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Estimating personal electric vehicle demand and its adoption timeframe: A study on consumer perception in Indian metropolitan cities

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ABSTRACT

India's transition to electric vehicles has entered its second decade. The government has set a target of having EV sales accounting for 30 % of private cars and 80 % for two-wheelers by 2030. However, despite several efforts of government and industry, the penetration of electric vehicles till-date has not been as per the set targets. This study aims to estimate the end-user demand and adoption timeframe of electric 4-wheelers (e-4 W) and 2-wheelers (e-2 W) in India's four large metropolitan areas. Binary logit choice models are developed based on a discrete choice experiment carried out by utilizing 2,400 face-to-face interview responses. In addition, ordered logit models are developed to assess the adoption timeframe of the EVs. The study results show a significant geographic variation in demand for e-4Ws and e-2Ws within India. This demand is also driven by vehicle attributes, demographics, infrastructural elements, and user attitudes. Existing vehicle owners are more likely to purchase an EV in the future, and are also likely to drive/ride it more. In addition, consumers who are young and wealthy, and living in homes with dedicated parking spaces are more likely to be early adopters of EVs. These findings would assist policymakers in designing a tailormade and phased EV implementation scheme in India.

1. Introduction

The transport sector in India accounts for 18 % of the total energy consumption and is the 3rd largest greenhouse gas emitting sector, within which, the road sector is the most significant contributor. Out of the 142 million tons of CO_2 emitted by the transport sector annually, 123 million tons is contributed by the road transport segment alone (Kaushik, 2022). In order to reduce/minimize tailpipe emissions, electric vehicles (EVs) are being promoted as an alternate to conventional internal combustion engine vehicles (ICEVs). Nations like Norway, Sweden, China, the United States of America (USA), etc., have adopted and are gradually increasing the share of EVs in their fleet (IEA, 2019; Irle, 2021). Norway is leading the EV adoption among all the nations in the world. The share of EVs in India however stands at 0.2 % during the drafting of this paper. The National Electric Mobility Mission Plan (NEMMP) 2020 was launched in India in 2013 with a target of deploying 5–7 million electric vehicles in the country by 2020 (Gulati, 2012). Subsequently, the Faster Adoption and Manufacturing of (Hybrid &) Electric Vehicles (FAME) scheme was launched in 2015 to promote and ensure sustainable growth of EVs in India. However, the current electric vehicle sales figures indicate that despite these schemes, the EV sales target has fallen short. In the financial year 2021, only 238,000 electric vehicles were sold, out of which, only 5,905 were passenger cars, and 143,000 were 2-wheelers, while the rest were 3-wheelers (Electric Vehicle Sales in India Declined in FY2020-21: SMEV, 2021). The Government of India (GoI) has further sanctioned $1,351 million for the second phase of FAME scheme (FAME II) for a period of 3 years starting from April 2019 (The Gazette of India Notification for FAME-II, 2019). Under this scheme, various subsidies and incentives have been introduced to speed up EV adoption in all categories of vehicles like cars, buses, 2-wheelers, etc. Various states within India have also introduced different schemes and targets to stimulate and promote electric vehicle adoption. For example, the government of West Bengal has set a target of 10 lakh EVs in the state by 2026 (Electric Vehicle Policy, 2021). While focusing on the acceleration of roll out of charging infrastructure, the government has announced the installation of 1 lakh public and semi-

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public charging stations by 2026 with a ratio of 8:1 for EV to public charging points. The Government of Assam has announced its state-specific policies and targets, which aim for a 25 % EV share in new vehicle registration by 2026 (Singh, 2021). The state of Karnataka's EV policy aims to transform the auto-rickshaws, taxis, corporate, and school fleets to 100 % electric by 2030. The government of Delhi announced the Delhi EV policy in August 2020, aiming to deploy 25 % of the newly registered vehicles to be operated on electric power by 2024 (GNCTD, 2020). As per the 2018 draft EV policy of the Government of Kerala, EV buyers will be exempted from road tax for the first three years. Also, buyers of EV 3-wheelers will get an incentive of ₹30,000 (Governement of Kerala, 2018). The state government of Uttar Pradesh will introduce 1000 EV buses in the state by 2030 and promote renewable energy-based charging and battery swapping stations (Government of Uttar Pradesh, 2018). Even after the introduction and implementation of these schemes, and despite the obvious advantages of EVs, significant barriers restrain their adoption, resulting in a small EV market share in India. At the same time, the worldwide electric car stock reached 10 million units in 2020, resulting in a 43 % rise over 2019, and a 1 % stock share (International energy agency, 2021), with battery electric vehicles (BEVs) making up two-thirds of new electric vehicle registrations. So, it can be seen that in the emerging markets and developing economies (EMDEs) EV adoption has been substantially slower. (Ayeshik & Nazrul, 2021; KPMG, 2018). Despite the extensive efforts of several state governments as well as the Government of India, which include the implementation of schemes, policies, and the expansion of EV infrastructure, the adoption of EVs in India has not met the desired goals and ambitions. Hence, it is imperative to thoroughly examine the factors influencing consumer reluctance towards choosing EVs (Bansal et al., 2021; Dhar et al., 2017), and also the likely EV adoption timeframe, in order to achieve the target by 2030. This study aims to assess consumer perceptions to uncover the underlying reasons behind this reluctance. Additionally, it seeks to provide policy recommendations that can effectively accelerate the adoption of EVs by addressing the identified gaps and proposing actionable solutions that can facilitate a more rapid transition towards a sustainable transportation system in India.

2. Literature review

The most widely used tool in assessing user preferences in vehicle ownership is discrete choice analysis. Electric vehicle adoption can be described as a choice between EVs and other alternative vehicles, differentiated based on their attributes or characteristics (Liao et al., 2017). Users choose by making a trade-off between the attributes and their levels. The attributes could be categorized by financial, technical, infrastructure, and policy features (Juvvala & Sarmah, 2021; Liao et al., 2017). The financial attributes refer to the different types of costs included in vehicle ownership such as purchase price, fuel cost, maintenance cost, etc. Many studies have used these attributes in their experimental design and implicated the negative and high significance in users' selection of vehicles (Axsen et al., 2013; Lieven et al., 2011; Shetty et al., 2020). Several studies in developed nations like Germany, USA, Denmark, Canada and Italy discovered the effect of individual's income on EV sales, which indicates that people with higher income are less price-sensitive than others (Achtnicht, 2012; Danielis et al., 2020; Hackbarth & Madlener, 2013; Hess et al., 2012; Huijts et al., 2012; Mabit & Fosgerau, 2011; Potoglou & Kanaroglou, 2007). In contrast, a study by Jensen et al. stated its effect to be insignificant (Jensen et al., 2013).

The operating or running cost of vehicles also plays an essential role in a consumer's decision-making. Most of the studies used fuel cost as an attribute in the form of either cost per 100 km or both fuel price and fuel efficiency (Musti & And, 2011). A few studies (Hess et al., 2012) have considered annual maintenance cost as an individual attribute, or have clubbed it with the total operation cost (Mabit & Fosgerau, 2011). In terms of technical attributes, the short driving range is identified as one of the most significant drawbacks or barriers to EV adoption (Bühler et al., 2014; Hackbarth & Madlener, 2013; İmre et al., 2021). However, few studies (Hess et al., 2012) found the effect of driving range to be insignificant, although this might have been a result of the limited driving range (30–60 miles) used in the experiment. Users with lower annual miles driven or vehicle kilometers traveled (VKT) have lower range preferences (Hoen & Koetse, 2014). Households owning multiple vehicles are less worried about the low driving range as they have an alternate conventional vehicle for long-distance trips (Jensen et al., 2013). In electric vehicle adoption, another significant attribute is recharging time. The gasoline vehicle can be refueled in a few minutes, but the situation is entirely different for electric vehicles. An electric vehicle may take 6–8 hrs. for a full charge if a slow charger is used. However, charging time has been reduced with technological advancements such as the introduction of fast chargers or rapid chargers, which can recharge up to 80 % of the battery in 15–30 min (Etezadi-Amoli et al., 2010). In terms of infrastructural attributes, the availability of charging stations in their vicinity also affects a consumer's choice to a certain extent (Kim, Rasouli, & Practice, 2014; Sachan et al., 2020). Most studies have found a positive impact of charging infrastructure, which can eventually save time from long queues and minimize the consumer's short-range anxiety (Liao et al., 2017). Also, certain policy attributes may play a significant role in the decision-making of users (Glerum et al., 2014; Horne et al., 2005; Hui et al., 2018). Studies (Hess et al., 2012; Mau et al., 2008; Potoglou & Kanaroglou, 2007) indicate that one-time cost reduction policies and tax subsidies are found to be a significant strategy, whereas free parking and toll reduction were found to be insignificant (Chorus et al., 2013; Hess et al., 2012; Qian & Soopramanien, 2011). Most of the studies were based on stated preference (SP) surveys due to the lack of presence of electric vehicles in the market. Table 1. summarizes the various choice models that have been used in estimating the adoption of EVs.

Based on reviewing the literature, it is observed that in the context of developing economies, including that of India, there exist multiple supply-side macro-level studies that forecast the sales of EVs, however, there is limited literature that estimates EV user demand by capturing the end-user preferences, unlike studies from the global north. In the Indian context, (Bhattacharyya & Thakre, 2020)) has detailed the factors that influence EV adoption by carrying out a detailed literature review. However, the study was not extended to estimate the demand. Another study (Bera & Maitra, 2019) prioritized the attributes that influence the choice of the specific type of EV, i.e., Plug-in Hybrid Electric Vehicles (PHEVs). Results indicate that in addition to the attributes specific to PHEV, technology such as battery warranty, electric range, and charging infrastructure have significant importance in selecting PHEV. The results indicate that driving range is given more preference, followed by the price of the EV, whereas seating capacity and torque were the least concerned factors for selecting an EV. Furthermore, (Sonar & Kulkarni, 2021)) has demonstrated an AHP-MABAC (analytic hierarchy process – multi-attributive border approximation area comparison) based approach in the selection of a particular EV model from among the given EV models available in the Indian market. The study by (Bansal et al., 2021) develops an integrated choice latent variable (ICLV) model to estimate the demand for EVs in India, wherein data was collected using online surveys. The study indicates that consumers are willing to pay an additional amount of US$10–34 for the purchase price to decrease the fast-charging time by 1 min, and US$7–40 to add 1 km to the driving range of EVs at 200 km. The study however does not consider vehicle attributes in its analysis and is also not able to capture the variability in demand for different types of personal EVs within India. The demand estimates developed by (Patil et al., 2021) are also limited to one city (Hyderabad) and one type of EV, i.e., the electric 2-wheeler, wherein the results show that top speed is likely to play a role in the adoption of e-2Ws. Lastly, a recent study by (Murugan & Marisamynathan, 2022) identified factors and strategies that significantly affect the adoption of e-2Ws in Ahmedabad, India by developing an

Table 1
Econometric choice model approaches for Electric Vehicle adoption.

Study	Econometric Model	Attributes Included	Findings
(Beggs et al., 1981)	Ranked Logit	Top speed, purchase price, fuel costs, driving range, acceleration, operating costs, seating capacity, and warranty	Results indicate that Range of the vehicle is most significant
(Calfee, 1985)	Disaggregate Multinomial Logit (MNL) Model	top speed, purchase price, operating costs, driving range, and seating capacity	Speed and Range of the vehicle had significant positive and price had negative impact on the model
(Bunch et al., 1993)	MNL and Nested Logit	Purchase price, dedicated versus multi-fuel, fuel costs, driving range, fuel availability, and air pollution	Refueling time and fuel costs are significant attributes.
(Potoglou & Kanaroglou, 2007)	Nested Logit Model	Vehicle size, purchase price, acceleration, annual fuel cost, fuel availability, pollution level, and incentives.	Reduction in cost variables, relief in purchase tax, and low emissions rates would encourage the adoption of a green vehicle.
(Achtnicht, 2012)	Standard Logit Model	Engine power, purchase price, fuel availability, fuel costs, and emissions	Inability to expand the number of charging stations signifies a significant barrier in EV adoption.
(Hackbarth & Madlener, 2013)	Mixed Logit Model	Purchase price, fuel costs, driving range, battery recharging time, refueling time, fuel availability, and policy incentives	Consumers are unwilling to purchase alternative fuel vehicles due to price difference and unavailability of charging infrastructure.
(Hackbarth & Madlener, 2013)	Structural Equation Model (SEM) and MNL	Purchase price, fuel costs, driving range, service station availability, vehicle size, tailpipe emissions, and vehicle type	Consumers' socio-economic attribute variables significantly influence the EV purchase decision.
(Sheldon & Dua, 2020)	Combined Multi-Criteria Decision Making (MCDM) with Rank-Ordered Utility (RUM) Model approach	Price, net present value of resale price, net present value of fuel costs, curb weight, range, previous year sales	Vehicle choice model predicts PEV market share under different policies. Achieving a 2.5 % PEV market share in 2017 improved fuel economy by ~ 2 %. The current PEV subsidy costs $1.90 per additional liter of gasoline saved. Adjusting subsidies based on income could lower the cost per additional PEV.
(Bansal et al., 2021)	Integrated Choice Latent Variable (ICLV) model	Price, running cost, driving range, slow charging time, fast charging time, availability of fast charging stations, reserved parking, specialized lanes in congested areas	Indian consumers exhibit a willingness to pay extra for shorter fast charging times, increased driving range, and lower operating costs in electric vehicles. Attitudinal factors strongly influence their preferences for EVs, while accounting for reference dependence enhances the accuracy of willingness-to-pay estimates.
(Patil et al., 2021)	MNL and Random Parameter Logit (RPL) model	Operating cost savings, top speed, range, charging time, acceleration, and purchase cost	Top speed was identified as the most influential attribute in choice decisions for electric two-wheelers (E2W), followed by acceleration and charging duration. The sensitivity analysis highlighted top speed as the key factor impacting choice decisions.
(Sonar & Kulkarni, 2021)	Integrated Hierarchy Process (AHP) with the Multi-Attributive Border Approximation Area Comparison (MABAC)	Driving range, price, battery capacity, charging time, seating capacity, torque	Study provides genuine preferences based on comprehensive selection criteria for electric vehicles. It identifies the top choice in terms of performance and highlights an affordable option for budget-conscious buyers.
(Murugan & Marisamynathan, 2022)	Ordered Probit Model	Charging facilities, free parking for e-bikes, subsidy on e-bike purchase, separate lanes for e-bikes, high speed e-bikes with improved battery, tax exemption on e-bikes	Gender, travel distance, fuel expenditure influence electric vehicle adoption. Preferred policies include high-speed electric bikes, tax exemptions, and accessible charging facilities.

ordered probit model. Results show that high-speed electric bikes with improved battery technology are likely to be one of the factors that motivate the adoption of e-2Ws. In essence, it is observed that there is a need for a study that considers (a) multiple types of EVs and their characteristics, (b) is able to capture the variability in demand by vehicle category type and geographically, and (c) extend the analysis to estimate the possible EV adoption timeframe (in years).

In order to fill these gaps in research, this study aims to estimate user behaviour of adopting personal electric 2-wheelers (e-2Ws) and electric four 4-wheelers (e-4Ws) in India. The paper specifically reports on a discrete choice experiment carried out in four large metropolitan areas of India. User choices were collected via offline stated preference questionnaire surveys conducted in New Delhi, Mumbai, Bengaluru, and Kolkata, and subsequently, a pair of binary choice models were estimated to assess the demand for e-2Ws and e-4Ws. Various vehicle attributes and their levels were developed keeping in mind the technological advancement in the future markets. Lastly, the study estimates the possible EV adoption timeframe for the next 5 years through ordinal logit model considering encouraging and discouraging EV attributes and understanding the influencing EV characteristics for the adoption of EVs. The paper also presents policy discussions based on the model findings. The next section presents details about the data collection and modelling processes.

3. Methodology

The study aims to analyse the demand for EVs in India and its possible adoption timeframe. A thorough review of the literature was carried to identify the consumer perception parameters and their levels for a stated preference experiment. Subsequently, a questionnaire was designed by incorporating the stated preference choices, which included both encouraging and discouraging factors. The survey questionnaire also enquired about the user's current travel habits, their perception towards electric and conventional vehicles, as well as their socio-economic characteristics. Subsequently a choice model was developed to estimate the users' probability of choosing an electric vehicle in the near future. The choice model predicts EV adoption, and the vehicle-related attributes and their levels were developed keeping in mind the technological advances for the future years trending in the markets. The demand was estimated separately for electric 2-wheelers and electric 4-wheelers. In addition, the ordered logit model predicts the possible adoption timeframe of EVs over the next 5 years considering the motivating and deterring factors of EV attributes of users. The study concludes by developing policy recommendations for the sustainable adoption of electric vehicles.

3.1. Data collection & modelling

For the study, a total of 2,400 samples were collected from 4 different geographies within India, viz., North – New Delhi; West – Mumbai; South – Bengaluru; and East – Kolkata. The study focused on a random sample of individuals who were legally eligible to acquire a driving license, which is above 18 years of age. A total of 600 samples were collected from each location. These four cities were selected to capture a nationwide perspective. The sample size was statistically significant at the city-level for each of the 4 study areas and was calculated based on the population of each of the cities (Bhaduri, 2019; Hussain et al., 2021; Krejcie & Morgan, 1970). The mathematical expression for calculating sample size for a large population is mentioned in the equation.

$$Samplesize = \frac{X^2NP(1-P)}{d^2(N-1)+X^2P(1-P)} \quad (1)$$

where X^2 is the chi-square value at a degree of freedom 1 for the desired confidence interval; N is the size of the population; P is the proportion of the population; d is the degree of accuracy (expressed as a proportion).

The minimum sample size required to perform the statistical analysis is 384. As such, the sample size was adequate for each location. Professional surveyors collected the data in different phases during January-June 2021, to minimize the spread of the Covid-19 pandemic, and the data were collected during the periods of lockdown restrictions relaxed. The survey was conducted at different sites within each city by randomly approaching individuals in residential areas, shopping malls, parking areas, bus stops, and fuel stations to capture a heterogeneous perception. The study primarily focused on stated preference (SP) data of vehicle attributes to capture the importance of consumers' perceptions towards electric vehicle adoption. At the same time, there were attributes that captured the current travel patterns of individuals, as is shown in Fig. 1. There wasn't a significant proportion of EV owners in the sample collected, and as such, their characteristics could not to separately considered for modeling.

3.2. Survey design

The acceptance of electric vehicles as a primary mode of transport is still at a nascent stage in India. The demand for new products depends on the fulfillment of the expectations of consumers. Studies related to vehicle choice have examined choice as a function of several factors, including; vehicle features (Brownstone et al., 2000; Dagsvik et al., 2002; Jensen et al., 2013), socio-economic characteristics (Egbue & Long, 2012; Ewing & Sarigöllü, 1998), travel pattern (Axsen & Kurani, 2013; Kurani et al., 1994), attitudinal factors (Hidrue et al., 2011; Krupa et al., 2014) and policies and/or regulations designed to encourage the purchase of cleaner fuelled vehicles (Hoen & Koetse, 2014; Potoglou & Kanaroglou, 2007). In this study, the encouraging and discouraging factors, which play an important role in adopting electric vehicles, have been identified from the literature study. Furthermore, these factors helped in designing the user perception and stated preference questionnaire.

The questionnaire consists of 4 sections:

1. Stated preference questions, in which consumers had to select between EV and ICEV in different scenarios of different levels of attributes.
2. Personal information of the individual's social and demographic status like age, personal monthly income, education, vehicle ownership, house ownership, household structure, etc.
3. Users' current travel characteristics and their attitudes
4. The possible adoption timeframe of EV vehicles for the next 5 years considering the encouraging and discouraging factors and user perception towards EV characteristics

3.3. Experimental design

A discrete choice experimental design was developed to analyse respondent's sensitivity to the characteristics of electric vehicles like the purchase cost, driving range, fuel cost, mileage, full charging time, tailpipe emissions, and annual maintenance cost. For each characteristic, three levels were formulated, based on a realistic range of values that are available in the market. To keep the levels within a realistic range, a few automobile industry experts were also consulted in addition to gathering data from literature. The factors used to develop the stated preference choice experiment, along with their levels, both for e-2Ws, e-4Ws, and their conventional counterparts are shown in Table 2 below. Table 2. presents the factors and levels used in the stated preference choice experiment, along with a brief explanation of the rationale for setting the levels. Subsequently, the rationale for setting the levels is also briefly explained.

(a) **Purchase Cost:** As the purchase price is the foremost factor when buying any vehicle, it is important to model the responsiveness of individuals to this variable when they face a choice involving electric vehicles, as it is new to the market. Due to the novelty of the technology and high battery price, electric cars are likely to be more expensive than ICEVs. The battery pack accounts for 40 % –50 % of electric vehicles' cost, due to which the cost

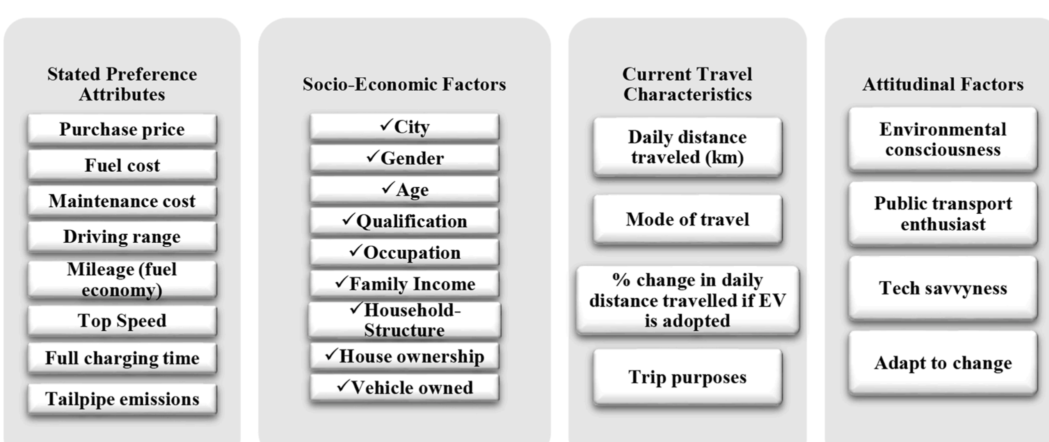

Fig. 1. Questionnaire Structure.

difference is significant between ICEV and EV. A study by Mauler et al. has detailed the trend in the market price of battery per kWh. The trend shows a drastic fall in per kWh price in batteries from 2010 to 2020 and expects a fall in the price of at least 50 % by 2030 (Mauler et al., 2021). Thus, keeping the downfall in consideration, the levels of purchase cost were decided.

(b) **Cost of Fuel per 100 km:** Electric vehicles have one major advantage over ICEVs, i.e., the lower cost of fuel. Charging the electric vehicle to drive for 100 km is much cheaper than refuelling an ICEV to drive for the same distance. So, considering the current price of electricity for EVs and fuel cost for ICEVs, the level of fuel cost per 100 km was considered.

(c) **Top Speed:** Two-wheeler consumers consider the lower speed of EVs as one of the major deterring factors (Kapoor, 2020). But with technological advancements in performance, the top speed of electric two-wheeler considerably matches the top speed of a petrol scooty/bike (i.e., motorcycle). It is also expected that the top speed of electric two-wheelers will also increase soon. Therefore, considering the current and expected future top speed, the levels were developed.

(d) **Driving Range:** Driving range of an EV is one of the most important factors, especially in India, as the charging infrastructure is not robust. Even though a few cities have developed the charging infrastructure, but their spatial coverage is minimal. So, people are concerned about the recharging of EVs. Also, as technological advancements will take place in the future, the battery's capacity will increase. Thus, taking these points into consideration, the levels of driving range were decided.

(e) **Mileage:** The mileage of a vehicle means the consumption of fuel per unit of distance. However, this attribute is only for ICEVs as it plays an important role while selecting a petrol/diesel car. The mileage varies according to the segment and model of the car. As we have seen in the past, the mileage of vehicles has significantly improved. Therefore, considering these factors, the current situation and assuming significant improvement in future, these levels were decided.

(f) **Tailpipe Emission:** The tailpipe emissions from ICEV have decreased significantly over the years as new emission standards have been introduced. Currently, India is following Bharat Stage – VI emission norms, and it is also expected that upgraded norms will be introduced in the next 5–10 years to further reduce tailpipe emissions (The Automotive Research Association of India (ARAI), 2018). This was taken into consideration while designing the levels.

(g) **Maintenance cost per year:** EVs only require infrequent checkups of electrical systems, including the battery, motor, and electronic components, which helps in reducing the maintenance cost as compared to ICEV (Slowik et al., 2018). The maintenance cost of ICEV increases as the usage and age of vehicles increase. The annual cost of maintenance, irrespective of fuel type and age of the vehicle, ranges between ₹ 8000–10000 (Harsh, 2020).

Table 2
Attributes and levels for the choice experiment for 4-wheeler & 2-wheeler.

Attributes	e-4 W Levels	ICEV 4 W Levels	e-2 W Levels	ICEV 2 W Levels
Price (in lacs for 4Ws; in thousands for 2Ws)	10 14 18 22	6 10 14 –	60 80 120 –	80 100 120 –
Cost of Fuel / Electricity, per 100 km driven (₹)	50 100 150	400 600 800	15 20 25	200 250 300
Driving Range (km)	150 300 450	400 600 800	50 100 150	150 250 350
Mileage (km/liter)	Not Applicable	15 20 25	Not Applicable	40 60 80
Full Charging Time (hrs)	2 6 10	Not Applicable	0.5 2 4.5	Not Applicable
Maximum Speed (km/h)*	–	–	40 80 120	80 100 120
Tailpipe Emission (g/km)	0	As per current scenario (140 g/km) 40 % less than the current scenario (84 g/km)	0	As per current scenario (140 g/km) 40 % less than the current scenario
Maintenance Cost per year (₹)	1000 1500	8000 10,000	150 300	1500 2000

*In literature, maximum speed is not reported to be a significant factor in the choice of e-4Ws, but it is one, while choosing an e-2 W.

Once the attributes and their levels were decided, the N-gene software generated the optimal orthogonal choice design to get the optimum number of choice sets. The total generated choice sets were 8 and 9 for 4-wheelers and 2-wheelers, respectively. A sample choice set card for 4 W and 2 W is shown in Fig. 2.

3.4. Survey results

Table 3 gives an overview of the socio-demographics of the survey respondents. Respondents belonged to diverse groups of age, professions, gender, income range, educational qualification, house ownership, household structure, housing type, etc. The sample characteristics are compared with census data, wherever available, and the same is shown in parenthesis against each attribute in the table. The gender ratio, wherein the male and female sample proportions were 64.3 % and 35.7 % respectively, was slightly skewed in favour of the male population lower than the census distribution. This discrepancy may be due to concerns of discomfort/inconvenience in participating in the survey by female participants. The age distribution shows a higher proportion in the 31–40 years age group (40.5 %), followed by 21–30 years (25.9 %). It is significant to observe that the age group 21–40 years is expectedly over-represented in the sample as surveyors could readily interact with them considering they are major users. The age distribution shows a higher proportion in the 31–40 years age group (40.5 %), followed by 21–30 years (25.9 %), which aligns with the major user demographic. Monthly household income is well-represented across different categories, with 20 k-35 k (21.6 %) and 36 k-50 k (20.8 %) being the most prevalent. In terms of education, graduates (56.4 %) dominate the sample, followed by post-graduates (25.9 %), while the proportion of individuals with doctorate-level education or above is relatively low (3.3 %). Regarding vehicle ownership, over half of the sample (54.2 %) do not own a car and 38.0 % own one car. Motorbike ownership is more prevalent, with 51.4 % owning a single motorbike, and a relatively higher percentage (26.0 %) having multiple motorbike ownership compared to car ownership (>1 car: 7.8 %). Overall, the sample represents a diverse range of demographic characteristics, providing valuable insights for further analysis. The collected data includes dummy codes for factors such as age, income, education, household structure, ownership, and housing type, which were used for modeling purposes.

The e-4 W market currently offers a wide range of options that parallel conventional vehicles in terms of features, providing comparable performance across various attributes. However, as Fig. 3 illustrates, perceptions among consumers differ: 37 % believe e-4Ws have smaller sizes, 27 % perceive them to be slower, and another 37 % consider them less safe compared to conventional four-wheelers. Furthermore, only 40

	Electric Car	Petrol/Diesel Car
Price of Vehicle	₹ 14 lakhs	₹ 10 lakhs
Fuel Cost Per 100 km	₹ 50	₹ 800
Driving Range	150 km	600 km
Full charging Time	6 hours	Not Applicable
Mileage	Not Applicable	15 kmpl
Tailpipe Emission	0	40% less than the current petrol/diesel car pollution (84g/km)
Maintenance Cost Per Year	₹ 1,500	₹ 8,000

	Electric 2-wheeler	Bike/Scooty (Petrol)
Price of 2-Wheeler	₹ 1.2 lakhs	₹ 80 thousand
Fuel Cost Per 100 km	₹ 15	₹ 300
Driving Range	50 km	350 km
Top Speed	40 kmph	120 kmph
Full Charging Time	4 hours	Not Applicable
Mileage	Not Applicable	40 kmpl
Tailpipe Emission	0	As per current petrol bike/scooty pollution (40g/km)
Maintenance Cost Per Year	₹ 150	₹ 2,000

Fig. 2. Example of choice-set for (a) four-wheelers and (b) two-wheelers.

Table 3
Sample characteristics of Socio-demographic variable.

Variables	Sub-categories	Sample distribution (census)[a] in %
Gender	Male	64.3 (51.5)
	Female	35.7 (48.5)
Age (in Years)	18 – 20 years	4.5 (9.5)
	21–30 years	25.9 (28.6)
	31–40 years	40.5 (22.9)
	41–50 years	19.9 (17.2)
	51–60 years	6.9 (11.2)
	Greater than 60	2.3 (10.7)
Monthly Household Income (INR)	Upto 20 k	21.6
	20 k – 35 k	21.6
	36 k – 50 k	20.8
	51 k – 65 k	19.1
	65 – 80 k	11.7
	Above 80 k	5.2
Education	12th / Higher Secondary	14.4
	Graduate	56.4
	Post Graduate	25.9
	Doctorate and above	3.3
Household Vehicle Ownership	Car ownership – 0	54.2
	Car ownership – 1	38.0
	Car ownership – >1	7.8
	Motorbike ownership – 0	22.6
	Motorbike ownership – 1	51.4
	Motorbike ownership – >1	26.0

*Values in parenthesis indicate the census distribution, Source: 2011 Census data India; [a]the percentages are rounded off to one decimal place.

% of respondents recognize that electric four-wheelers have superior acceleration and a mere 41 % acknowledge their lower maintenance requirements. These findings highlight the pressing need to educate consumers about EV features to enhance their perceptions positively. Similarly, the e-2 W sector has evolved to offer vehicles that closely match the performance of their petrol counterparts in speed, acceleration, and size. Despite these advancements, a significant portion of the survey participants still hold perceptions about e-2Ws, with 40 %, 42 %, and 35 % viewing them as inferior in size, speed, and safety, respectively, and 41 % undervaluing their pickup and range.

Descriptive statistics from Fig. 4 show that nearly 80 % of respondents value the environmental friendliness of EVs, considering it a key factor for both e-4Ws and e-2Ws, with 83 % regarding it as influential or very influential for e-2Ws. In contrast, the high resale value is deemed less critical, with only about 34 % for e-4Ws and 32 % for e-2Ws viewing it as influential.

Fig. 5 points to the high initial purchase cost and lengthy recharging times as significant barriers to EV adoption, with nearly two-thirds of participants identifying these factors as influential or very influential. Interestingly, power delivery, driving range, and style are perceived as less significant concerns, with a smaller segment of respondents considering them influential. Specifically, power delivery and limited range are seen as the least influential deterrents, with only about 18 % and 25 %, respectively, viewing them as not influential or very not influential.

Fig. 6 indicates a correlation plot for attributes of both 4Ws and 2Ws, where independent variables were tested for correlation, and correlated variables were excluded from further analysis. The modeling exercise tested various utility specifications, avoiding the inclusion of correlated variables in the same utility equation simultaneously. This approach ensures a robust analysis by mitigating potential bias from interrelated factors.

3.5. Model structure

This study considered two choices, i.e., electric vehicle or conventional vehicle, to develop binary logit models. It is assumed that a utility function can illustrate the preferences of an individual respondent between the given available alternatives. The respondent selects the alternative of the highest utility. The utility of choice of vehicle for respondent j and vehicle type i is defined as follows:

$$U_{\psi,j} = V_{\psi,j} + \varepsilon_{\psi,j} \tag{2}$$

where, $V_{\psi,j} = f(\beta, x_{\psi,j})$ and $\varepsilon_{\psi,j}$ i s the random component.

The vehicle type with the highest utility is selected. Hence, the probability of vehicle type ψ selected by the decision-maker (respondent) j from a choice set C_j is (Ben-akiva & Bierlaire, 1999);

$$P(\psi|C_j) = P[U_{\psi j} \geq U_{mj} \forall m \in C_j] = P[U_{ij} = \underbrace{max}_{m \in C_j} U_{mj}] \tag{3}$$

In case of binary logit, log likelihood function will be

$$L = \sum_{n=1}^{N} y_{En} \log\left(\frac{e^{\beta x_{En}}}{e^{\beta x_{En}} + e^{\beta x_{Cn}}}\right) + y_{Cn} \log\left(\frac{e^{\beta x_{Cn}}}{e^{\beta x_{En}} + e^{\beta x_{Cn}}}\right) \tag{4}$$

The probability of selecting preferred vehicle based on binary logit model can be described mathematically as

$$P_n(E) = \frac{1}{1 + e^{-\beta' x_n}} \tag{5}$$

$$P_n(C) = \frac{e^{-\beta' x_n}}{1 + e^{-\beta' x_n}} \tag{6}$$

where, $P_n(E)$, $P_n(C)$ and β refers to the probability of choosing an EV, and ICEV, and coefficients of variables, respectively.

3.6. Ordered logit model (OLM)

The probable adoption timeframe of electric vehicles is estimated for the upcoming 5-years by considering their current (revealed) perceptions of the encouraging and discouraging factors of EVs and the socio-economic factors. This probable timeframe of adoption of EV is ordinal in nature. For a variable having an ordinal answer, the ordered logistic model is a frequent regression model. When computing dependent

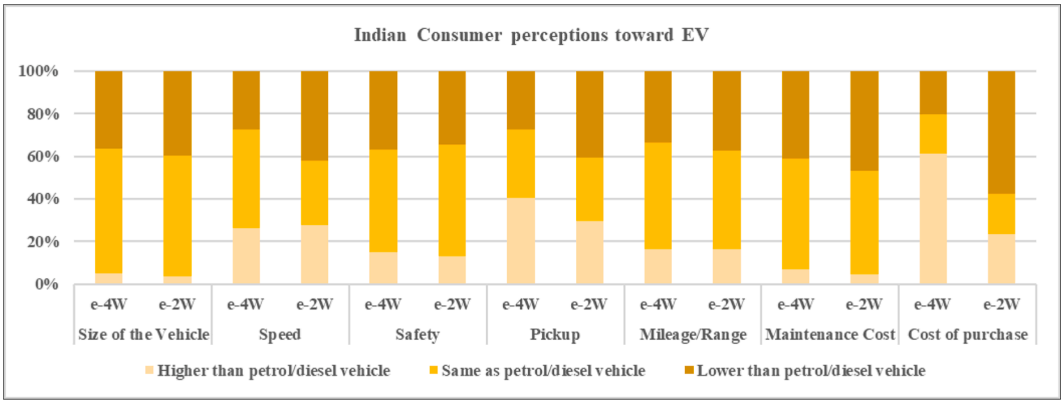

Fig. 3. Indian consumer perception on vehicle attributes towards e-4 W and e-2 W.

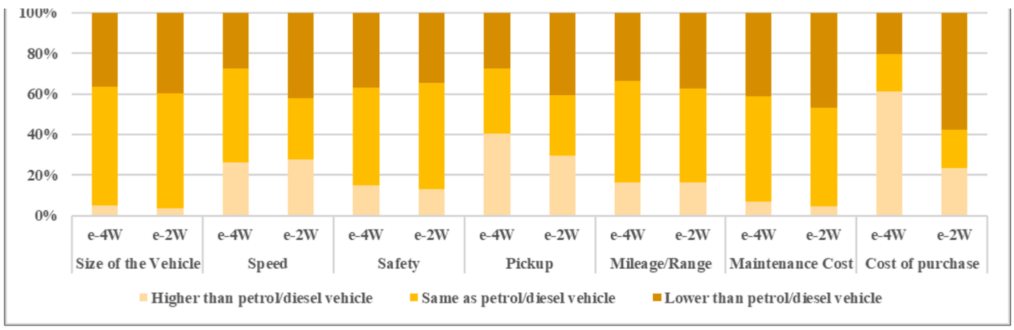

Figure. 3. Indian consumer perception on vehicle attributes towards e-4W and e-2W

Descriptive statistics from Figure 4 show that nearly 80% of respondents value the environmental friendliness of EVs, considering it a key factor for both e-4Ws and e-2Ws, with 83% regarding it as influential or very influential for e-2Ws. In contrast, the high resale value is deemed less critical, with only about 34% for e-4Ws and 32% for e-2Ws viewing it as influential.

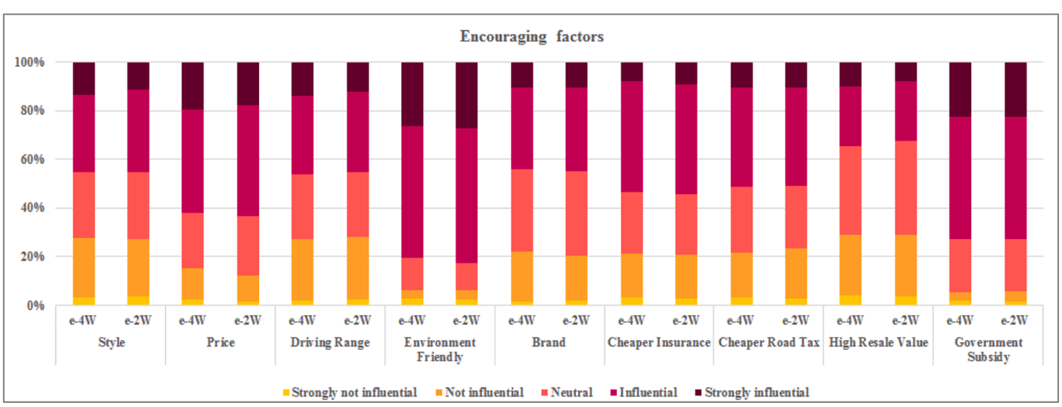

Fig. 4. Perception of respondents towards the Encouraging factors of e-4 W and e-2 W.

variables on an ordinal scale, the ordered logit model is utilised. The ordered logistic model is based on the cumulative probabilities of the response variable.

Let Y_i be an ordinal response variable with M categories for the i[th] subject, alongside with a vector of covariates a_i. The regression model provides a relationship between the variables and a set of category probabilities, which is specified as:

$$\rho_{ci} = Q_r(\text{Ò®}i = y_m|a_i), m = 1, 2\cdots M. \tag{7}$$

Ordinal response regression models are commonly described in terms of easy one-to-one transformations, such as cumulative probabilities, as defined below:

$$c_{ci} = Q_r(\text{Ò®}i \le y_m|a_i), m = 1, 2, \cdots M. \tag{8}$$

Note that the last cumulative probability is necessarily equal to 1, so the model specifies only C − 1 cumulative probability.

An ordered logit model for an ordinal response Y_i with M categories is defined by a set of $M - 1$ equations where the cumulative probabilities $c_{ci} = Q_r(\text{Ò®}i \le y_m|a_i)$ are related to a linear predictor $\alpha'_{ai} = \alpha_0 + \alpha_{1a1i} + \alpha_{2a2i} + \alpha_{3a3i} + \cdots$ through the logit function:

$$\text{logit}(c_{ci}) = \log\left(\frac{c_{ci}}{(1 - c_{ci})}\right) = \beta c - \alpha'_{ai}, \; c = 1, 2, \cdots, M-1 \tag{9}$$

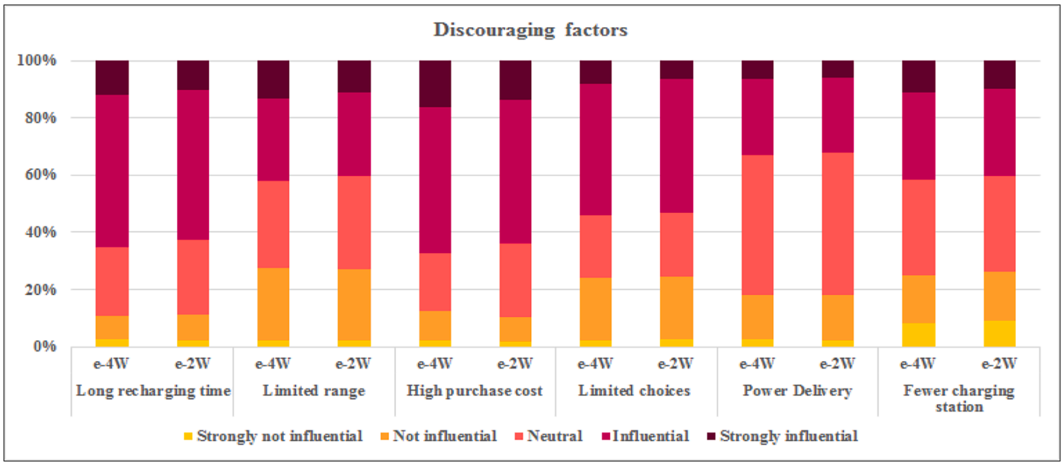

Fig. 5. Perception of respondents towards the discouraging factors of e-4 W and e-2 W.

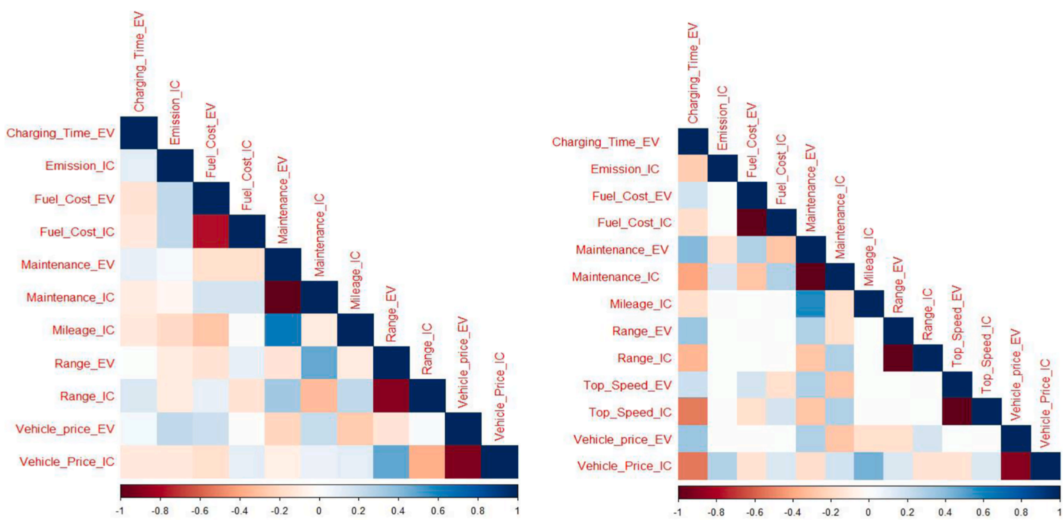

Fig. 6. Correlation matrix for 4 W and 2 W attributes.

The parameters βc in the following equation (9) are all threshold parameters, and they are always in ascending order ($\beta_1 < \beta_2 < \ldots\ldots < \beta_{M-1}$). It is nearly impossible for a modeler to estimate the overall intercept α_0 and all the C-1 thresholds at the same time. This is due to the fact that adding an arbitrary constant to the overall intercept α_0 can be offset by adding the same constant to each threshold βc. The overall constant is frequently left out of the linear predictor (i.e.,$\alpha_0 = 0$), or the first threshold is set to zero (i.e.,$\alpha_1 = 0$)

4. Estimating EV demand – Modelling results

4.1. Binary logit modelling results

For modeling, the dataset was split into two –training dataset and testing dataset. The models were estimated using the training dataset and were further validated using the test dataset by developing a confusion matrix (Brownlee, 2016). Two binary logit models were estimated to assess the demand for e-2 W and e-4 W in India. In the model, ICEV was kept as a base. The model was developed using the Apollo library on the R platform and results are indicated in Table 4. Subsequently, three scenarios of probable shift to electric vehicles are developed. Lastly, the logistic growth function is used to estimate the probable shift to electric vehicles for each year between 2022–2030.

Among the vehicle-related attributes, vehicle purchase price of EVs has a significant negative impact on their demand. In case of the e-2 W, the vehicle price is likely to have a larger impact, as compared to the case of an e-4 W. Such findings are in line with previous studies, where the purchase price variable was mostly negative and highly significant (Liao et al., 2017); (Choi et al., 2018; Hackbarth & Madlener, 2013). The other vehicle-related cost attributes, i.e., fuel cost and maintenance cost, also have an impact on EV adoption, however the magnitude of their impacts is likely to be lower than that of the vehicle price in case of 4-wheelers. Interestingly, results indicate that if fuel cost and maintenance cost of conventional 4-wheelers increase, the likelihood of choosing e-4 W will increase, which is reflected in earlier studies as well (Glerum et al., 2014; Huijts et al., 2012; Jensen et al., 2013). Similar results were obtained in case of 2-wheelers, however maintenance of conventional 2-wheelers would have to increase 7 times in order to induce a shift to e-2 W. Such choice behaviour towards e-2 W has also been documented in earlier studies (Guerra, 2019; Jones et al., 2013; Weinert et al., 2007). Finally, it is worth noting that users would choose e-4 W if emissions from conventional 4-wheelers are high, however, this factor is insignificant in case of choice of e-2 W. The top speed and range for e-2 W have a positive significant impact, as has been shown in previous studies from different regions (Eccarius & Lu, 2020; Guerra, 2019; Jones et al., 2013; Scorrano, 2021). Similar results for range were observed in case of e-4 W adoption as well, which are also reflected in previous studies (Haustein & Jensen, 2018; Kim, Rasouli, & Practice, 2014). Besides, the short driving range is crucial in e-4 W adoption which is in line with existing literature (Liao et al., 2017). In addition, the negative estimates of the charging time attribute indicate the necessity of decreasing the charging time to increase the demand of both e-2 W and e-4 W.

As the survey was conducted in four million-plus cities in India, the models could capture the regional variation in demand of e-2 W and e-4 W. The modeling results indicate that Delhi is likely to witness a higher demand for EVs as compared to Kolkata, Bengaluru, or Mumbai. In case of e-2 W, Kolkata is likely to have second highest demand, followed by

Table 4
EV demand estimation parameter.

Parameters	Estimate	t-stat	Odd's Ratio	Sig.	Estimate	t-stat	Odd's Ratio	Sig.
	4-wheelers				2-wheelers			
Alternative Specific Constants (ASCs)								
Electric Vehicle	1.62	4.81	5.10	***	−5.82	−10.06	0.00	***
Vehicle attributes								
Vehicle price for EV	−1.09	−24.89	0.35	***	−0.65	−1.66	0.52	*
Top Speed for EV	–	–	–	–	0.44	8.02	1.56	***
Range for EV	0.36	7.27	1.44	***	0.45	8.96	1.57	***
Charging time for EV	−0.42	−7.59	0.65	***	−0.47	−6.34	0.62	***
Fuel cost for ICEV	0.20	3.43	1.22	***	0.19	3.77	1.21	***
Mileage for ICEV	–	–	–	–	−1.42	−18.55	0.24	***
Maintenance cost for ICEV	0.44	4.37	1.56	***	1.99	14.01	7.37	***
Emission for ICEV	0.41	4.87	1.50	***	–	–	–	–
Location (Delhi)								
Kolkata	−1.92	−12.79	0.14	***	−0.36	−2.38	0.69	***
Bengaluru	−1.81	−12.86	0.16	***	−0.48	−2.66	0.61	***
Mumbai	−1.03	−8.46	0.35	***	−0.74	−4.21	0.47	***
Socio-demographic variables								
Gender variable (Female)								
Male	0.17	2.08	1.19	**	–	–	–	–
Age variable								
21–30	–	–	–	–	0.66	3.50	1.94	***
31–40	–	–	–	–	0.49	1.67	1.63	*
41–50	–	–	–	–	0.48	2.50	1.62	***
50–60	–	–	–	–	0.42	1.97	1.52	**
Educational Qualification Variable (up to 12th grade)								
Graduates	0.23	2.61	1.26	***	0.46	3.18	1.58	***
Post-Graduates	–	–	–	–	0.15	1.77	1.16	*
Doctorate and above	0.45	3.20	1.58	***	0.68	2.19	1.98	**
Income variable (up to 20 K)								
21 K – 35 K	–	–	–	–	0.03	1.65	1.03	*
36 K – 50 K	0.37	1.68	1.45	*	–	–	–	–
50 K – 65 K	0.38	3.05	1.46	***	0.19	1.69	1.21	*
66 K – 80 K	0.40	3.45	1.49	***	0.30	2.07	1.36	**
80 K – 1 lac	0.58	3.89	1.80	***	–	–	–	–
Greater than 1 lac	0.72	3.37	2.06	***	0.50	1.73	1.65	*
Profession variable (Unemployed)								
Employed (Public Sector)	0.12	2.46	1.13	***	–	–	–	–
Self-employed	–	–	–	–	0.25	2.16	1.28	**
Retired	0.57	2.03	1.77	**	0.35	1.89	1.42	*
Vehicle Ownership								
2-wheeler	–	–	–	–	0.05	1.92	1.05	*
4-wheeler	0.22	2.30	1.25	**	0.03	1.03	1.44	*
Household ownership (Owner)								
Rented	−0.08	−1.83	0.91	*	−0.17	−1.79	0.84	*
Travel Characteristics								
Travel Distance	0.046	1.9740	1.04	**	–	–	–	–
Type of housing (Individual house without dedicated parking)								
Apartment complex with dedicated parking	0.23	2.20	1.26	**	0.69	5.64	2.00	***
Individual house with dedicated parking	0.06	1.69	1.07	*	0.08	1.71	1.08	*
Apartment complex without dedicated parking	–	–	–	–	−0.58	−3.76	0.55	***
Attitudes								
I am an environmentally conscious person	0.29	1.83	1.33	*	0.17	1.64	1.19	*
I am a technology enthusiast	–	–	–	–	0.36	3.35	1.44	***
I believe in adapting to changes	–	–	–	–	0.23	2.48	1.26	***
I like to travel by public transport	−0.39	−4.66	0.67	***	0.14	1.70	1.15	*
Use of EV in future								
Everyday commute to work/school	0.03	1.99	1.04	**	0.12	2.12	1.13	**
Occasional shopping	–	–	–	–	0.11	2.09	1.11	**
Occasional out-of-city trips for family vacation	−0.03	−1.66	0.96	*	−0.29	−6.03	0.74	***
Utilization of EV								
Addition in VKT (+10 %)	0.62	4.15	1.87	***	–	–	–	–
Primary Vehicle	0.23	2.44	1.26	***	–	–	–	–
Goodness-of-fit								
Log-likelihood (Start)	−3314.63				−3118.46			
Log-likelihood (Final)	−2231.31				−2168.28			
Adjusted Rho-square	0.31				0.29			
*** 99 % significance level	** 95 % significance level				* 90 % significance level			

Bengaluru and Mumbai. In case of e-4 W, Mumbai is likely to have the second highest demand, followed by Bengaluru and Kolkata. Among socio-demographic variables, modeling results show that gender plays a significant role in choice of e-4 W, whereas age is significant in case of e-2 W choice. Men are relatively more interested in e-4 W as compared to their female counterparts, whereas the younger generation (21–30 years) is relatively more interested in e-2 W when compared to the older generation (above 50 years). Literature is inconsistent when it comes to gender, where some studies also found men to be more likely users of EVs (Kim et al., 2014; Rasouli & Timmermans, 2016), whereas others (Jensen et al., 2013; Qian & Soopramanien, 2011) have reported women to be more likely users of EVs. It is however evident from the literature that the younger generation (Burghard & Dütschke, 2019; Weinert et al., 2007) are more likely users of EVs.

When it comes to income, results show that as income increases the likelihood of choosing EVs increase. This was observed in cases of both e-2 W and e-4 W. Such significant positive effect of income has been demonstrated in literature as well (Guerra, 2019). Results also indicate that users with higher level of education (i.e., graduate degrees and doctorates) are more likely to choose EV. The results indicate that current vehicle ownership is likely to have a positive effect for both e-2 W and e-4 W's likely adoption. According to the results, respondents who currently own a 2 W are more likely to purchase an e-2 W. On the other hand, both 2 W and 4 W ownership was found to have a positive impact on the respondent's likelihood of adopting an e-4 W. In simpler terms, people who have already used a conventional vehicle technology are more likely to choose EV as compared to the person who has never owned a vehicle. This could be due to the fact that the first-time vehicle might be too conservative to venturing into EV since the present EV market penetration is considerably low. Another factor that played a significant role is house ownership. House owners who live in individual houses with dedicated parking are more likely to choose EVs, as opposed to users who live in rented accommodation in individual houses without dedicated parking. The people living in dwelling units (both apartment and individual house) with dedicated parking are likely to choose e-4 W. Similar effect was deduced in other studies (Hackbarth & Madlener, 2013; Hidrue et al., 2011; Hoen & Koetse, 2014) as well. Furthermore, it is interesting to note that EVs are more likely to be adopted by individuals who are retired, as opposed to the ones who are employed.

The model also incorporated attitudinal factors to assess their impact on EV choice. Environmentally conscious individuals are more likely to adopt e-4 W, whereas technology enthusiasts are more willing to buy an e-2 W. Literature presents several instances where environmental consciousness is an attitude among EV users (Achtnicht et al., 2012; Hackbarth & Madlener, 2016; Hidrue et al., 2011; Jensen et al., 2013; Kim et al., 2014). A study (Wolf & Seebauer, 2014) also indicates that pro-environmental and tech-savvy are more inclined towards choosing e-2 W. The modeling results interestingly indicate that users who like traveling on public transport are more likely to choose e-2 W, but are not likely to choose e-4 W. Additionally, modeling results also indicate that people are likely to consider e-4 W as their primary vehicle, and also are likely to drive it 10 % more than an ICEV, which may lead to a possible increase in VKT. The model was validated using the confusion matrix and the estimated accuracy of the 4-wheeler and 2-wheeler models is 79 % and 76 % respectively. The models with this range of accuracy were found to be reliable as per previous studies (Burghard & Dütschke, 2019).

4.2. Ordered logit modelling results – Probable EV adoption timeframe

4.2.1. Electric four-wheeler adoption timeframe model

The modeling results from Table 5 show the regional difference within the Indian cities towards the adoption timeframe of electric vehicles. The results indicate that users in Delhi, the capital of India, are likely to be early adopters of e-4 W when compared to Mumbai, Bangalore, and Kolkata. This is likely due to Delhi's popular EV policy which encourages (with subsidies and tax incentives) the ICEV car users to shift to electric vehicles (GNCTD, 2020). The model showcased that the younger generation has the highest willingness to adopt e-4 W whereas with the increase in age, people show more resistance to the adoption of EVs. People in the age group of 21–30 years show highest adoption rate of e-4 W as they are likely to be more tech-savvy and are accustomed to new and upcoming technologies, which is aligned with the previous findings (Burghard & Dütschke, 2019; Kim et al., 2014; Rasouli & Timmermans, 2016). It is also verified from the descriptive analysis of the survey data which shows that younger generations (up to 30 years) are willing to shift to e-4 W in upcoming 5 years. Also, higher income group people are more willing to adopt electric four wheelers in the later years. People belonging to households earning 35 k and above per month are relatively more willing to adopt e-4 W in later years. Such significant influence of income is due to the resource available to them to buy the new vehicles which are evident in the literature (Guerra, 2019). On the other hand, respondents who currently own 4 W are less willing to buy new vehicle and hence show less interest in adopting e-4Ws early.

People were asked about their opinion towards encouraging and discouraging factors associated with EVs, such as driving rage, government subsidy and cheaper insurance. Results show that the advancement of these parameters with respect to conventional vehicles will increase the likelihood of early adoption of e-4 W. Whereas longer charging time and higher initial cost of EV showed an opposite relationship. This can be attributed to the lack of choices in the present e-4 W market. Buyers are willing to wait for major brands to launch better options. However, respondents who opined that environment-friendliness would be an important factor for EV adoption also indicated late adoption of such vehicles. This might be attributed to the fact EVs have been recently criticized for higher emissions at power generation sources and need further development to be an ideal clean transport alternative (Beak et al., 2020). In the survey people were also asked about their perception towards EV with respect to ICEV. Intuitively, the cost attribute is observed to influence late adoption of the EV four-wheeler. On the other hand, all other vehicle attributes (mileage range, speed, safety, size of vehicle, and pickup speed) which accentuate ride-experience positively influences quicker adoption of EV.

4.2.2. Electric two-wheeler adoption timeframe model

The residents of Delhi are also more likely to be early adopters of e-2Ws than other cities. The model showcased that younger users (21–30 years) have the highest willingness to adopt e-2 W while with an increase in age, people show more resistance to adopting them. People in the age group of 50 years and above show the highest resistance towards adopting e-2 W probably because they are not tech-savvy and are less accustomed to dealing with new and upcoming technologies, which is consistent with the previous findings (Parsons et al., 2014). Expectedly, respondents from higher-income households are more willing to be early adopters of electric two-wheelers. In fact, people coming from households earning 65 k and above per month have shown the highest willingness to adopt e-2 W in upcoming years. Interestingly, respondents with a greater number of two-wheelers in their household currently are relatively less inclined towards buying a new e-2 W, as they are already in possession of the conventional one. Besides, parking facility also proves to be a vital parameter in the adoption of vehicles and it is also reflected from the model that the availability of parking space encourages users towards early adoption of e-2 W.

People were also asked about their perception towards various encouraging and discouraging factors associated with e-2 W like style, brand, government subsidies, long recharge etc. The findings showed that the advancement of these parameters with respect to conventional vehicles will increase the adoption of e-2 W in the upcoming years. Whereas brand, long recharge, resale value and limited range of EV showed major deterring factors for the adoption of e-2 W. Currently, EV do not prove to be an alternative to ICEV for long-distance travel due to

Table 5
Estimation results of e-4 W and e-2 W adoption timeframe model.

Parameters – EV	Estimate	t-stat	Odd's Ratio	Sig.	Estimate	t-stat	Odd's Ratio	Sig.
	4-wheelers				2-wheelers			
Threshold								
[Future EV Adoption Plan = 1|2]	−5.61	−9.63	0.00	***	−2.96	−5.92	0.05	***
[Future EV Adoption Plan = 2|3]	−4.22	−6.62	0.01	***	−0.50	−1.35	0.60	–
[Future EV Adoption Plan = 3|4]	−2.03	−3.12	0.13	***	1.01	2.10	2.75	**
[Future EV Adoption Plan = 4|5]	−0.89	−1.89	0.41	**	2.20	5.10	9.02	***
Location (Delhi)								
Kolkata	0.31	2.10	1.36	**	0.52	2.85	1.68	***
Bengaluru	0.22	1.85	1.25	*	0.02	1.99	1.02	**
Mumbai	0.10	1.98	1.10	**	0.08	1.90	1.08	*
Socio-demographic variables								
Age variable								
Group of 21–30 years	−0.22	−3.68	0.80	***	–	–	–	–
Group of 50–60 years	0.85	3.12	2.33	***	1.86	4.68	6.42	***
Income variable								
21 K – 35 K	–	–	–	–	−0.12	−1.85	0.89	*
36 K – 50 K	−0.52	−4.96	0.59	***	−0.39	−2.12	0.68	**
66 K – 80 K	−0.99	−8.12	2.69	***	−0.86	−5.21	0.42	***
Vehicle Ownership								
2-wheeler	0.12	1.99	1.12	**	−0.08	−1.96	0.92	**
4-wheeler	−0.19	−2.05	0.83	**	−0.48	−3.15	0.62	***
Type of housing								
Household with 2 W parking	–	–	–	–	−0.05	−2.15	0.95	**
Household with 4 W parking	−0.12	−1.88	0.89	*	−0.12	−3.21	0.88	***
Encouraging factors of EV*								
Style	–	–	–	–	−0.18	−1.92	0.84	*
Brand	–	–	–	–	0.15	2.16	1.16	**
Environment friendly	0.11	2.15	1.11	**	0.21	3.01	1.23	***
Cheap insurance	−0.18	−2.22	0.84	**	–	–	–	–
Government subsidy	−0.22	−3.12	0.80	***	−0.15	−1.91	0.86	*
Driving range	−0.29	−3.52	0.75	***	–	–	–	–
Discouraging factors of EV*								
Long recharge	0.10	2.01	1.10	**	0.25	4.52	1.28	***
Limited range	–	–	–	–	0.13	2.01	1.13	**
Higher initial cost	–	–	–	–	0.22	3.19	1.25	***
User perception of EV characteristics**								
Cost of Purchase	–	–	–	–	0.12	1.89	1.12	*
Maintenance Cost	0.19	2.12	1.20	**	0.28	3.56	1.32	***
Mileage Range	−0.17	−2.09	0.84	**	−0.9	−6.85	0.40	***
Speed	−0.08	−1.97	0.92	**	−0.17	−2.01	0.84	**
Safety	−0.13	−2.00	0.87	**	0.03	1.83	1.03	*
Size of Vehicle	−0.41	−3.14	0.66	***	–	–	–	–
Pickup	−0.15	−1.90	0.86	*	–	–	–	–
Goodness-of-fit								
Log-likelihood (Start)	−2251.62				−2789.15			
Log-likelihood (Final)	−1102.02				−1712.95			
Adjusted Rho-square	0.38				0.34			
*** 99 % significance level	** 95 % significance level				* 90 % significance level			

* All of these indicators were collected in a likert scale of 1–5 based on how respondents put importance on each of the following attributes.
The scale varies from Strongly "Strongly Not Influential – Not Influential – Neutral – Influential – Strongly Influential" in ascending order.
** All of these indicators were collected in a likert scale of 1–3 based on how respondents put importance/benefits on each of the following attributes of EV as compared to ICEV. The scale varies from Strongly "Lower than petrol/diesel vehicle – Same as petrol/diesel vehicle – Higher than petrol/diesel vehicle" in ascending order.

its limited range. Hence, people show concern towards this parameter. This can be due to the lack of variety of options of renowned brands in the present market for the purchase of e-2 W. Buyers are willing to wait for major brands to launch better options. Also, presently there is no proper framework for EV insurance and subsidies so; buyers might like to wait for new and improved policies. At the same time, the majority of the respondents have very limited ideas about the re-sale value of EVs as those are yet to be launched in the market on a mass scale. Hence, their concern related to re-sale value gets reflected in their inhibition of purchasing the EV. Similar to the e-4 W questionnaire, the respondents were also asked about their perception towards e-2 W with respect to ICEV. The estimates suggest that buyers are likely to wait to adopt an e-2 W as they perceive the purchase price and maintenance cost to be higher than ICEV currently. At the same time, better mileage range and speed would also ensure faster adoption of e-2 W since such attributes will make the EV more efficient as compared to ICEV.

4.3. Willingness to pay

The willingness to pay (WTP) represents the maximum price that a consumer is willing to pay for receiving a certain quantity of service or good and thus represents a subjective value the consumer assigns to a certain quantity. The WTP can be derived from the developed choice model's coefficient as follows:

$$\mathrm{WTP} = \frac{\text{Marginal utility (Generic attribute)}}{\text{Marginal Utility (Monetary Attribute)}} = \frac{\beta_{\text{attribute}}}{\beta_{\text{Vehicle cost}}} \tag{10}$$

The results of the model indicate that the consumers are willing to pay ₹3074 (US$41) to add 1 km in driving range for a new e-4 W. This is slightly lesser than the other countries like Netherlands (US$63) (Hoen & Koetse, 2014), US$33–71 (USA) (Parsons et al., 2014), US$20–235 (Denmark) (Jensen et al., 2013), US$25–92 (California, USA) (Bansal et al., 2021; Hess et al., 2012), China (US$75) (Huang & Qian, 2018) and

US$22–422 with the mean value of US$116 (Hackbarth & Madlener, 2016). Also, Indian consumers are willing to pay an additional ₹570 (US $7.7) for a charging facility in order to reduce charging time by 1 min. In contrast, Canadians and Germans are willing to pay around US$33 (Ferguson et al., 2018) and US$25 (Hackbarth & Madlener, 2016), respectively. For e-2 W, Indian consumers are willing to pay ₹679 (US $9) to increase the top speed by 1 km/hr. A study in Vietnam indicates the WTP of US$4.39 for the increase in top speed by every 1 km/hr (Jones et al., 2013). Another study (Guerra, 2019) suggests that Indonesian people are willing to pay 7–13 % additional amount for e-2 W with a 10 km longer range, 10 km/h faster speed, or an hour shorter charging time. Lastly, the study indicates that consumers are willing to pay ₹695 (US$8) for the addition of every km in the vehicle range. In another study based in India has estimated the willingness to pay in the range of US$3.7-US$6.4 for increments in 1 km range (Bansal et al., 2021). Also, according to this study, Indian people are willing to pay ₹726 for avoiding every 1hr in charging time.

4.4. *Probable scenarios of electric vehicle adoption*

The attributes and their levels in the stated preference choice sets were prepared after studying the expected changes in electric vehicle attributes within the next ten years. The choice model estimates that the Indian consumers' adoption of electric e-4 W and e-2 W is likely to be 35 % and 68 %, respectively (Figs. 6 and 7). Therefore keeping this probable shift as a mean or reference scenario, two other scenarios – 1) Low Shift Scenario, and 2) High Shift Scenario, were developed (as indicated in Figs. 7 and 8).

Studies on electric vehicle projections (Graham & Havas, 2021; Kah, 2019; Kampman et al., 2011; Shukla et al., 2014) consider optimistic and pessimistic scenarios with a 15–25 % variation from the mean projections (KPMG, 2020; Shetty et al., 2020). In this study, the variation of projections considered from the reference scenario is 20 %, resulting in the High Shift scenario projection of 42 % and the Low Shift scenario of 28 % e-4 W adoption. These results complement another similar study in the Indian context (Shukla et al., 2014). The study results indicate that the tendency to choose electric vehicles depends upon various socio-demographics, vehicle-related attributes, charging infrastructure, and consumer attitudes. In Low Shift Scenario, the study assumes pessimistic conditions where there is a slow rollout of charging infrastructure, higher electric vehicle prices, lesser awareness among people and lesser subsidies by the government. In High Shift scenario, the study assumes the optimistic conditions where the electric vehicle price is lower, increased gasoline price, aggressive targets of various state governments with different push and pull measures and availability of multiple segments and options of EVs in the market. These attributes may influence more people to adopt EVs.

Low shift scenario

- **Electric 4-wheeler (e-4 W):** The projections of the low shift scenario indicate that, by the year 2025, 2 % of 4-wheelers sold will be electric. The e-4 W sales in India is likely to take a steep rise and might attain 10 % in 2028, 18 % in 2029, and 28 % by the year 2030.
- **Electric 2-wheeler (e-2 W):** The e-2 W projections for the low shift scenario show that sales may reach 5 % in 2024. After that, it may reach up to 13 % in 2026, 28 % in 2028, and 51 % by 2030.

Mean shift Scenario

- **Electric 4-wheeler (e-4 W):** The mean shift scenario indicates a probable shift of 2 % by 2025. In 2027, a shift of 15.62 % to EV from ICEV. Afterward, a steep growth of 33.42 % shift to electric vehicles by 2030 may be achieved. The forecast indicates that the year-on-year growth rate for e-4 W is likely to be around 60 % in the initial years. As the growth continues, the influx of electric vehicles will be more. The absolute growth percentage change indicates that a steep growth slope will be in the year 2028–2030.
- **Electric 2-wheeler(e-2 W):** The e-2 W projections for the mean shift scenario indicate that sales may reach 13 % in 2025. After that, it may reach up to 20 % in 2026, 42 % in 2028, and 68 % by 2030. The result indicates that absolute percentage growth in the years 2026, 2027, and 2028, is likely to be 12 %, 14 %, and 15 % respectively. Whereas year-on-year percentage growth is higher in the initial stage as the no. vehicles are less, further growth percentage it will decrease, but the no. of vehicles will increase.

High shift Scenario

- **Electric 4-wheeler (e-4 W):** The high shift scenario indicates that the adoption of electric vehicles is likely to be 3 % by 2025, 9 % by 2027, and this rapid shift may result in a shift of 42 % by 2030.
- **Electric 2-wheeler (e-2 W):** The e-2 W projections for the high shift scenario indicate that the sales may reach 8 % in 2023 and 22 % in 2025. After that, it may reach up to 34 % in 2026, 63 % in 2028, and 85 % by 2030.

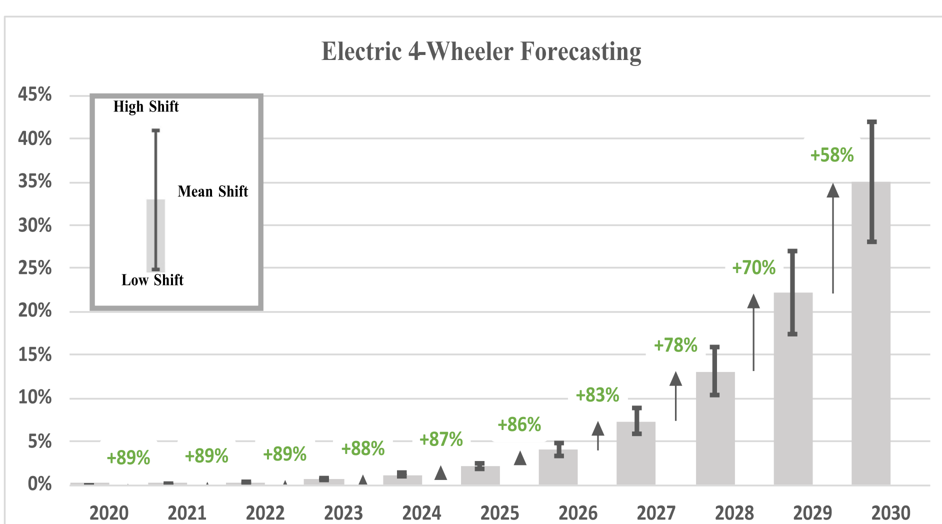

Fig. 7. Electric 4-wheeler demand scenarios.

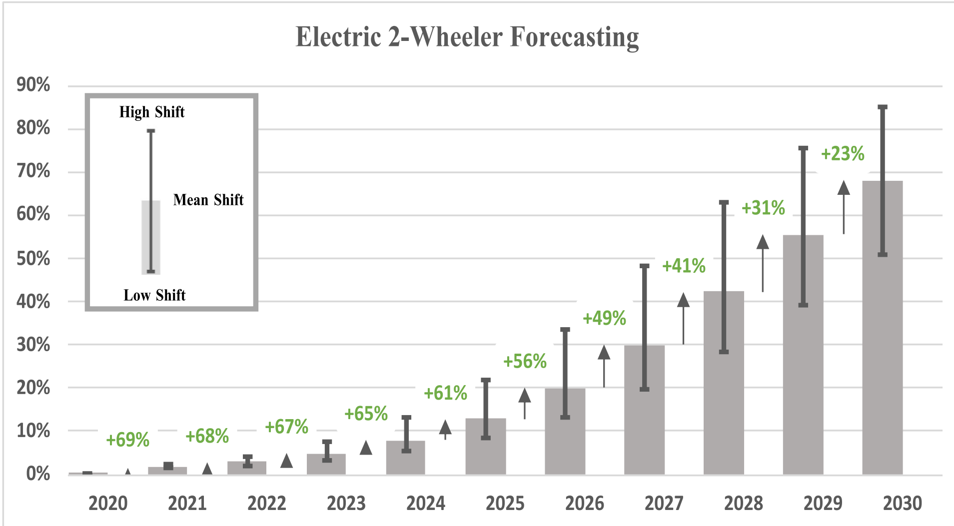

Fig. 8. Electric 2-wheelers demand scenario.

As per the projection, India will be in the investment period between 2024–2026 for e-2Ws. Beyond this period, India will enter in to the accelerated growth period, which may continue till the year 2029, after which the growth rate may flatten. For e-4Ws, the investment period may continue until 2028, while the accelerated growth period may continue beyond 2030.

5. Policy discussion

The National Electric Mobility Mission Plan (NEMMP) 2020 initiated by the Government of India marked a significant step towards fostering electric vehicle (EV) adoption but fell short of its ambitious targets. Subsequent initiatives, including FAME I and II, along with state-specific policies, aimed to bridge this gap through financial incentives, GST rate reductions, and enhanced charging infrastructure. Despite these efforts, the adoption of EVs in India faces persistent challenges, highlighting the need for a more nuanced and dynamic policy approach.

Key Recommendations:

Enhanced Incentive Structures: The current study underscores the importance of vehicle attributes beyond cost, such as range and charging time, in influencing consumer demand. Policies should thus prioritize subsidies and incentives that make long-range and fast-charging EVs more financially accessible. Additionally, incentives for vehicles with higher top speeds could stimulate the demand for e-2Ws, catering to the consumer's preference for performance alongside sustainability.

Economic Strategies to Reduce EV Costs: Since the price of electric vehicles remains a major hurdle, targeted economic strategies are crucial. Reducing or eliminating various taxes and duties can make EVs more affordable. Initially, these efforts should be vigorous to establish a strong EV market. The study also shows that consumers are ready to pay extra for specific EV features, suggesting that subsidies could gradually decrease as the EV market matures, especially for middle to high-income groups.

Geographical and Socioeconomic Diversification of Policies: Given the heterogeneity across India, a one-size-fits-all approach is insufficient. The study identifies Delhi and Mumbai as potential early adopters due to socio-economic factors and existing infrastructure. Policies should be tailored to the specific needs and capacities of different regions, emphasizing the development of charging infrastructure in urban areas with high vehicle ownership and poorer air quality. In contrast, for cities like Kolkata with lower GDP per capita, focus should be on more affordable e-2Ws and patience in adoption timeframes.

Infrastructure Development: Ownership of a house and, by extension, the availability of private parking emerges as a significant determinant of EV adoption. National and local policies must encourage the development of EV-ready residential and commercial buildings. Amendments to building bylaws to include EV charging provisions are a step in the right direction and should be implemented across all urban areas. Moreover, public charging infrastructure must also be expanded, with incentives for the installation of charging stations in existing buildings.

Incentives for Replacing Older Vehicles: The study highlights that older conventional vehicles, due to their higher maintenance costs and emissions, are prime candidates for replacement with EVs. The vehicle scrapping policy should be leveraged to accelerate this transition, offering additional incentives for ICEV owners to switch to EVs.

Consumer Awareness and Education: Despite the emphasis on financial incentives, consumer awareness regarding the benefits of EVs, including lower operational costs, reduced emissions, and maintenance advantages, is crucial. Educational campaigns should address common misconceptions and highlight the long-term benefits of EV ownership, especially in regions identified as early adopters.

In summary, while India has made commendable efforts to promote EV adoption, the insights from this study suggest a need for more targeted, flexible, and consumer-oriented policy interventions. By addressing the specific attributes that influence consumer choice, along with the socioeconomic and geographical diversities of the Indian market, policymakers can more effectively accelerate the transition to a sustainable electric mobility future.

6. Conclusions and future research

The present study empirically assesses the adoption potential of electric vehicles (both four-wheelers and two-wheelers) based on consumer perception while research into this topic is still in its infancy. Importantly, to the best of authors' knowledge, none of the previous studies attempted to understand the spatio-temporal variation of EV adoption while we adopt a two-pronged approach, i.e., willingness to own an EV and its adoption timeframe to account for the said effect. Although, there have been a few recent studies which highlighted the role of individual differences, those have either focused on a specific EV group or been limited to a particular geographic boundary. Building on the previous ones, the current study attempts to suggest robust and deeper policy insights based on its ability to evaluate variation across multiple dimensions. As per the study results, India is likely to witness a 35 % and 68 % demand for e-4Ws and e-2Ws, respectively. The results are in-line with the government's targets, however, there is significant geographical variation in the demand, which is further driven by specific vehicle attributes, such as range of EVs and fuel prices for ICEVs; socio-economic factors such as age, income, etc.; infrastructural factors, including type of residential accommodation; and finally on the attitudes of individuals, which indicate consumers with greater environmental consciousness and an attitude to adapt to changes are more likely to choose an EV. These results point towards the need for a more targeted and phased approach to satisfy vehicle electrification targets, rather than a one-size-fits-all national strategy.

Indian consumers continue to have misconceptions about EV attributes such as e- 2Ws are slower, costlier, and have lower range when compared to their conventional counterparts, and e-4Ws have lesser size, speed, and safety than conventional 4-wheelers. Nowadays, technological advancements have enabled the EV manufacturers to rollout vehicles with comparable features, which means electric vehicles are no lesser than conventional vehicles in performance. However, many such misconceptions are a result of lack of knowledge about new technologies, and this is where greater education and awareness can play a role. In addition, the range anxiety among potential EV owners could be minimized by making them aware of the current average trip distances in urban areas in India, which are well within the EV range per charge. There is a greater need to spread awareness among the general population about the EVs, about not only the one-time purchase price, but their long-term benefits, and especially about their features, which are rapidly evolving given the technological enhancements. Awareness campaigns such as the ones introduced by Niti Aayog, i.e., "Shoonya"; the "Go Electric" campaign designed by the Central government; "Switch Delhi EV" campaign as promoted by the Delhi government are likely to boost EV adoption. Policymakers also need to be made aware that because of the users' willingness to pay for specific EV features, the EV subsidies, which are needed initially, could be eventually phased out.

6.1. Limitations and future scope

The study was limited to the private two-wheelers and four-wheelers. Taxis, ride-hailing fleets, three-wheelers that provide last-mile connectivity, buses, and commercial vehicles were not considered. The study does not include the analysis and effect of EV adoption on vehicular emission and its direct and indirect benefits to the environment and society as well as the energy economics required for the smooth and efficient adoption of EV. Further studies would provide a better understanding of the potential impact of EVs on vehicular emissions and associated benefits.

CRediT authorship contribution statement

Vikas Nimesh: Conceptualization, Data curation, Formal analysis, Methodology, Software, Validation, Writing – original draft, Writing – review & editing. **B.S. Manoj:** . **Eeshan Bhaduri:** Writing – review & editing. **V. Mahendra Reddy:** Supervision, Writing – review & editing. **Arkopal Kishore Goswami:** Funding acquisition, Project administration, Supervision, Writing – review & editing.

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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