(1.68)
Battery recharging time	−0.0812***(-4.14)	−0.0875***(-3.85)
Battery range	0.0084***(4.30)	0.0063***(2.90)
Tailpipe emission	−0.0306***(-8.62)	−0.0095***(-2.92)
Public charging availability	0.0045***(2.87)	0.0059***(3.37)
Battery warranty	0.1024***(3.21)	0.0905***(2.59)
Non-random/Fixed parameters		
Purchase price#	−0.0033***(-12.18)	−0.0049***(-14.43)
Heterogeneity around the mean of random parameter		
Fuel cost savings	–	0.0130**(2.39)
Battery recharging time	−0.0736**(-2.30)	−0.1398***(-4.30)
Battery range	0.0101***(3.31)	–
Tailpipe emission	0.0088*(1.76)	−0.0121**(-2.52)
Public charging availability	0.0047*(1.93)	–
Battery warranty	0.0968*(1.89)	–
Goodness of fit		
Log likelihood function	−789.340	−695.326
Adjusted ρ^2	0.1905	0.2133
Sample size		
No. of respondents	482	433
No. of observation	1446	1299

Notes: Cells with a dash indicate statistically insignificant heterogeneity around the mean of random parameters.
T-statistics are mentioned in the parenthesis.
***, ** and * denotes significance at 1%, 5% and 10% level respectively.
#Purchase price in ₹1000.

5. Results and discussion

After filtering for data quality, the prepared database of discrete choice responses was analyzed using NLogit v5.0 (Greene, 2012) to develop separate Mixed Logit (ML) models for commuters and non-commuters in each city. For the modeling purpose, the cost parameter, namely “purchase price” was considered to be “fixed” or “non-random”, and all other attributes were considered to be “random” following a “constrained” triangular distribution. For simulation purpose, this study used 500 Halton draws in the maximum simulated likelihood estimation process for ML model (Bhat, 2000; Hensher & Greene, 2003). In the following sub-section, ML model estimation results are presented and discussed, followed by the evaluation and interpretation of WTP values derived from the model estimates.

5.1. Model estimation results

Initially, to investigate the preference heterogeneity of each user group across the two cities, joint models were developed considering city heterogeneity. For both commuters and non-commuters, the joint model included the city attribute as a dummy variable, using “0” to denote “Kolkata” and “1” to denote “Delhi.” The results of ML model with city heterogeneity for commuters and non-commuters are reported in Table 6.

It may be seen from Table 6 that there is statistically significant heterogeneity across commuters of Delhi and Kolkata for most of the attributes (such as battery recharging time, battery range, tailpipe emission, public charging availability, and battery warranty), which clearly indicates that the two cities are different in terms of consumer preference towards PHEVs. Similar results are obtained for non-

Table 7
Summary of ML model estimates for complete dataset without taste heterogeneity.

City	Delhi		Kolkata	
Consumer category	Commuter	Non-commuter	Commuter	Non-commuter
Attribute	**Random parameter**			
Fuel cost savings	0.0217*** (4.54)	0.0195*** (4.41)	0.0321*** (7.17)	0.0065* (1.66)
Battery recharging time	−0.1493*** (-5.49)	−0.2340*** (-7.76)	−0.0840*** (-4.11)	−0.0883*** (-3.76)
Battery range	0.0173*** (6.23)	0.0084*** (3.34)	0.0097*** (4.57)	0.0064*** (2.85)
Tailpipe emission	−0.0199*** (-4.93)	−0.0219*** (-5.35)	−0.0336*** (-8.40)	−0.0096*** (-2.87)
Public charging availability	0.0094*** (4.84)	0.0037* (1.87)	0.0048*** (2.93)	0.0059*** (3.36)
Battery warranty	0.1783*** (3.84)	0.0826** (2.14)	0.1249*** (3.51)	0.0926** (2.57)
	Non-random/Fixed parameter			
Purchase price[#]	−0.0029*** (-7.74)	−0.005*** (-10.13)	−0.0039*** (-9.31)	−0.0049*** (-9.92)
Goodness of fit				
Log likelihood function	−329.653	−321.2879	−466.7319	−375.0924
Adjusted ρ^2	0.2025	0.2553	0.1835	0.1686
Sample size				
No. of respondents	203	212	279	221
No. of observations	609	636	837	663

Notes: T-statistics are mentioned in the parenthesis.
***, ** and * denotes significance at 1%, 5% and 10% level respectively.
[#] Purchase price in ₹1000.

commuters, with statistically significant decomposition effect on mean estimates of several attributes (such as fuel cost savings, battery recharging time, and tailpipe emission) across Delhi and Kolkata. Therefore, due to the evidence of differences in consumer (commuter and non-commuter) preference across the two cities, it was preferred to split the dataset of two cities to develop separate travel behavior models for valuation of attributes.

5.1.1. Model estimation results of complete dataset without taste heterogeneity

The model estimation results of separate ML models for the complete dataset of commuters and non-commuters in both Delhi and Kolkata without taste heterogeneity are presented in Table 7. It may be observed from Table 7 that all the attributes significantly impact choice preference for PHEVs, and signs of all the attribute coefficients are as expected. Also, adjusted ρ^2 values indicate satisfactory goodness of fit, and are considered acceptable in the present context (Achtnicht, 2012; Danielis et al., 2020; Helveston et al., 2015; Lane et al., 2018). Table 7 shows that the parameter estimates of fuel cost savings, battery range, public charging availability, and battery warranty are significant, with the expected positive signs, indicating that the overall disutility towards PHEV choice decreases with an increase in the magnitude of these attributes. On the other hand, attributes such as battery recharging time, tailpipe emission, and purchase price enter the model negatively, with highly statistically significant estimates, suggesting that consumers place a strong disutility towards PHEVs with higher magnitude of these attributes.

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

In this section, taste heterogeneity with respect to sociodemographic

Table 8
Summary of ML model estimates with taste heterogeneity for commuters and non-commuters in Delhi.

Consumer category	Commuters	Non-Commuters
Attributes		
Random parameters		
Fuel cost savings	0.0204**(2.29)	0.0138**(1.98)
Battery recharging time	−0.2307*** (-4.41)	−0.2493*** (-4.87)
Battery range	0.0175***(3.49)	0.0081**(1.99)
Tailpipe emission	−0.0138*** (−2.82)	−0.0137** (-2.06)
Public charging availability	0.0156***(3.97)	0.0084*(2.50)
Battery warranty	0.1536*(1.85)	0.0850*(1.81)
Non-random/Fixed parameters		
Purchase price[#]	−0.0034*** (-7.66)	−0.0053*** (-9.95)
Heterogeneity around the mean of random parameter		
Fuel cost savings: Education[a]	–	–
Fuel cost savings: Monthly family income[b]	–	0.0162*(1.74)
Fuel cost savings: Garage availability[c]	–	–
Battery recharging time: Education	–	–
Battery recharging time: Monthly family income	–	−0.1564*** (-2.60)
Battery recharging time: Garage availability	0.1734***(3.03)	0.0865*(1.84)
Battery range: Education	–	–
Battery range: Monthly family income	0.0162***(2.76)	–
Battery range: Garage availability	–	–
Tailpipe emission: Education	−0.0126*(1.71)	−0.0204** (-2.43)
Tailpipe emission: Monthly family income	−0.0143*(-1.65)	–
Tailpipe emission: Garage availability	–	–
Public charging availability: Education	–	–
Public charging availability: Monthly family income	–	–
Public charging availability: Garage availability	−0.0117*** (-2.76)	–
Battery warranty: Education	–	–
Battery warranty: Monthly family income	0.3265***(3.23)	–
Battery warranty: Garage availability	–	–
Goodness of fit		
Log-likelihood function	−305.919	−306.363
Adjusted ρ^2	0.216	0.248
Sample Size		
No. of respondents	203	212
No. of observations	609	636

Notes: Cells with a dash indicate statistically insignificant heterogeneity around the mean of random parameters.
T-statistics are mentioned in the parenthesis.
***, ** and * denotes significance at 1%, 5% and 10% level respectively.
[#]Purchase price in ₹1000.
[a] Education was split into two categories to investigate heterogeneity: Consumer with education up to higher secondary were coded as '0' and those who are graduate or higher were coded as '1'.
[b] Monthly family income was split into two categories to investigate heterogeneity: Consumer with income ≤1,50,000/month were coded as '0' and those with income >1,50,000/month were coded as '1'.
[c] Garage availability was split into two categories to investigate heterogeneity: Consumer with absence of garage availability were coded as '0' and those with presence of garage availability were coded as '1'.

variables such as age, gender, education, monthly family income, car ownership, garage availability, and trip length are presented for the complete dataset of commuters and non-commuters in Delhi and Kolkata. The main objective of the heterogeneity analysis was to investigate the influence of such variables on PHEV preference. The summary of ML model estimates with taste heterogeneity for both commuters and non-commuters in Delhi and Kolkata are presented in Table 8 and Table 9 respectively.

It is important to mention that in Tables 8 and 9, an inclusive model is reported only for those combinations of variables with significant

Table 9
Summary of ML model estimates with taste heterogeneity for commuters and non-commuters in Kolkata.

Consumer category	Commuters	Non-Commuters
Attributes		
Random parameters		
Fuel cost savings	0.0228**(2.32)	0.0132*(1.73)
Battery recharging time	−0.2031***(-3.80)	−0.1401***(-2.68)
Battery range	0.0088*(1.76)	0.0112**(2.31)
Tailpipe emission	−0.0120*(-1.65)	−0.0092**(-2.14)
Public charging availability	0.0154***(3.36)	0.0130***(3.37)
Battery warranty	0.0691*(1.75)	0.1132**(2.10)
Non-random/Fixed parameters		
Purchase price[#]	−0.0044***(-9.55)	−0.0054***(-9.36)
Heterogeneity around the mean of random parameter		
Fuel cost savings: Education[a]	−0.0176**(-2.20)	–
Fuel cost savings: Monthly family income[b]	0.0344***(3.91)	–
Fuel cost savings: Garage availability[c]	–	–
Battery recharging time: Education	–	–
Battery recharging time: Monthly family income	–	–
Battery recharging time: Garage availability	0.1256**(2.29)	0.1089*(1.92)
Battery range: Education	–	–
Battery range: Monthly family income	0.0138***(2.88)	–
Battery range: Garage availability	–	–
Tailpipe emission: Education	−0.0145**(-2.10)	–
Tailpipe emission: Monthly family income	−0.0263***(-3.27)	−0.0197*(-1.70)
Tailpipe emission: Garage availability	–	–
Public charging availability: Education	−0.0070*(-1.93)	–
Public charging availability: Monthly family income	–	–
Public charging availability: Garage availability	−0.0105**(-2.22)	−0.0077*(-1.83)
Battery warranty: Education	–	–
Battery warranty: Monthly family income	0.1897**(2.88)	–
Battery warranty: Garage availability	–	–
Goodness of fit		
Log-likelihood function	−425.013	−358.249
Adjusted ρ^2	0.224	0.166
Sample Size		
No. of respondents	279	221
No. of observations	837	663

Notes: Cells with a dash indicate statistically insignificant heterogeneity around the mean of random parameters.
T-statistics are mentioned in the parenthesis.
***, ** and * denotes significance at 1%, 5% and 10% level respectively.
[#]Purchase price in ₹1000.
[a] Education was split into two categories to investigate heterogeneity: Consumer with education up to higher secondary were coded as '0' and those who are graduate or higher were coded as '1'.
[b] Monthly family income was split into two categories to investigate heterogeneity: Consumer with income ≤1,50,000/month were coded as '0' and those with income >1,50,000/month were coded as '1'.
[c] Garage availability was split into two categories to investigate heterogeneity: Consumer with absence of garage availability were coded as '0' and those with presence of garage availability were coded as '1'.

parameter estimates and taste heterogeneity. For heterogeneity study, the sociodemographic variables were included in the model as a separate dummy variable, as specified in the footnotes of Tables 8 and 9. For a particular sociodemographic variable, a statistically significant interaction effect with a random parameter indicates the presence of heterogeneity and vice versa. For example, in Table 8, with respect to education level (whether up to higher secondary or graduate or higher), a statistically significant decomposition effect is observed on the mean estimates of tailpipe emission for Delhi commuters. The results indicate that in Delhi, the education level substantially influences commuter preference for PHEV in terms of its tailpipe emission characteristics. Further, the absence of significant coefficient estimates for other attributes indicates that commuters with different education levels do not perceive them statistically significantly different. All the other sociodemographic variables and their respective interaction effects can be interpreted in a similar manner.

5.2. Willingness-to-pay estimation and discussions

The estimated coefficients from Mixed Logit (ML) models represent the marginal contribution of each attribute. However, except for interpretation in terms of sign and significance, these parameter estimates have no economic meaning. Hence, to determine the economic significance of change in each attribute, the marginal willingness-to-pay (WTP) for each attribute is calculated. The marginal WTP for an attribute is the derivative of utility with respect to attribute divided by the (negative of the) derivative of utility with respect to price i.e., the ratio of parameter estimate of a specific attribute to the purchase price parameter, ceteris paribus (Hensher et al., 2015; Train, 2009). In addition to mean WTPs, the 95% confidence interval of WTPs is evaluated using the Delta method of estimation (Bliemer & Rose, 2013; Gatta et al., 2015). Table 10 presents the summary of mean WTPs and the corresponding confidence intervals for complete dataset of commuters and non-commuters in Delhi and Kolkata without taste heterogeneity.

From Tables 10, it can be observed that in Delhi and Kolkata, commuters are willing to pay significantly higher (₹7483 in Delhi and ₹8231 in Kolkata) for 1% fuel cost saving compared to non-commuters (₹3900 in Delhi and ₹1327 in Kolkata). The results indicate that commuter preference for PHEV is substantially influenced by fuel cost savings. The outcome is in line with Mpoi et al. (2023), where respondents who regularly commute to work by car are more willing to pay extra for an EV as compared to others due to anticipated reduction in fuel costs. For 1h reduction in battery recharging time, both commuters (₹51,483 in Delhi and ₹21,538 in Kolkata) and non-commuters (₹46,800 in Delhi

Table 10
Summary of WTP estimates for complete dataset without taste heterogeneity.

City	Delhi				Kolkata				Unit of WTP
User category	Commuter		Non-commuter		Commuter		Non-commuter		
Attribute	Mean WTP	95% CI	Mean WTP	95% CI	Mean WTP	95% CI	Mean WTP	95% CI	
Fuel cost savings	7483	[4373–10,327]	3900	[2284–5484]	8231	[6272–10,314]	1327	[177–2814]	₹/%
Battery recharging time	51,483	[32,364–68,970]	46,800	[35,906–57,268]	21,538	[11,105–32,301]	18,020	[9027–26,647]	₹/h
Battery range	5966	[4109–7613]	1680	[734–2610]	2487	[1502–3485]	1306	[460–2151]	₹/km
Tailpipe emission	6862	[4037–9483]	4380	[2789–5926]	8615	[6687–10,645]	1959	[672–3207]	₹/%
Public charging availability	3241	[1808–4589]	740	[342−1494]	1231	[409–2075]	1204	[472–1911]	₹/%
Battery warranty	61,483	[32,921–88,103]	16,520	[1863–31,016]	32,026	[16,070–48,443]	18,898	[4988–32,416]	₹/yr.

Table 11
Sensitivity analysis input parameter estimates.

City	Symbol	Delhi		Kolkata	
User category		Commuter	Non-commuter	Commuter	Non-commuter
Attribute					
Fuel cost savings	α	0.0217	0.0195	0.0321	0.0065
Battery recharging time	β	−0.1493	−0.2340	−0.0840	−0.0883
Battery range	γ	0.0173	0.0084	0.0097	0.0064
Tailpipe emission	δ	−0.0199	−0.0219	−0.0336	−0.0096
Public charging availability	ε	0.0094	0.0037	0.0048	0.0059
Battery warranty	ξ	0.1783	0.0826	0.1249	0.0926
Purchase price	η	−0.0029	−0.005	−0.0039	−0.0049

and ₹18,020 in Kolkata) in two cities indicate substantially high WTP values. Hence, the results indicate that improvement in battery recharging time would eventually increase the attractiveness of PHEVs among different categories of consumers in the Indian context. Comparatively, consumers in Delhi are willing to pay approximately 2.5 times higher than those in Kolkata for each hour of reduced recharging time. It may be seen from Table 5 that in Delhi, majority of the consumers (51% of commuters and 55% of non-commuters) lack access to garage, where the car batteries can be recharged overnight at home. On the other hand, in Kolkata, most of the consumers have this facility. As a result, improvement in battery recharging time is more appealing among consumers in Delhi as compared to Kolkata for PHEV mode choice. For per km increment in battery range, non-commuters in Delhi and Kolkata indicate WTP values of ₹1680 and ₹1306 respectively. On the other hand, commuters in Delhi and Kolkata show WTP values of 3.5 times (₹5966) and 1.9 times (₹2487) higher respectively, for per km increase in battery range. Hence, battery range is another attribute that significantly impacts commuter's choice of PHEV in both cities. Further, Table 10 shows that commuters in Delhi (₹5966) are willing to pay 2.4 times higher as compared to commuters in Kolkata (₹2487) for improved battery range. The differences may be due to Delhi's larger city size (1483 sq.km.) compared to Kolkata (187 sq.km.), leading to longer trip lengths for most Delhi commuters (57% travelling $\geq$30 km), as indicated in Table 5.

Whereas, in Kolkata, commuters are majorly found to commence shorter trips (66% travelling $<$30 km). Hence, the perceived benefit of improved battery range is higher among commuters in Delhi as compared to Kolkata.

For 1% reduction in tailpipe emission, non-commuters in Delhi and Kolkata are willing to pay ₹4380 and ₹1959 respectively. On the other hand, commuters in Delhi and Kolkata indicate WTP values of 1.5 times (₹6862) and 4.39 times (₹8615) higher respectively, for 1% tailpipe emission reduction compared to non-commuter respondents. The results highlight commuters' stronger inclination towards PHEVs due to emission reduction benefits. The outcome corroborates the study findings of Williams et al. (2011), where environmental advantages are cited as one of the primary reasons for using PHEVs for commuting purposes. Further, for 1% increase in public charging availability, commuters in Delhi are willing to pay 4.3 times higher (₹3241) as compared to non-commuters (₹740). Conversely, in Kolkata, both commuters (₹1231) and non-commuters (₹1204) show similar WTP. In Delhi, the commuters majorly have trip length $\geq$30 km (57%), whereas most of the non-commuters have trip length $<$30 km (56%). As the availability of public charging facility on routes provide an opportunity to recharge and reuse the battery range before trip completion, the commuters in Delhi indicate higher perceived benefit towards improvement in public charging availability as compared to non-commuters for PHEV adoption. The findings align with earlier studies emphasizing the preference of frequent car commuters for a dense network of charging stations (Potoglou & Kanaroglou, 2007; Hjorthol, 2013). On the other hand, in Kolkata both commuters (66%) and non-commuters (80%) have trip length $<$30 km. Hence, similar trip length across the two groups could be responsible for statistically indifferent WTP values for public charging availability. With respect to battery warranty, Table 10 shows that non-commuters in Delhi and Kolkata value per year increase in battery warranty at ₹16,520 and ₹18,898 respectively. Whereas, commuters in Delhi and Kolkata indicate 3.7 times (₹61,483) and 1.7 times (₹32,026) higher WTP respectively as compared to non-commuters. The results reveal commuters' strong preference for PHEVs with high battery warranty. Interestingly, Delhi commuters value battery warranty 1.9 times more (₹61,483) than Kolkata commuters (₹32,026). The battery warranty is usually directly proportional to the average annual vehicle kilometre traveled (VKT) by the car (Ambrose & Kendall, 2016; Higgins et al., 2017). Therefore, the commuters in Delhi, who majorly commute longer trips (due to relatively larger city size), also have higher average annual VKT and thus indicate higher perceived benefit towards increment in warranty period of the battery.

The WTP study indicates that the consumer preference towards PHEV is highly sensitive to intended predominant trip purpose. In both Delhi and Kolkata, commuters demonstrate a significantly higher WTP

Table 12
Results of sensitivity analysis.

Attribute	Base	Scn 1	Scn 2	Scn 3	Scn 4	Scn 5	Scn 6	Scn 7	Scn 8	Scn 9	Scn 10	Scn 11	Scn 12	Scn 13	Scn 14
Fuel cost savings	20	40	60	20	20	20	20	20	20	20	20	20	20	20	20
Battery recharging time	7	7	7	3	1	7	7	7	7	7	7	7	7	7	7
Battery range	30	30	30	30	30	60	90	30	30	30	30	30	30	30	30
Tailpipe emission	75	75	75	75	75	75	75	50	25	75	75	75	75	75	75
Public charging availability	20	20	20	20	20	20	20	20	20	60	100	20	20	20	20
Battery warranty	3	3	3	3	3	3	3	3	3	3	3	5	8	3	3
Purchase price (in ₹ 1000)	1232	1232	1232	1232	1232	1232	1232	1232	1232	1232	1232	1232	1232	1479	1725
User category		Probability shift from base to alternative scenario (in %)													
Commuter-Delhi		21.37%	40.87%	29.00%	42.02%	25.38%	47.69%	24.37%	46.01%	18.58%	35.92%	17.64%	41.84%	−34.29%	−61.36%
Non-commuter-Delhi		19.26%	37.14%	43.66%	60.56%	12.53%	24.68%	26.71%	49.86%	7.39%	14.69%	8.24%	20.36%	−54.84%	−84.32%
Commuter-Kolkata		31.04%	56.63%	16.64%	24.68%	14.30%	28.03%	39.69%	68.58%	9.57%	18.97%	12.43%	30.25%	−37.69%	−66.01%
Non-commuter-Kolkata		6.49%	12.93%	17.48%	25.89%	9.57%	18.97%	11.94%	23.55%	11.75%	23.17%	9.23%	22.75%	−46.07%	−76.01%

for PHEV attributes compared to non-commuters. Hence, improvement in the PHEV operation-specific attributes such as fuel cost savings, battery recharging time, battery range, tailpipe emission, and battery warranty would help promote PHEVs among commuters in India. Although, both the study cities are metro cities, it is interesting to observe differences in consumers' WTP for several attributes such as battery recharging time, battery range, and battery warranty. More likely these differences are due to difference in city characteristics (such as city size, characteristics of residential development-with or without garage availability within building premises) and trip characteristics (such as average daily trip length for journey to work). Hence, the requirements of PHEV models may vary from one city to another due to differences in city and trip characteristics.

6. Sensitivity analysis

The sensitivity analysis was conducted to analyze the relative impact of improvement in PHEV-related attributes on commuter and non-commuter preference for PHEVs. The ML model estimates obtained for both commuters and non-commuters (shown in Table 7) in Delhi and Kolkata, for complete dataset without taste heterogeneity were used to perform sensitivity analysis. Initially, a base scenario of PHEV was assumed, which was defined by the base levels of each attribute considered in the present study. For purchase price, the base level included 25% higher than the average price commuters and non-commuters in Delhi and Kolkata are willing to pay for their next car purchase. Subsequently, several alternative improvement scenarios of PHEV were generated by considering the improved level of each attribute at a time and keeping the levels of all other attributes same as base scenario. Finally, the evaluation of improvement scenarios was performed by computing the percentage change in the choice probability for the improvement scenarios relative to the base scenario. Equation (1) presents the utility equation used for evaluation of improvement scenarios. Also, the coefficient estimates used for developing the utility equation are presented in Table 11.

$$U = \alpha\ (\textit{Fuel cost savings}) + \beta\ (\textit{Battery recharging time}) + \gamma\ (\textit{Battery range}) + \delta\ (\textit{Tailpipe emission}) + \varepsilon\ (\textit{Public charging availability}) + \xi\ (\textit{Battery warranty}) + \eta\ (\textit{Purchase price}) \tag{1}$$

Where, U = Utility of PHEV; α, β, γ, δ, ε, ξ, η = coefficient estimates of fuel cost savings, battery recharging time, battery range, tailpipe emission, public charging availability, battery warranty, and purchase price obtained from the developed ML models (shown in Table 7).

The alternative improvement scenarios considered for simulation, and the results of sensitivity analysis are summarized in Table 12. The sensitivity of the demand with respect to improvement in attributes is discussed separately in the following section.

Fuel cost savings: For increase of fuel cost saving in Scn 1 (40%) and Scn 2 (60%), the choice probability of commuters in Delhi relative to the base scenario increase by 21.37% and 40.87%, respectively, and by 19.26% and 37.14%, respectively for Delhi non-commuters. The results indicate that future PHEV designs with improvement in fuel cost savings would enhance the appeal of PHEV as a mode among both commuters and non-commuters in Delhi and similar results were observed for Kolkata respondents. The outcome corroborates past study findings, where improvement in fuel economy is found to play an important role towards influencing EV choice (Hidrue et al., 2011; Ziegler, 2012; Danielis et al., 2020).

Battery recharging time: For improvement scenarios of reduction in battery recharging time in Scn 3 (3 h) and Scn 4 (1 h), commuters in Kolkata, show positive probability shift by 16.64% and 24.68% respectively, compared to base scenario, while for non-commuters, the corresponding probability shift is found to be 17.48% and 25.89%

respectively. The results clearly indicate that the improvement in battery recharging time for future PHEV designs would strongly motivate both commuters and non-commuters in Kolkata to choose PHEV as a mode. Similar findings could be observed for Delhi commuters. This result is aligned with the past study findings, where reduction in battery recharging time is found to have a strong positive impact on consumer preference for EVs (Hidrue et al., 2011; Helveston et al., 2015; Li et al., 2022). Further, from the results, it may be observed that the estimates obtained for consumers in Delhi are about 1.7–2.5 times higher as compared to Kolkata consumers. Sensitivity analysis results clearly indicate that Delhi consumers are more sensitive in terms of battery recharging time with regard to PHEV adoption compared to their Kolkata counterparts.

Battery range: Overall, the sensitivity results reveal that improvement in the battery range would serve as a motivator towards the choice of PHEV among both user groups in both cities. The findings are in agreement with the past studies (Hackbarth & Madlener, 2013; Hoen & Koetse, 2014; Rommel & Sagebiel, 2021). However, in each city, the commuters are expected to be early adopters of PHEV for further enhancement in battery range. Further, both WTP study and sensitivity analysis reveal that commuters in Delhi are more sensitive towards improvement in battery range as compared to their Kolkata counterpart.

Tailpipe emission: For tailpipe emission reduction in Scn 7 (50%) and Scn 8 (25%), the choice probability of Delhi commuter increases by 24.37% and 46.01% respectively, compared to the base scenario, and by 26.71% and 49.86% respectively for non-commuters. Also, in Kolkata, commuters exhibit positive probability shifts compared to the base scenario. The results reveal that improvement in emission reduction capabilities of future generation PHEVs would act a strong driver towards the choice of PHEV among both commuters and non-commuters in both Delhi and Kolkata. The findings are in line with past studies, where lower vehicular emission is found to play a crucial role in encouraging consumers to choose EVs over CVs (Potoglou & Kanaroglou, 2007; Hackbarth & Madlener, 2013; Nie et al., 2018).

Public charging availability: For increase of public charging availability in Scn 9 (60%) and Scn 10 (100%), the percentage increase in the choice probability relative to the base scenario is found to be 18.58% and 35.92%, respectively among commuters in Delhi, and by 7.39% and 14.69% respectively, among non-commuters. Hence, for improvement in public charging availability, estimates derived for commuters are about 2.5 times higher as compared to that of non-commuters in Delhi. In Kolkata, for Scn 9 and Scn 10, commuters indicate a positive shift of 9.57% and 18.97% respectively, compared to the base scenario, while among non-commuters, the corresponding increase in choice probability is found to be 11.75% and 23.17% respectively. Hence, the results indicate similar estimates for commuters and non-commuters in Kolkata for improvement scenarios of public charging availability. Overall, the results reveal that improvement in public charging availability would act as a driver towards enhancing the usage of PHEV among both commuters and non-commuters in both Delhi and Kolkata. This is in line with the findings of previous studies, where limited charging infrastructure is identified as one of the primary barriers towards widespread diffusion of EVs (Rommel & Sagebiel, 2021; Tanaka et al., 2014; Ziegler, 2012). The results corroborate the fact that city characteristics have a strong influence on public charging availability with respect to PHEV uptake.

Battery warranty: For increment of battery warranty in Scn 11 (5 yrs) and Scn 12 (8 yrs), Delhi commuters indicate increase in choice probability by 17.64% and 41.84% respectively, relative to the base case, while non-commuters indicate an increase by 8.24% and 20.36%, respectively. Similarly, the Kolkata commuters also indicate a positive shift in choice probability among commuters. The results indicate that future PHEV specifications with expanded warranty coverage are likely to attract both user groups in both cities to adopt PHEVs. Also, comparison of WTP values and the estimates of sensitivity analysis show that Delhi commuters are marginally more sensitive to improvement in battery warranty than Kolkata commuters.

Purchase price: For increment of purchase price in Scn 13 (₹14,79,000) and Scn 14 (₹17,25,000), the probability to choose the improvement scenario relative to the base scenario decrease by 34.29% and 61.36% respectively among commuters in Delhi, and by 54.84% and 84.32% respectively, among Delhi non-commuters. Similarly, in Kolkata, for Scn 13 and Scn 14, commuters indicate decrease in the choice probability by 37.69% and 66.01% respectively, while Kolkata non-commuters indicate a decrease in choice probability by 46.07% and 76.01%, respectively relative to the base case. The results clearly indicate strong disutility of both commuters and non-commuters in Delhi and Kolkata towards the purchase price of PHEV. The higher purchase price of PHEV as compared to CVs is identified as one of the major barriers towards PHEV adoption. Such observations are found to be consistent with the findings of previous studies (Gong et al., 2020; Li et al., 2022; Nie et al., 2018; Tanaka et al., 2014). For improvement of purchase price with respect to base scenario in Scn 13 and Scn 14, the results show that for every ₹1,00,000 increment in purchase price, the disutility to choose PHEV increase by about 16%. Hence, the findings clearly point towards introducing higher purchase subsidy for increased PHEV adoption.

7. Conclusion, contribution, and limitations

In this study, an analysis of consumer perception towards PHEV adoption in two Indian major metro cities, namely Delhi and Kolkata were carried out in a discrete choice modeling framework for commuter and non-commuter. Based on the key findings and observations, the following concluding remarks can be made:

Both reduction in battery recharging time and increase in battery warranty were associated with higher WTP estimates for all user groups pointing towards an added focus on these two operation-specific attributes from the manufacturers to boost the PHEV penetration. It was interesting to note that the consumer preference towards PHEV is highly sensitive to trip purpose. Commuters in both cities are found to have substantially higher WTP for several operation-specific attributes such as fuel cost savings, battery recharging time, battery range, tailpipe emission, and battery warranty as compared to non-commuters, indicating that the improvement in these attributes would primarily appeal commuters. Hence, the appropriate stakeholders should formulate marketing strategies for promoting PHEVs, focusing on commuters in the major Indian metro cities as early users of PHEVs.

Although, both the study cities are metro cities, it is interesting to observe several differences in consumers' WTP with respect to battery recharging time, battery range, and battery warranty. For improvement in battery range and battery warranty, commuters in Delhi show higher WTP as compared to Kolkata commuters. The reason may be attributed to the larger city size and consequently higher trip length ($\geq$30 km) and higher average annual vehicle kilometre traveled for most of the commuters in Delhi as compared to Kolkata commuters. Also, consumers in Delhi (both commuters and non-commuters) show higher WTP for reduction in battery recharging time relative to Kolkata consumers. The absence of home-based charging capability/garage, for most of the consumers in Delhi (51% of commuters and 55% of non-commuters) as compared to Kolkata consumers, who majorly have garage availability (89% of commuters and 74% of non-commuters), justifies higher WTP for improvement in battery recharging time. Hence, due to difference in the city characteristics (such as city size, characteristics of residential development-with or without garage availability within building premises) and trip characteristics (such as average daily trip length for journey to work), the requirements of PHEV models may vary from one metro city to another metro city. Therefore, the car manufacturers are recommended to develop multiple models of PHEVs to encourage the penetration of PHEVs in a country-wide context, which can cater to the requirements of different users across different cities. The results also indicate the significant influence of sociodemographic variables such as age, income, education, garage availability, etc. on PHEV adoption.

The sensitivity analysis clearly shows strong disutility of both commuters and non-commuters in Delhi and Kolkata towards the purchase price of PHEV. The higher purchase price of PHEVs as compared to CVs could be tackled by appropriate levels of purchase subsidy. Further, the WTP study and sensitivity analysis also reflect the reduction in disutility of consumers towards PHEVs with public charging availability. However, lowering the purchase price through subsidies is found to be more vital than offering public charging stations for boosting the sales of PHEVs among Indian consumers. Such information could be used by the Government to formulate effective policy measures for promoting faster adoption of PHEVs in the Indian context. It is also worth noting that Kolkata commuters represent a user category with pro-environmental behavior, indicated by their higher sensitivity for reduction in tailpipe emission as compared to Delhi commuters, despite Delhi being a more polluted city (Chowdhury et al., 2017). Such findings indicate the important role of the government towards organizing public educational campaigns to raise awareness of consumers regarding features, environmental and social benefits of electric vehicle technology, and incentives available for using such technology to increase consumers' willingness to purchase PHEVs in Indian context.

The major contributions of this study are outlined here. Firstly, it has identified and analyzed a set of priority operation-specific attributes influencing commuter and non-commuter preference towards PHEV in Indian scenario using step-by-step approach including design of survey instrument, data collection, and discrete choice analysis. Secondly, it is essential to incorporate city characteristics and their respective consumers' perspective while developing city-specific marketing strategy for increased PHEV penetration. In this connection, this work makes a unique attempt to investigate the commuter and non-commuter respondents' perception from two major Indian metropolitan cities, namely, Delhi and Kolkata. Such analysis and related findings would help the planners and manufacturers to develop specific strategies which would attract a wider section of consumers belonging to a particular city. As, electric vehicle in general, PHEV in particular is a relatively new mode in Indian market, such initiatives would be instrumental. One of the major contributions lies in formulating a guideline for promoting PHEVs in the Indian context. Based on the available literature review, this study seems to be one of the initial studies to discuss and analyze key policy measures for faster adoption of PHEVs in Indian context. Hence, other developed or developing countries aiming at improving PHEV patronage may consider the key findings as inputs for their respective cities.

Before closing, the authors would like to mention the limitations of this study and the future scope of work. First, the limitation of this study lies in its selection bias favoring individuals displaying a pronounced inclination towards PHEV purchases. To enhance comprehensiveness, future research should employ a more stratified and inclusive sampling methodology to capture a wider spectrum of perspectives on PHEVs. Second, the present study investigated the influence of sociodemographic and trip characteristics on commuter and non-commuter preference towards PHEV attributes. Further research is required to explore the impact of consumers' innovativeness, social influence, knowledge, and experience with PHEVs on choice preferences for relative attributes. Third, as a future scope of work, it would be interesting to include "opt-out" option in the experiment design and analyze its influence on consumer preferences and WTP estimates for PHEV attributes. Fourth, although the valuation of PHEV operation-specific attributes in terms of willingness to pay (WTP) values provides useful information regarding commuter and non-commuter preference towards PHEVs, it also highlights the need to conduct future research towards demand estimation of PHEVs by developing demand models considering PHEVs and CVs. Fifth, in the present study, interesting findings related to city-specific influence on consumer behavior and requirements towards PHEV-related attributes were obtained. As a future extension of the work, it would be interesting to include more cities, model the variation across cities using relevant attributes, and investigate its influence on PHEV patronage. The derived findings and observations may be useful for the formulation of suitable policy interventions to increase market penetration in the respective cities.

CRediT authorship contribution statement

Reema Bera Sharma: Writing – original draft, Visualization, Validation, Methodology, Investigation, Formal analysis. **Bandhan Bandhu Majumdar:** Writing – review & editing, Writing – original draft, Visualization. **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.

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Appendix A1. Passenger Car Growth in India and Externalities

Due to rapid urbanization, the urban population in India has increased significantly from 391 million in 2011 to 471 million in 2019 and is estimated to be around 594 million by 2036 (MoHFW, 2020; Urban population). The surge in urban population, coupled with increased disposable income is fueling a noticeable upswing in the ownership of passenger cars within major cities (Bera & Maitra, 2019). As per MORTH (2019), India had 22 cars per 1000 population, and the number is predicted to be 35 cars per 1000 population by 2025 (Ghate & Sundar, 2014), and 170 cars per 1000 population by 2040 (IEA, 2017). The growth in passenger car ownership is further responsible for urban air pollution and negative health impacts among urban residents (Miglani, 2019). In India, the detrimental consequences of rising pollution levels were connected to 1.67 million deaths, accounting for 17.8 percent of the total deaths, and putting it as the fifth leading cause of death in the country (Singh & Yadav, 2021; Yadav et al., 2021). Also, India continues to be the leading country globally for premature deaths caused by transport-related air pollution (Lancet commission, 2017), and the increasing fleet of passenger cars has been cited as one of the primary reasons for the rising levels of air pollution in India (Dutta et al., 2021). In addition to the detrimental environmental impact, the importation of crude oil to sustain the expanding fleet of passenger car poses a significant risk to economic advancement and jeopardizes future energy security (Upadhyayula et al., 2019). In India, passenger cars alone consume more than 30% of the petroleum produced from crude oil (Press Information Bureau, 2014). In 2018–19, India imported 226.5 Million Metric Tonnes (MMT) of crude oil valued at 112 billion USD, resulting in an import dependence of 88%, which has been progressively increasing over the years as domestic production is declining (Petroleum Planning & Analysis Cell, 2021). As a result, India is in the third position, behind the United States (US) and China in terms of crude oil import (Nouni et al., 2021).

Appendix A2. Policy Initiatives to Promote EVs in India

Electric Vehicles (EVs) are receiving growing attention from policymakers across the globe, since they are predicted to play a key role in meeting the objectives of reduction in carbon emission and crude oil dependence, set under the Paris Climate Change Agreement (UN Climate Change, 2015). With similar motive, the Government of India has also taken several initiatives to promote the adoption of EVs. Department of Heavy Industry (DHI), under Ministry of Heavy Industries and Public Enterprises, Government of India, launched 'National Electric Mobility Mission Plan 2020 (NEMMP) to address the issues related to vehicular emission, national energy security, and for promotion and development of indigenous manufacturing capabilities of EVs (GoI, 2012). Through this national mission document, the Government of India announced ambitious goal to achieve total hybrid and electric vehicle sales of about six million units in India by 2020. Subsequently, the 'Faster Adoption and Manufacturing of (Hybrid &) Electric Vehicles (FAME)' India scheme was launched by DHI in March 2015 to promote and ensure sustainable growth of EVs in India (GoI, 2015). In the Phase-I of FAME India scheme, the government supported 2,78,000 EVs with a total purchase subsidy of approximately USD 48 million. Subsequently, in April 2019, DHI launched Phase-II of FAME India scheme, with a substantial budget subsidy of USD 140 million for the next three years, for building a robust domestic eco-system for EVs (GoI, 2019).

Appendix B. Past Stated Preference (SP) Studies on Electric Vehicles (EVs)

Hidrue et al. (2011) developed Latent Class (LC) model and used the derived coefficients to estimate US consumers' perceived benefit for five vehicle attributes of EVs, namely fuel cost, charging time, acceleration, pollution, and driving range in terms of WTP values. The study findings reveal that consumers have higher WTP for fuel cost savings, reduction in charging time, and increase in driving range as compared to pollution reduction and performance improvement. With respect to sociodemographic variables, the study concluded that consumers' likelihood to purchase EVs increases with youth, education, living in a home having accessible charging outlet, and desire to buy small or medium-sized vehicles. Hackbarth and Madlener (2013) conducted Germany-wide SP experiment to investigate consumers' WTP for several vehicle and infrastructure attributes and government incentives. By developing Mixed Logit (ML) model, the study concluded that consumers indicate high WTP for fuel savings, emission reduction, increase in driving range and charging infrastructure as well as for enjoying vehicle tax exemption and free parking or bus lane access. Helveston et al. (2015) developed discrete choice ML models using SP data to investigate consumer preference towards EVs in US and China. The study findings indicate that Chinese respondents have higher choice preference towards mid-range PHEVs and BEVs as compared to American respondents. With respect to vehicle attributes, Chinese respondents show nearly two times and three times higher WTP for operating cost and acceleration time, respectively relative to their American counterparts. In another study, Nie et al. (2018) included several vehicle attributes such as driving range, pollution, charging time, maximum speed, fuel cost, and purchase price, and developed MNL and ML models to investigate EV preferences of potential EV purchasers and unlikely electric vehicle purchasers in Shanghai, China. The results indicate that potential EV purchasers are willing to pay more for each of the EV attributes included in the study than their non-purchaser counterparts. Investigation of the impact of sociodemographic and socio-psychological attributes indicates that probability of being potential EV purchaser increase with individual annual income, environmental awareness, and acceptance of new technology. Danielis et al. (2020) in their study, developed MNL and ML models to investigate Italian drivers' preferences towards EVs through valuation of vehicle and infrastructure attributes such as fuel economy, fast charging time, distance between charging stations, driving range, purchase price, and policy attributes such as free parking in urban areas. The study findings indicate that improvement in fuel economy and electric range plays an important role towards EV choice.

Gong et al. (2020) developed LC models to investigate the influence of government incentives such as access to bus lanes, rebate on upfront costs, and rebate on parking fees on consumers' decision to buy EVs in Australia. The results show that because the initial price of EVs is currently higher than conventional cars, the policy instrument in the form of rebate on initial price is most effective. Rommel and Sagebiel (2021) designed and fielded a stated choice experiment in Germany to examine the WTP for the attributes of EVs by developing LC models. The study findings indicate that consumers showing more interest in PHEVs and BEVs as compared to CVs have higher WTP for increase in availability of charging stations, lower running cost, and improvement in driving range. Li et al. (2022) developed hybrid choice (HC) model by integrating vehicle attributes such as price, cruising range, fuel cost, battery warranty, quick charging time, and psychological attributes such as environmental awareness, perceived environmental benefits, and subjective norms, and policy attributes such as tax exemption, access to HOV lanes, tradable driving credit (TDC) and personal carbon trading (PCT) to investigate factors influencing consumer choice of EVs in China. The results reveal that policy attributes such as TDC and PCT are more powerful than other attributes towards encouraging consumers to adopt EVs. Jia and Chen (2023) conducted statewide SP vehicle fuel type choice survey in Virginia, US to investigate heterogeneous preference for EVs by developing ML, LC, and LC-ML models. The results suggest that providing monetary incentives and deploying public charging facilities are more effective towards accelerating EV adoption, as compared to manufacturing EVs with longer battery ranges. Also, the heterogeneity study reveal that the market diffusion of PHEVs is found to be more influenced by financial incentives while BEV adoption is more responsive towards charging infrastructure deployment.

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