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Furqan Ahmad Bhat, Gaurav Yash Tiwari, Ashish Verma


PII: S0967-070X(24)00039-8

DOI: https://doi.org/10.1016/j.tranpol.2024.02.004

Reference: JTRP 3268

To appear in: *Transport Policy*

Received Date: 10 April 2023

Revised Date: 2 January 2024

Accepted Date: 4 February 2024

Please cite this article as: Bhat, F.A., Tiwari, G.Y., Verma, A., Preferences for public electric vehicle charging infrastructure locations: A discrete choice analysis, *Transport Policy* (2024), doi: https://doi.org/10.1016/j.tranpol.2024.02.004.

# **Preferences for the public electric vehicle charging infrastructure locations:** A discrete choice analysis

**Furqan Ahmad Bhat, M. Tech**
Research Scholar
Department of Civil Engineering
Indian Institute of Science Bengaluru
Bengaluru, Karnataka, India – 560012
Email: furqanbhatofficial@gmail.com

**Gaurav Yash Tiwari, M. Tech**
M.Tech. Student
Department of Civil Engineering
Indian Institute of Science Bengaluru
Bengaluru, Karnataka, India – 560012
Email: gauravyash@iisc.ac.in

**Ashish Verma, Ph.D.**
Corresponding Author
Professor
Department of Civil Engineering
Indian Institute of Science Bengaluru
Bengaluru, Karnataka, India – 560012
Email: ashishv@iisc.ac.in

**ABSTRACT**

Electric vehicles are finding it difficult to make faster inroads into the markets, and one of the most cited barriers to the faster adoption of electric vehicles in the academic literature is the lack of charging infra-structure and the associated range anxiety. However, densifying the charging infrastructure network is cost-intensive and should be meticulously planned. This study estimates discrete choice models with workplace, leisure place and highway as the location choice alternatives to investigate the electric vehicle public charging location preferences of the potential electric vehicle buyers. Mixed multinomial logit models and integrated choice and latent variable models are developed based on the attributes of the charging stations, viz. charging time, waiting time, charging cost, distance to the nearest charging station, emissions, and the characteristics of the individuals such as age, gender, income, and daily travel distance. This study finds negative utility associated with higher values of charging times, waiting times, charging costs, distance to the nearest charging station, and emissions. The results also indicate that the marginal disutility related to waiting time is higher than that of charging time. In terms of socio-demographics, females and higher income groups are found to prefer the workplace as their place of charging. However, as the age increases, the inclination towards highway charging stations increases. This study also discusses some important policy implications that can help decision-makers and stakeholders better plan electric vehicle charging infrastructure.

**Keywords:** Electric vehicles (EVs); Charging infrastructure; Location preference; Charging time; Waiting time; Charging cost; Accessibility

**Acknowledgment**

The authors thank UK Research and Innovation (UKRI) SP/ESCL-21-0001 for the financial support. The authors would also like to thank Ruth Babbington, Amy Davis, Domas Zemaitis, Sandhya Nagaraju, Chris Harrison, Sathsara Abeysinghe, Mo Abrahams and Thomas Gofrey-Brown from Energy Systems Catapult for their inputs throughout the project. The authors would also like to thank

Eclat engineering private limited for their assistance in data collection. The authors acknowledge the important contribution made by Poornashree, Anusha, Atish, Bhumika, Deeksha, Ann and Vaibhav in data collection and processing.

**Author contributions**

The authors confirm contribution to the paper as follows: study conception and design: Bhat, Tiwari and Verma; Data collection: Bhat, Tiwari and Verma; analysis and interpretation of results: Bhat; draft manuscript preparation and revision: Bhat and Verma. All authors reviewed the results and approved the final version of the manuscript.

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**ABSTRACT**

Electric vehicles are finding it difficult to make faster inroads into the markets, and one of the most cited barriers to the faster adoption of electric vehicles in the academic literature is the lack of charging infra-structure and the associated range anxiety. However, densifying the charging infrastructure network is cost-intensive and should be meticulously planned. This study estimates discrete choice models with workplace, leisure place and highway as the location choice alternatives to investigate the electric vehicle public charging location preferences of the potential electric vehicle buyers. Mixed multinomial logit models and integrated choice and latent variable models are developed based on the attributes of the charging stations, viz. charging time, waiting time, charging cost, distance to the nearest charging station, emissions, and the characteristics of the individuals such as age, gender, income, and daily travel distance. This study finds negative utility associated with higher values of charging times, waiting times, charging costs, distance to the nearest charging station, and emissions. The results also indicate that the marginal disutility related to waiting time is higher than that of charging time. In terms of socio-demographics, females and higher income groups are found to prefer the workplace as their place of charging. However, as the age increases, the inclination towards highway charging stations increases. This study also discusses some important policy implications that can help decision-makers and stakeholders better plan electric vehicle charging infrastructure.

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## 1. Introduction

Continuous economic growth and technological development have caused unchecked motorisation and a fast expansion of the world's transportation infrastructure. These changes have sparked grave concerns about the deteriorating environmental circumstances, the depletion of fossil fuels, the growing dependency on fuels derived from petroleum, and the rising exhaust emissions. The transportation sector is responsible for approximately 25% of global greenhouse gas emissions, most of which can be ascribed to road transportation (Napoli et al., 2020). Interestingly, this sector is also one of the fastest expanding sectors among all the fossil-based energy-consuming sectors, and as such, the global emissions from this sector are projected to swell up to 50% by 2050 (IEA, 2020a, 2020b). The unprecedented surge in fossil demand and the associated global warming has been a cause of severe weather occurrences such as storms, droughts, and floods. In addition to these disasters' extreme economic and financial significance, the growing exhaust emissions are also responsible for serious health issues such as respiratory problems, memory loss and birth disorders (Fuller et al., 2022; Landrigan et al., 2018). Recognising these threats, many nations have pledged to ambitious goals of reducing fossil demand and curtailing greenhouse gas emissions. These commitments have put the automotive industry in a serious predicament, and as such, the decarbonisation of this sector is a fundamental goal of various nations.

Towards this goal, electric vehicles (EVs) are seen as a viable mid-term solution that can potentially lessen the reliance on fossil-based fuels and help relieve urban pollution risks (Jia et al., 2019; Napoli et al., 2020). As such, the transportation policies of various national governments in recent years have been driven by the objective of increasing the penetration rates of electric vehicles in the automobile market. However, despite all the monetary and non-monetary incentives provided to manufacturers and consumers, the share of electric vehicles remains low. Although the global acceptance of electric vehicles has seen an increasing trend over these years, the growth of the electric vehicle market remains slow (IEA, 2022).

Consumers' range anxiety is the most widely cited reason that restrains the widespread adoption of electric vehicles (Bhat et al., 2022; Bhat and Verma, 2022; Chakraborty and Chakravarty, 2023; Guo et al., 2018; Ruoso and Ribeiro, 2022; She et al., 2017). Range anxiety is a psychological barrier triggered by the apprehension of exhausting the charge left before reaching the destination. Range anxiety, coupled with the lack of public charging infrastructure, deters many potential buyers from adopting an electric vehicle (Franke and Krems, 2013; Hardman et al., 2018). Hence, alleviating this psychological barrier is vital for the mass acceptance of electric vehicles. For widespread adoption of electric vehicles, measures need to be taken that mitigate the limitations of electric vehicles, which question their reliability, such as the range of electric vehicles and the limited availability of public charging infrastructure. One efficient approach to tackle this issue is to provide adequate public charging stations. However, it is also important to understand the perceptions and sensitivities of potential users to various attributes of charging facilities before actually providing charging infrastructure. Exploring the preferences for charging stations should play a pivotal role in advancing the adoption of electric vehicles and shaping the landscape of sustainable transportation. Understanding where users prefer these stations is crucial for enhancing user convenience, addressing the challenge of range anxiety, and encouraging a broader acceptance of electric vehicles. This insight informs urban planning, guiding the integration of electric vehicle infrastructure into city development plans and ensuring that charging stations are strategically placed in areas of high demand. Beyond user convenience, the strategic placement of charging stations contributes to the economic sustainability of private charging networks. In essence, the study of charging station preferences is pivotal for creating a robust and user-friendly electric vehicle infrastructure, facilitating the widespread acceptance of a more sustainable mode of transportation. However, there exists a gap in the existing literature with respect to understanding the perception towards the charging location and factors affecting the choice of charging station location. Thus, this study focuses on the following research questions:

- Which locations are preferred by potential electric four-wheeler buyers to charge their vehicles?
- What are the factors that affect the potential electric four-wheeler buyer's decision to choose a charging location?

## 2. Related studies, motivation, and objectives

Before trying to understand the number of charging stations or their location, it is essential to get clarity on whether or not public charging stations are required. To put this into perspective, (S. A. Funke and P. Plotz, 2017) found that 500 optimally placed charging stations can satisfy the demand for 500,00 electric vehicles in Germany. Similarly, 77 optimally placed charging stations can support approximately 3700 kilometres of autobahn for electric vehicles with a driving range of 100 kilometres (Jochem et al., 2015). In terms of charging location preferences, it has been found that approximately 90% of charging events occur at home, with slow or fast public charging infrastructure sharing a minor proportion (Baresch and Moser, 2019). Additionally, more than 95% of all trips can be managed by home charging alone. However, in developing economies like India and China, where the population density is relatively high, a vast majority of the population does not have dedicated parking spaces and hence has to park their vehicles on the streets (Patt et al., 2019). As such, all vehicle owners do not have home charging facilities available to them. In such a scenario, public charging infrastructure becomes crucial for the wider adoption of electric vehicles (Funke et al., 2019; He et al., 2016). Public charging stations are also vital in improving the visibility of the charging infrastructure network and reducing the range anxiety among potential buyers even if the facilities are not efficiently utilised (Morrissey et al., 2016). However, a balance also needs to be maintained between the density of the charging infrastructure and the type of charging stations (Globisch et al., 2019). Electric vehicles, in most countries, are still in the nascent stages of development. The charging infrastructure tends to be underutilised in the initial growth phases because of the lower demand. As such, the service providers are also facing this dilemma and are always eyeing an ideal method for expanding public charging infrastructure. This problem is of great interest to the research community as well. As such, several research studies have focussed on finding an optimal solution to the placement of public charging infrastructure. Although very important, these studies try to solve the charging station location problem as an optimisation problem based on an objective function subject to certain constraints (Dong et al., 2014; He et al., 2017; Qiao et al., 2023; Shahraki et al., 2015). For example, Dong et al., (2014) approached the infrastructure planning for charging electric vehicles using an activity-based method that utilises multiday travel data and aimed to deploy charging stations to maximise the electric vehicle miles travelled. Analysing vehicle trajectory data, Shahraki et al., (2015) developed an optimisation model to maximise the electrification of vehicle-miles-travelled (VMT) by selecting the most effective charging station locations. Sun et al., (2020) developed a method based on the characteristics of travel behaviours of urban residents, considering both short-distance commuters and long-distance travellers to meet the charging demand for both parking vehicles and vehicles on long journeys.

However, charging infrastructure should be viewed as a complex system in which electric vehicle users make a trade-off while choosing a charging station. The trade-off is made based on various attributes of the charging facility and consumers' preferences. These trade-offs that the electric vehicle users make should enter as constraints or decision variables into these optimisation problems. For instance, while trying to place charging stations optimally, the costs that users associate with every additional unit of distance that they have to travel to reach a charging station should enter the optimisation problem. These trade-offs can also be in terms of charging time and cost or in terms of waiting time at a charging station and distance to the nearest charging station. Moreover, decision-makers require an urgent understanding of these trade-offs to comprehend how consumers make their decisions so that the expanded charging infrastructure is efficiently utilised. Hence, a study that analyses and understands the impact of various factors that affects the location preference of a charging station was long overdue. Hence, it is important to understand user requirements and preferences for charging stations both in terms of their location and attributes. However, there are limited studies that analyse user perceptions and inclinations for charging stations, particularly in the context of developing economies. Thus, to understand the user preferences for electric vehicle charging locations and the evaluation criteria for charging stations, this study has the following objectives:

1. To understand the charging station location preferences for potential electric vehicle buyers.
2. To understand the influence of various charging station attributes affecting the evaluation of charging station location.

3. To analyse the impact of socio-demographic variables and travel characteristics on the choice of charging station location.

Although limited, there are some studies in the academic literature that try to understand the perceptions and preferences of electric vehicle charging stations. Philipsen et al., (2015) conducted a user-centred evaluation of fast-charging stations in cities has been conducted to identify preferred locations and user preferences for charging infrastructure. Based on the interviews of various focus groups to progress towards building a charging network based on user preferences, preferred charging locations and their evaluation criteria were identified. In their subsequent study, Philipsen et al., (2016) used statistical methods and identified motorway service stations, workplaces, and gas stations to be the most preferred locations for electric vehicle charging. The study also analysed the various evaluation criteria used by the present and potential future users in evaluating a charging station and found reliability, dual use, and accessibility to be the biggest factors. The study also revealed the willingness to accept waiting times to be quite low as compared to the willingness to make detours. Battery electric vehicle users exhibit heterogeneous behaviour when it comes to choosing fast-charging stations. Sun et al., (2015) use discrete choice models to study the influence of factors such as detour distance, charger location, remaining charge, and time of travel on the choice of charging station. Their study reveals private users on working days prefer stations encountered later in peak hours, while commercial users prefer stations encountered earlier. In their subsequent study, Sun et al., (2016) explore how battery-electric vehicle users choose where to fast-charge their vehicles and the distance they are willing to detour for fast-charging. The study reveals that private users are generally willing to detour up to about 1750 m on working days and 750 m on non-working days, while commercial users are willing to detour up to 500 m on both working and non-working days. Globisch et al., (2019) analysed the factors that influence the attractiveness of public charging infrastructure for electric vehicles, including spatial coverage, charging duration, and infrastructure cost. Their results reveal the majority of car drivers are unwilling to pay a monthly basic fee for the existence of public charging infrastructure. The study also indicated charging duration has a strong influence on the evaluation of infrastructure. Karolemeas et al., (2023) used a mixed-method approach, including a systematic literature review, stakeholder interviews, and the Analytical Hierarchy Process (AHP) to develop a methodological framework for identifying suitable locations for electric vehicle charging points. Charly et al., (2023) identified suitable locations for community electric vehicle charging points using a Geographic Information System (GIS)-based approach. The study classified the charging infrastructure into shared-residential, en-route, and destination charging types and selected each type's selection criteria according to the characteristics of targeted end-users.

As can be observed, different studies have used different methods to analyse the preference for charging infrastructure. However, none of the studies (except for Philipsen et al., (2016) who have used a statistical ranking-based method) have analysed the relative sensitivity to different attributes of a charging station. This is particularly true in the case of a developing economy. Hence, a study that analyses and understands the impact of various factors that affects the location preference of a charging station is very necessary. This study fills that gap in the academic literature by (a) studying the impact of various service attributes such as charging cost, charging time, waiting time, distance to the nearest charging station, and emissions on the choice of charging station and (b) evaluating the impact of various socio-demographic variables such as age, gender, income, knowledge of electric vehicles and average daily distance travelled on the preference of charging station.

### *2.1. Scope of study*

Where should the electric vehicle charging stations be placed? Which type of charging stations should be installed? How many charging stations should be set up? These are some of the fundamental questions staring at decision makers and policymakers while they decide to deploy electric vehicle public charging infrastructure. This study investigates the location preferences of potential electric vehicle buyers for the electric vehicle public charging station based on the attributes of the charging stations and the characteristics of the individuals.

Several countries are working hard to expand their charging infrastructure network to increase the penetration of electric vehicles. However, there is a cost associated with the development of charging infrastructure, and as such, excess charging stations cannot be provided. At the same time, the service providers would also not want the charging stations to be underutilised. This is especially true in the context of developing economies where there are budgetary constraints. Hence, it becomes imperative to understand where the charging station should be placed, the type of charging station to be placed at different locations, the number of charging piles to be placed at a station, the density of charging stations and the pricing policy. This study investigates the consumers' location preferences for charging locations and the impact of various charging station attributes. Charging infrastructure deployment and electric vehicle adoption has been widely and rightfully addressed as a chicken-and-egg problem, especially in the context of developing economies such as India where the adoption of electric vehicles is still in its nascent stages. This study can help stakeholders understand electric vehicle users' charging station preferences. For instance, by evaluating the marginal impact of charging time on location choices, organisations deploying charging stations may readily identify the type of chargers (fast or slow) needed at different city locations. A similar investigation into waiting time or accessibility can help understand the requirements of charging piles at a charging station or the charger density in a region. A further expansion of this study can help policymakers, and decision-makers understand the willingness to pay for different attributes of electric vehicle charging stations.

## 3. Study area and potential buyers

The Bangalore metropolitan region consists of three districts, namely Bangalore urban, Bangalore rural, and Ramanagaram. Located in the southeastern part of the state on the Deccan Plateau, Bangalore metropolitan region (henceforth referred to as Bengaluru) holds the distinction of being the third most populous city and the fifth most populous urban area within India. Bengaluru, once known as Bangalore, functions as the capital city of the Indian state of Karnataka, positioned in the southern region. Known as the "Silicon Valley of India," Bengaluru has ascended as a significant nexus for technology and innovation. With a population estimated to exceed 13 million individuals, the city ranks as the 24th most populous globally and is the fastest-growing Indian city, trailing only Delhi (World Population Review, 2023). The plan of the Bangalore metropolitan region is shown in figure 1.

The past few decades have witnessed Bengaluru undergoing rapid urbanisation, with over 90% of its inhabitants residing in urban localities (Eswar and Roy, 2018). This urban expansion, paralleled by robust economic advancement, has fuelled a notable surge in private vehicle ownership. Consequently, this phenomenon has engendered traffic congestion and escalated vehicular emissions. In terms of carbon dioxide emissions stemming from urban commuting, Bengaluru occupies the third position, following Delhi and Chennai (Roychowdhury and Dubey, 2018). Presently, the city encompasses approximately 10 million registered vehicles, out of which around 9 million are accounted for by private vehicles, including two-wheelers and four-wheelers (Kidiyoor, 2022).

Keeping in view the growing transportation needs of the expanding city, Karnataka was the first state in India to introduce its own electric vehicle and energy storage policy in 2017 (Government of Karnataka, 2017). The underlying objective of this policy is to establish Karnataka as the preeminent centre for electric vehicle manufacturing and infrastructure development on a national scale. This policy framework encompasses an array of incentives and subsidies intended to catalyse electric vehicle adoption. Such incentives encompass exemptions from road tax and registration fees, reduced electricity tariffs for charging stations, and, most importantly, financial support for the establishment of charging infrastructure (Government of Karnataka, 2017).

In alignment with its aspirations, Karnataka has drawn electric vehicle manufacturers and facilitated investments within this burgeoning sector. The state has already fostered the growth of numerous electric vehicle manufacturing companies and research centres, thereby nurturing a thriving electric vehicle ecosystem (Government of Karnataka, 2023a). To nurture this ecosystem, the state government fervently encourages innovation and research. Prioritising the development of a skilled workforce, the government has spearheaded the establishment of cutting-edge research and innovation centres (Government of Karnataka, 2017). These initiatives encompass an array of training programs and skill development endeavours aimed at cultivating an adept workforce specialising in electric vehicle technology. In the context of workforce development, Karnataka has fostered synergy between the electric mobility industry and educational institutions through collaborative research programs. These initiatives aim to foster a pool of qualified professionals equipped with the requisite expertise to invigorate and sustain the electric vehicle industry's trajectory within Karnataka.

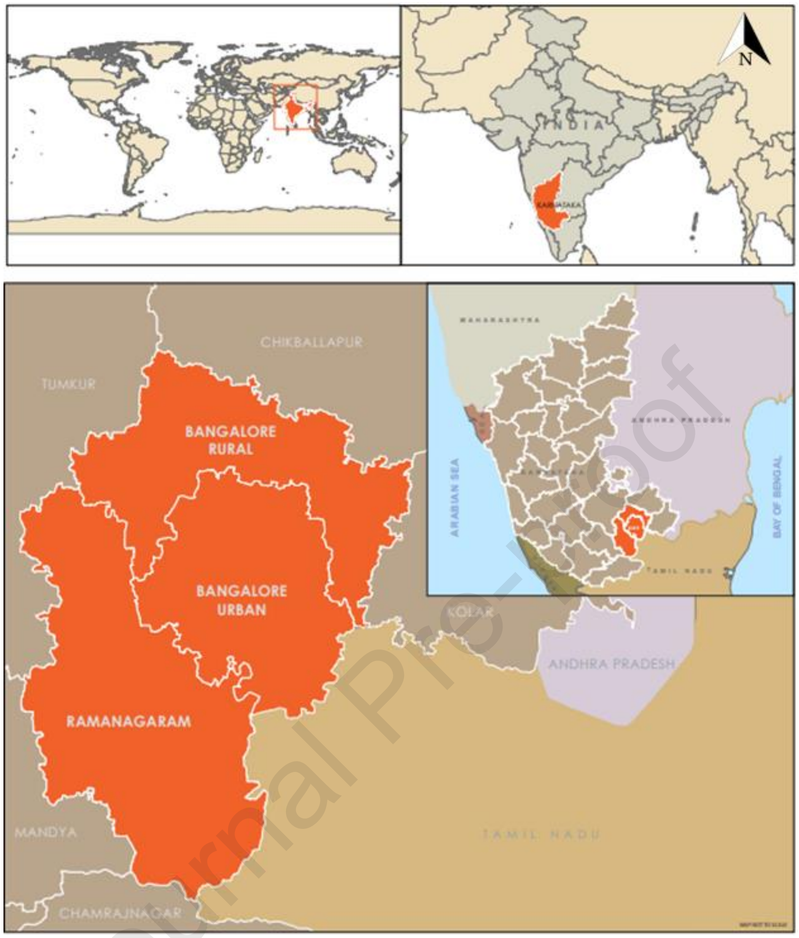


**Figure 1:** Bangalore metropolitan region (Source: Bangalore Metropolitan Region Development Authority (BMRDA))

Diligent efforts have been channelled into bolstering the charging infrastructure across the expanse of Karnataka (The Hindu, 2022). A concerted drive has spurred public and private entities to establish charging stations strategically positioned within commercial complexes, residential areas, and key highways. Notably, the Bangalore Electricity Supply Company (BESCOM) has been actively engaged in deploying charging infrastructure throughout the state (Government of Karnataka, 2023b). As a result, the state's share of electric vehicle sales surpassed 5% in the first quarter of 2022. During the same period, the city of Bengaluru, which has been at the forefront, recorded a 9 per cent sales proportion for electric automobiles. Because of these reasons, Bengaluru was chosen as the study area, and the data for this study was gathered from potential electric four-wheeler purchasers from Bangalore Metropolitan Region.

The data for this study was collected from the potential electric four-wheeler buyers of BMR using face-to-face interviews on a survey platform (Qualtrics) using face-to-face interviews. Potential buyers were defined as the people (i) who had either purchased a four-wheeler in the previous six months or were planning on buying one in the next six months and (ii) participate in the decision-making of their families. Several prior studies have classified potential electric vehicle buyers as those showing interest in near-future purchases (Bansal et al., 2021; Chhikara et al., 2021). However, this current study expands this category to encompass individuals who have recently acquired four-wheelers, in addition to those intending to make a near-future purchase. We have specifically targeted this demographic as our sample, given their likely comprehensive assessment of the wide array of available options.

Consequently, they possess an in-depth familiarity with the market landscape (Bhat and Verma, 2023). Electric vehicles represent a recent innovation and consequently experience frequent alterations and developments both in terms of technology and policies. This study assumes that the market conditions will remain relatively consistent over the course of a year. Accordingly, respondents who procured a four-wheeler within the previous six months could have potentially opted for an electric four-wheeler. Similarly, individuals planning to acquire a four-wheeler within the ensuing six months could feasibly select an electric four-wheeler, all within the same market framework.

## 4. Methodology

This section describes the methodology used for this study. A survey instrument was designed, and data was collected from potential four-wheeler buyers using face-to-face interviews. Further discrete choice models were used to analyse the stated preference data to understand the charging location preferences of potential buyers based on attributes such as charging cost, charging time, waiting time, distance to the nearest charging station, and emissions. The methodology is further detailed in the subsequent sub-sections.

### *4.1. Survey instrument design and data collection*

The survey instrument was divided into four sections. The first section of the questionnaire employed the stated preference discrete choice experiment to study the electric vehicle adoption behaviour. Respondents had to choose between electric and conventional vehicles based on certain vehicle attributes. The second section of the questionnaire assessed respondents' level of agreement on several issues related to environmental friendliness, technological awareness, social norms, perceived infrastructural readiness, perceived risks, and perceived fee on a five-point Likert scale ranging from strongly disagree to strongly agree. However, the data from section one is collected to study the impact of various vehicle attributes on electric vehicle adoption behaviour and the data from section two is collected to study the impact of various latent variables on adoption intention (and possibly charging location), which is beyond the scope of this study. Hence data from section one and section two of the questionnaire is not used in this study. The third section of the questionnaire was used to collect information on the respondents' socio-demographics and travel habits. The fourth section of the questionnaire had a stated preference choice experiment to study the charging station location preferences. The respondents were asked to choose their preferred charging location based on five charging station attributes: charging cost, charging time, waiting time, distance to the nearest charging station, and emissions under the hypothetical situation that they own an electric vehicle. The attributes used to describe a charging station were derived from the existing studies on preference for a charging station. Speed (charging duration) and cost of charging has been discussed as major factors influencing charging behaviour in several existing studies (Fotouhi et al., 2019; Globisch et al., 2019; Sun et al., 2016). Charging infrastructure density (or accessibility) and waiting times have also been found to significantly impact the choice of charging stations (Globisch et al., 2019; Philipsen et al., 2016, 2015; Sun et al., 2016). Although the impact of emissions from a charging station on the choice of a charging station has not been studied in earlier studies, we believe that it could be an important parameter influencing the choice-making behaviour and hence have included it in our study. A detailed description of these attributes was given at the beginning of the section to avoid misunderstandings, and the survey enumerators were trained to explain the instrument to the respondents. The respondents were asked to assume that the provided alternatives differed only in terms of these attributes. Charging time is the time a vehicle takes to charge from 10% to 90%. Charging cost is the cost per unit of energy (kWh), a standard unit used and understood locally. Distance to the nearest charging station refers to the distance a person has to travel from the intended destination to find a charging station. Waiting time is the time a person must wait at a charging station to plug in their vehicle for charging. Emissions refer to the energy source in terms of renewable and non-renewable mix used to fuel the charging station. It should be noted that respondents in the choice experiment were given three alternative locations to choose from: leisure place, workplace, and highway. These places were well described in the questionnaire to avoid confusion. Home charging was not given as an alternative considering the focus of the study was on planning for public charging infrastructure. To decrease the hypothetical prejudice, the survey included a concise "cheap talk" to promote truthful responses, and the respondents were requested to consider their preferences as real-life decisions.

The alternatives, the attributes used to describe the alternatives and the levels of the attributes are decided based on the literature review and applicability in the Indian scenario. Motorway service stations, gas stations, workplaces, shopping, leisure, and educational institutions are essential for installing public charging infrastructure (Philipsen et al., 2016). The different levels of all the attributes are summarised in Table 1.

**Table 1:** Attributes and their levels in the choice experiment

| Attribute | Number of levels | Levels |
|---|---|---|
| Charging time | 3 | 45 minutes - 1 hour, 5 – 6 hours, 8 – 9 hours |
| Charging cost | 4 | Rs. 8, Rs. 10, Rs. 12, Rs. 18 per unit of electricity |
| Waiting time | 5 | No waiting time, 10 minutes, 20 minutes, 30 minutes, 40 minutes |
| Accessibility (distance to the nearest charging station) | 4 | 500 metres, 1000 metres, 2000 metres, 3000 metres |
| Emissions | 5 | 100% reduction, 75% reduction, 50% reduction, 25% reduction, 0% reduction in comparison to conventional vehicles |

The level of service offered by electric vehicles is significantly affected by the charging time required and the density of the charging network (Gong et al., 2020; Qian et al., 2019). As a result, this study places emphasis on investigating the influence of charging time and charging infrastructure as fundamental attributes. In India, there are two primary categories of charging facilities for electric vehicles: AC slow charging facilities and DC fast charging facilities. AC slow charging is typically available at homes and workplaces, requiring an estimated charging time of 8-9 hours to fully charge an electric four-wheeler. On the other hand, DC fast chargers are predominantly located at recreational establishments such as shopping malls, restaurants, and cinema halls, as well as along highways, providing a significantly reduced charging time of approximately 1 hour. Bansal et al., (2021) in their study assume three levels of fast-charging rates (30 minutes, 60 minutes, and 90 minutes) and three levels of slow-charging rates (6 hours, 8 hours, and 10 hours). Given that the charging time of four-wheeler electric vehicles varies from 1 hour using a fast charger to 10 hours using a slow charger, we have used three levels of charging times, viz. Forty-five minutes to 1 hour, 4 to 5 hours, and 8 to 10 hours. The Indian government, under its flagship FAME-II scheme, aims to provide a charging station within a square grid of 3 kilometres (Ministry of Power, 2022). The attribute of accessibility in the choice experiment was thus decided to have four levels ranging from 500 to 3000 metres. The levels of charging costs are decided based on the current and the planned future rates of operations by the Bengaluru electricity supply company (BESCOM). Four levels were considered for electric vehicles based on electricity charges per unit of energy (kWh), ranging from Rs. 8 per unit for slow charging to Rs. 18 per unit for fast-charging facilities (CarDekho, 2023; Government of Karnataka, 2023b). Electric vehicles have gained significant attention in the market as environmentally friendly and sustainable transportation options. Therefore, it is vital to investigate the influence of exhaust emissions. It is important to acknowledge that while electric vehicles themselves produce zero tailpipe emissions, the term "emissions" in this context pertains to the source of energy production for these vehicles. Such research can prove instrumental in shaping effective marketing strategies and policy frameworks for electric vehicle charging infrastructure. In this study, we examine five distinct emissions levels of electric four-wheelers relative to conventional vehicles (based on the source of production of electricity), represented by percentages: 0%, 25%, 50%, 75% and 100% of the emissions produced by conventional four-wheeler.

In the recent times, efficient designs, as highlighted by (Kessels et al., 2006) and (Rose and Bliemer, 2009), have gained popularity. However, caution is advised in choosing priors for model parameters in these designs, as demonstrated by (Walker et al., 2018). Given the absence of studies in the Indian context, there is a lack of a solid foundation for selecting priors on model parameters. Hence, the orthogonal factorial design method was used to design the choice experiment using the software IBM SPSS 26.0 (IBM Corp., 2019). Orthogonal design reveals 84 choice scenarios, of which four choice cases were chosen randomly and presented to each respondent. An example of the choice scenario is shown in Figure 2.

| | Leisure | Workplace | Highway |
|---|---|---|---|
| **Charging time** | 45 minutes to 1 hour | 8 - 9 hours | 8 - 9 hours |
| **Charging cost** | Rs. 18/unit | Rs. 10/unit | Rs. 18/unit |
| **Waiting time** | 30 minutes | 10 minutes | 30 minutes |
| **Accessibility (Distance to the nearest charging station)** | 1.5 km | 1.5 km | 1.5 km |
| **Emissions from electricity generation (Power source)** | Same emissions (fossil-based fuel) | 50% emissions ( mixed fuel type) | Zero emissions (renewable sources) |

**Figure 2:** A sample of the choice scenario

As already mentioned, the research is carried out in Bengaluru, a major metropolis in Karnataka, India's southern state. In addition to English, Kannada and Hindi are two widely spoken and understood languages in the city. As a result, language specialists translated the questionnaire, initially written in English, into Kannada and Hindi. The questionnaire was then sent to some of the subject experts from academia, administration, and industry for assessment. Based on their responses, a few changes were made to the questionnaire. A face-to-face pilot survey followed this in all three languages. One hundred twelve samples gathered during the pilot survey were analysed to test the reliability and validity of the questionnaire, and a few minor changes were made to the questionnaire. Between February and April 2022, the interviewers visited different locations such as vehicle registration offices (transport offices), households, vehicle showrooms, shopping malls, literary and other registered clubs, and workplaces to find potential customers and gather data. The people were randomly selected at these locations and screened using the initial screening questions to confirm if a respondent was a potential buyer. A total of 1659 potential electric vehicle buyers were identified out of the 2959 people that were approached. The incomplete questionnaires, questionnaires with the same answers to all questions, questionnaires with contrary answers to reverse coded questions and questionnaires filled in a very short duration were considered invalid and hence discarded. Finally, a total of 1243 responses (equal to 1243*4 observations) were deemed useful for this study, ensuring a response rate of 42%. As already mentioned, the target population for this study consists of potential buyers of electric four-wheelers. However, in developing economies like India, gathering demographic information for such a specific population segment can pose challenges, primarily due to the limited availability of publicly accessible disaggregated census data. Consequently, assessing the sample's representativeness becomes a complex endeavour (Bansal et al., 2021). Huang and Qian (2018) in a similar study to analyse the consumers' preferences for electric vehicles in China collect data from shoppers at local shopping malls. The authors argue that shopping places are suitable places to collect data because this captures the mainstream consumers of a city. However, data for this study was collected by ensuring a geographical spread across the study area and good representativeness from different strata of socio-demographic groups. Table 2 shows the demographic details of the collected sample. It is worth noting that potential buyers in this context may also include respondents who already own an electric four-wheeler. However, due to the relatively limited penetration of electric four-wheelers in the Indian market, the collected sample size of actual electric vehicle owners was only around 200. In addition, power analysis on RMSEA value revealed sufficient power and sample size (Preacher and Coffman, 2006). Demographic descriptions of the sample obtained are presented in Table 2.

**Table 2:** Summary of sample demographics (n = 1243)

| **Demographics** | | **Sample (Percentage)** |
|---|---|---|
| Age | 18 – 22 years | 124 (9.97%) |
| | 23 – 28 years | 393 (31.62%) |
| | 29 – 35 years | 441 (35.48%) |
| | 36 – 45 years | 230 (18.50%) |
| | Above 46 years | 55 (4.42%) |
| Gender | Male | 705 (56.72%) |
| | Female | 538 (43.28%) |
| Monthly household income (INR) | Less than 20,000 | 50 (4.02%) |
| | 20,000 – 40,000 | 154 (12.39%) |
| | 40,000 – 80,000 | 337 (27.11%) |
| | 80,000 – 1,00,000 | 352 (28.32%) |
| | 1,00,000 – 3,00,000 | 251 (20.19%) |
| | Above 3,00,000 | 99 (7.96%) |
| Daily distance | Less than 10 kms | 144 (11.58%) |
| | 10 kms – 20 kms | 425 (34.19%) |
| | 20 kms – 30 kms | 356 (28.64%) |
| | 30 kms – 50 kms | 216 (17.38%) |
| | 50 kms – 100 kms | 88 (7.08%) |
| | More than 100 kms | 14 (1.13%) |



As the legal driving age for motorized vehicles in India is 18, our study focuses exclusively on participants aged 18 and above. In our empirical model, we treat age, knowledge, and income as continuous variables, while gender and electric vehicle ownership are considered categorical. To ascertain participants' knowledge levels the respondents were asked directly to rate their level of knowledge on a 5-point scale. However, to ensure that the respondents have appropriately rated their knowledge, we posed a series of questions related to electric vehicles, covering aspects such as charging times, range, purchase price, and incentives. For instance, questions like (i) the distance an electric four-wheeler can cover on a single charge, (ii) the possibility of charging an electric vehicle at home using a regular electrical outlet, and (iii) the typical duration for a full charge were included. While socio-demographic variables such as age, gender, income, and education were directly obtained from respondents, evaluating an individual's knowledge about electric vehicles involved assessing their responses to specific questions on the topic. This method allowed us to classify respondents into five levels (which are treated as continuous) based on their demonstrated understanding of key aspects related to electric vehicles.

### *4.2. Modelling approach*

This section describes the methodology used for this study. Mixed multinomial logit model (MMNL) and integrated choice and latent variable model using the stated preference data described in the previous section are used to study the impact of charging station attributes and socio-demographic attributes on the individual's decision to choose a charging location. In the existing studies, the knowledge about electric vehicles has been included in two ways. For instance, Bansal et al., (2021) consider knowledge as a categorical variable in their study to analyse the electric vehicle adoption behaviour. Simsekoglu, (2018) in their study to understand the electric vehicle adoption behaviour consider knowledge as a continuous variable. On the other hand, Giansoldati et al., (2020) and Chu et al., (2019) consider knowledge as a latent variable in their respective studies. Hence, in this study we develop mixed multinomial models considering knowledge as a categorical variable in which we consider only the self-assessed knowledge. We further estimate integrated choice and latent variable models considering knowledge as a latent variable.

#### *4.2.1. Mixed multinomial logit model*

The multinomial logit model assumes independent and identically distributed error terms. However, due to the panel nature of the stated preference data wherein multiple observations are taken from the same respondent, there can be correlations across these observations (Hensher and Greene, 2003). Also, the multinomial logit model estimates deterministic coefficients for the variables and hence does not consider the taste variation or the behavioural heterogeneity, which implies that different individuals can have different sensitivity to different variables. This taste heterogeneity can be accommodated to a certain extent in a multinomial logit model by incorporating interaction terms. However, that can only be done for variables captured in the data, and coefficients are still deterministic. The mixed multinomial logit model is an advanced version of the multinomial logit model, which takes care of all these downsides. The mixed multinomial logit model relaxes the assumption of independently distributed error terms and considers the correlations across different observations. Moreover, mixed logit models also consider taste heterogeneity across individuals by estimating random coefficients for variables as a probability distribution. In the case of the mixed multinomial logit model, the utility expression of an alternative $i$ as perceived by an individual $n$ is of the form:

$$U_{in} = \boldsymbol{\beta}'_n X_{in} + \eta_{in} \tag{1}$$

where $X_{in}$ represents alternative attributes as well as individual characteristics and $\boldsymbol{\beta}_n$ represents the vector of parameters to be estimated. $\eta_{in}$ represents the error term which is still assumed to follow an independently and identically distributed Gumbel distribution. However, as can be observed, the beta parameters have a subscript $n$ which indicates that these parameters vary over individuals in the population with some probability density $f(\beta)$. The probability of an individual $i$ choosing an alternative $n$ is given by (Train, 2003):

$$p_{in} = \int \left( \frac{e^{\beta' x_{in}}}{\sum_j e^{\beta' x_{jn}}} \right) f(\beta) d\beta \tag{2}$$

#### *4.2.2. Integrated choice and latent variable model*

The framework used in the study is based on the advanced discrete choice model which is the integrated choice and latent variable (ICLV) model. The ICLV model involves the simultaneous estimation of the discrete choice and latent variable models. This advanced model for discrete choice enables the integration of an individual's attitudes and perceptions into their decision-making process (Ben-Akiva et al., 2002; Morikawa et al., 2002).

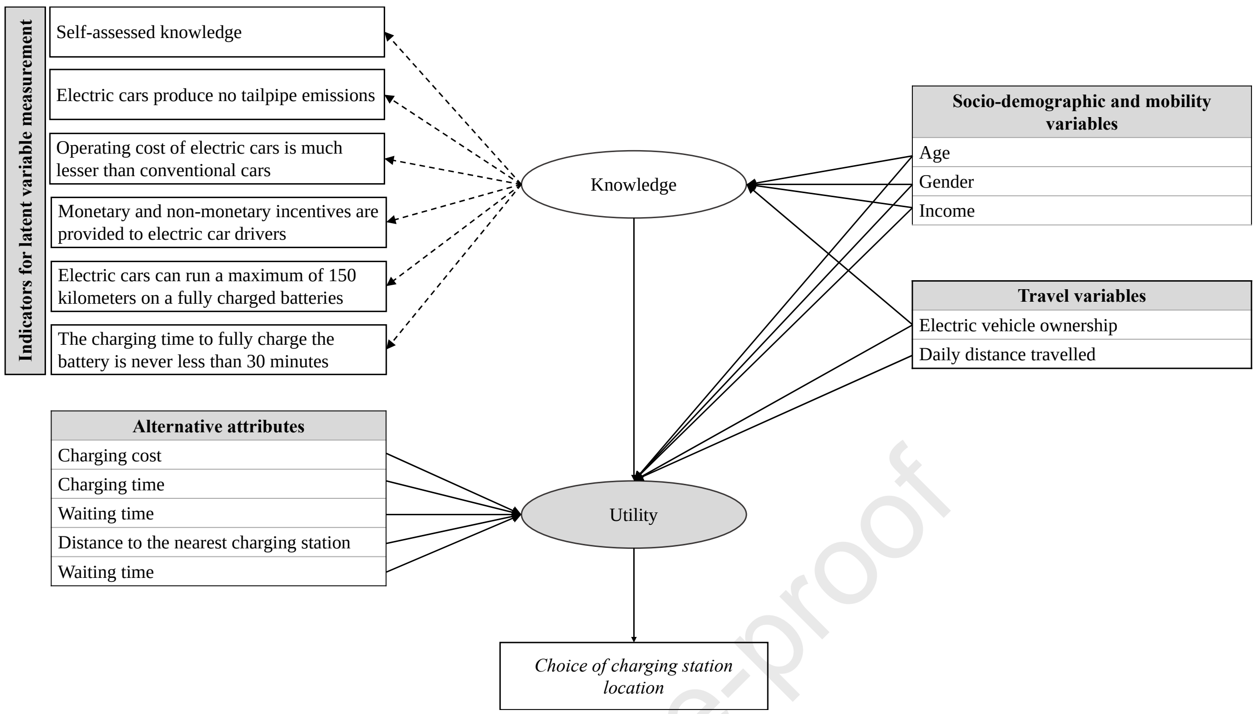


**Figure 3:** ICLV flowchart

### *Discrete Choice Model*

Utility functions are specified in the discrete choice model (DCM) for each alternative: leisure place, workplace, and highway, respectively.

$$U_{l,n,t} = \beta * X_{l,t} + \alpha * Z_n + \vartheta_{l,n,t} \quad (3)$$

$$U_{w,n,t} = \beta * X_{w,t} + \alpha * Z_n + \vartheta_{w,n,t} \quad (4)$$

$$U_{h,n,t} = \beta * X_{h,t} + \alpha * Z_n + \vartheta_{h,n,t} \quad (5)$$

where $U_{l,n,t}$ is the true utility of the charging facility at a leisure place for the decision maker $n$, at choice occasion t, $U_{w,n,t}$ is the true utility of the charging station at the workplace for the decision maker $n$, at choice occasion t, $U_{h,n,t}$ is the true utility of the charging station at the highway for the decision maker $n$, at choice occasion t, $X$ is a vector of alternate specific attributes, $Z$ is a vector of latent variables, $\vartheta$ represents the error term which captures the unobservable factors that influence the decision of a person; it is assumed to be i.i.d gumbel with location and scale parameters to be 0 and 1, respectively. Since this study uses panel data (multiple observations from an individual), the conditional likelihood for the sequence of choices $t = \{1,2 \dots T\}$, made by respondent $n$, conditional on $Z_n$ is given by:

$$P_n(i \in C_n \mid Z_n) = \prod_t ((\exp(\beta * X_{i,n,t} + \alpha * Z_n))/(\sum_j \exp(\beta * X_{i,n,t} + \alpha * Z_n))) \quad (6)$$

The expression shown above shows the conditional likelihood of an individual's choice. The unconditional likelihood can be calculated by integrating the above expression over the distribution of the latent variables (with the dimension of integral being equal to the number of latent variables):

$$P_n(i) = \int P_n(i \in C_n \mid Z_n) dF_z(Z_n) \tag{7}$$

where $F_z$ represents the distribution of $Z$ and $C_n$ represents the choice alternatives available to an individual $n$. In this study we have assumed all alternatives to be available to all the individuals.

### *Latent Variable Model*

The latent variables or the perception of the person are determined using the structural relationship in which the latent variables are influenced by the characteristics of decision-makers. The expression for the structural relationship is given as follows:

$$Z_{lv,n} = b_{lv} W_n + \sigma_{lv} \Psi_{lv,n} \tag{8}$$

In the above expression $Z_{lv,n}$ represents the latent variable $lv$ of a person $n$, $W_n$ indicates the socio-demographic characteristics of a person $n$ and $\sigma_{lv}\Psi_{lv,n}$ is the random components of the latent variables, which follows a multivariate normal distribution with mean zero and standard deviation $\sigma_{lv}$ .

Knowledge about electric vehicles is the only latent variable used in this study which is measured using set of a indicators as shown in Figure 3. The responses to the indicators are modelled using measurement equations.

$$y_{s,n} = d_s Z_n + \varepsilon_{s,n} \tag{9}$$

where $y_{s,n}$ represents the discrete categorical value (measured on a Likert scale from 1 to 5) for indicator $s$ and individual $n$, $\varepsilon_{s,n}$ represents the random components of the indicators, which is assumed to follow standard multivariate normal distribution. Here, $d_s$ represent the influence of perception of a person which leads to the Likert scale score for a psychometric indicator. To apply ordered choices, psychometric indicators are treated as a latent variables $x_{s,n}$. This is a continuous variable which is called propensity and models the probability that the attitude $x_{s,n}$ lies within a particular range to give the observed response $y_{s,n}$:

$$x_{s,n} = d_s Z_n + \varepsilon_{s,n} \tag{10}$$

Considering attitudinal responses as ordinal choices, which is measured on a five-point Likert scale, the likelihood of the series of attitudinal responses by individual $n$ can be written as:

$$\mathrm{P}\{y_n \mid Z_n\} = \prod_s \left( \Phi\left(\mu_{x_{s,n}} - d_s Z_n\right) - \Phi\left(\mu_{x_{s,n-1}} - d_s Z_n\right) \right)^{\delta_{njs}} \tag{11}$$

where $\Phi$ represents cumulative density function of a standard normal distribution and $\mu_{x_{s,n}}$ represents the threshold values of the distribution of psychometric indicator $s$ for a person n. Furthermore, $\delta_{njs}$ represents the binary indicator which will be 1 if a person $n$ chooses a particular value $j$, for psychometric indicator $s$.

Similarly, to obtain the unconditional likelihood integrate the above expression over all the values of $Z_n$.

$$P(y_n) = \int P(y_n \mid Z_n) dF_z(Z_n) \tag{12}$$

## 5. Results and discussions

This section describes the modelling results. As mentioned in the previous section, this study employed mixed multinomial logit models and integrated choice and latent variable models to study the choice of charging station location. The choices or the alternatives available to the respondents (and hence the dependent discrete variables) were leisure place, workplace and highway and the choices were made by the respondents based on the alternative attributes such as charging time, charging cost, waiting time, distance to the nearest charging station and emissions coupled up with their socio-demographic characteristics. The results of MMNL models are given in Table 3 and the results of ICLV models are given in Table 4 and Table 5. In addition to the models presented in Table 3 and Table 4, a number of other models were estimated. These models are presented in appendix and explained in the subsequent sub-section.

### *5.1. Mixed multinomial logit model*

As mentioned in the previous section, the multinomial logit model specification does not consider the panel nature of the data. Since multiple observations were recorded from the same individuals for this study, mixed multinomial logit models are estimated, and the results are presented in Table 3. The models were estimated using the apollo package (Hess and Palma, 2019) in R studio.

One of the major issues associated with the mixed multinomial logit model is the distributional assumption of the random parameters, which has a significant impact on the results and interpretations. The most common distributions used in the existing literature are normal, triangular, and uniform distributions. Other distributions such as log-normal (or negative log-normal), log-uniform (or negative log-uniform) or bounded triangular have also been used in the existing studies when the response variables are assumed to follow a specific sign. It is logical to assume that all the alternative attributes considered in this study (charging time, charging cost, waiting time, distance to the nearest charging station, and emissions) should have negative coefficients associated with them, as the increase in these variables should decrease the marginal utility. The next important step in the estimation of mixed multinomial logit models is fixing the number of draws. We used 2000, 2500 and 3000 MLHS draws to estimate mixed logit models, and the results from 3000 draws are reported below.

Based on the assumption that charging time, charging cost, waiting time, distance to the nearest charging station, and emission should have a negative impact on the utility, the coefficients were assumed to follow negative log-normal, negative log-uniform, and zero-bounded triangular distributions. We used 2000, 2500 and 3000 MLHS draws to estimate mixed logit models, and the results from 3000 draws are reported below. All the coefficients were first assumed to follow negative log-normal distributions, and the results are reported in Tables A-3 and A-4. Moreover, results in Table A-3 assume the utility (or disutility) associated with charging time at leisure, workplace, and highway to be the same. In contrast, the specification in Table A-4 assumes the charging time coefficients are different for leisure places and workplaces compared to highway. Furthermore, it is important to acknowledge that negative log-normal distribution is not the only possible distribution for these variables. Subsequently, the coefficients were assumed to follow zero bounded triangular distributions, and the results are presented in Table A-5 and Table A-6. In addition to these models, we also estimated models where all the coefficients associated with the charging station attributes were assumed to follow negative log-uniform distribution. However, the expected values for some of the coefficients from these models were not logical (i.e., the expected values were too high), and for others were statistically insignificant and hence are not reported in this study. The relatively high expectation of these variables could be attributed to the long and heavy-tailed nature of log distributions, the effects of which have been observed in some of the earlier studies as well (Hess et al., 2005).

Finally, observing the results from Tables A-3, A-4, A-5 and A-6, charging time, waiting time and emissions are assumed to follow the negative log-normal distribution and distance to the nearest charging station is assumed to follow the zero-bounded triangular distribution and the results are presented in Tables A-7 and A-8. The coefficient of charging cost is assumed to be fixed. This is done to make the computation of willingness to pay for different attributes of charging stations possible and convenient (although willingness to pay is not evaluated in this study due to the restrictions on space). Comparing the log-likelihood values, it can be found that MMNL Model A-18 and MMNL Model A-22 (Table A-7 and Table A-8) are the best-fit models and are presented in Table 3 as MMNL Model 1 and MMNL Model 2 respectively. In addition to the models presented in this study, various other combinations of distributional assumptions for the vehicle attributes were explored. However, only the best-performing models are reported in this study. In the models presented, when considering negative log-normal distributions $\mu_{ln}$ and $\sigma_{ln}$ represents the represents the mean and standard deviation of the underlying normal distribution. In the models presented, when considering triangular distributions, $b_{tr}$ represents the spread of the underlying zero-bounded triangular distribution.

**Table 3:** Results from MMNL models

| **Variables** | **MMNL Model 1** | **MMNL Model 2** |
|---|---|---|
| | **Coefficient** | **Coefficient** |
| ASC: Leisure | $1.49^{***}$ | $1.25^{***}$ |
| ASC: Workplace | $1.09^{***}$ | $1.15^{***}$ |
| ***Charging station attributes*** | | |
| Charging cost (INR) | $\beta_{cc} = -0.01^{***}$ | $\beta_{cc} = -0.01^{***}$ |
| Charging time (hours) | $\mu_{ln,ct} = -5.12^{***}$ | $\mu^{lw}_{ln,ct} = -7.74^{***}$ |
| | | $\sigma^{lw}_{ln,ct} = 3.30^{***}$ |
| | $\sigma_{ln,ct} = 2.01^{***}$ | $b^{h}_{tr,ct} = -0.07^{***}$ |
| Waiting time (hours) | $\mu_{ln,wt} = -1.23^{***}$ | $\mu_{ln,wt} = -1.40^{***}$ |
| | $\sigma_{ln,wt} = 1.13^{***}$ | $\sigma_{ln,wt} = 1.25^{***}$ |
| Distance to the nearest charging station (kms) | $b_{tr,dist} = -0.23^{***}$ | $b_{tr,dist} = -0.23^{***}$ |
| Emissions | $\mu_{ln,em} = -4.39^{***}$ | $\mu_{ln,em} = -4.31^{***}$ |
| | $\sigma_{ln,em} = 2.05^{***}$ | $\sigma_{ln,em} = 2.00^{***}$ |
| ***Socio-demographic variables*** | | |
| Male: Workplace | $\beta^{w}_{male} = -0.25^{***}$ | $\beta^{w}_{male} = -0.25^{***}$ |
| Male: Highway | $\beta^{h}_{male} = -0.17^{**}$ | $\beta^{h}_{male} = -0.21^{***}$ |
| Age: Leisure (Years) | $\beta^{l}_{age} = -0.015^{***}$ | $\beta^{l}_{age} = -0.018^{***}$ |
| Age: Workplace (Years) | $\beta^{w}_{age} = -0.011^{***}$ | $\beta^{w}_{age} = -0.013^{***}$ |
| Income: Leisure (10,000s INR) | $\beta^{l}_{inc} = -0.014^{***}$ | $\beta^{l}_{inc} = -0.014^{***}$ |
| Income: Highway (10,000s INR) | $\beta^{h}_{inc} = -0.009^{***}$ | $\beta^{h}_{inc} = -0.010^{***}$ |
| Knowledge Medium: Workplace | -- | -- |
| Knowledge High: Workplace | $\beta^{w}_{knowH} = -0.30^{***}$ | $\beta^{w}_{knowH} = -0.27^{***}$ |
| Knowledge Medium: Highway | -- | -- |
| Knowledge High: Highway | $\beta^{h}_{knowH} = -0.26^{***}$ | $\beta^{h}_{knowH} = -0.22^{n.s.}$ |
| ***Travel variables*** | | |
| Daily distance: Leisure (kms) | $\beta^{l}_{dist} = -0.008^{***}$ | $\beta^{l}_{dist} = -0.005^{***}$ |

| | | | | | | |
|---|---|---|---|---|---|---|
| Daily distance: Workplace (kms) | $\beta^{w}_{dist}$ | $=$ | $0.007^{***}$ | $\beta^{w}_{dist}$ | $=$ | $0.010^{***}$ |
| EV ownership: Workplace | $\beta^{w}_{VO}$ | $=$ | $0.30^{***}$ | $\beta^{w}_{VO}$ | $=$ | $0.29^{***}$ |
| EV ownership: Highway | $\beta^{h}_{VO}$ | $=$ | $0.21^{***}$ | $\beta^{h}_{VO}$ | $=$ | $0.23^{***}$ |
| Log-likelihood | | $-5143$ | | | $-5135$ | |

**Note:** $^{***}$ denotes significance at a p-value less than 0.01; $^{**}$ denotes significance at a p-value less than 0.05 and $^{*}$ denotes significance at a p-value less than 0.10; -- denotes that the parameter is not statistically significant

MMNL Model 2 assumes the charging time at leisure and workplace to follow negative log normal distribution with mean -7.74 and standard deviation of 3.30 and charging time at highway to follow zero bounded triangular distribution with a spread of -0.07. The model also assumes distance to the nearest charging station to follow zero bounded triangular distribution and waiting time and emissions are assumed to follow negative log normal distribution. The standard deviation for charging time, waiting time, distance to the nearest charging station, and emissions are statistically significant, implying the heterogeneity in preference across individuals for these variables. The higher values of standard deviations also indicate a wide range of taste heterogeneity across individuals for these variables, which can be captured by incorporating more interaction terms. For example, the mean and standard deviation of charging time (which is assumed to follow negative log-normal distribution) is found to be -7.74 and 3.30 respectively. However, mean in the context of negative log-normal distribution is not a direct measure of average charging time itself. Instead, it represents the logarithm of the median charging time. Since the log-normal distribution is skewed, the median is often a more interpretable measure of central tendency than the mean. Exponentiating the mean (-7.74), gives the median of the charging time distribution. The standard deviation of 3.30 reflects the spread or dispersion of the logarithm of charging times. A larger standard deviation indicates a more dispersed distribution. Similarly, exponentiating the standard deviation gives the multiplicative factor by which the median charging time varies. For example, if the median charging time is 0.0004 hours (result of exponentiating -7.74), then the standard deviation being 3.30 implies that the charging times are quite dispersed.

As can be observed from MMNL Model 2 (Table 3), the expected value of charging time is found to be lower than the expected value of waiting time. This is in line with some of the earlier studies that have found willingness to wait for charging to be low as compared to other features (Philipsen et al., 2016). In terms of socio-demographic variables, the coefficient of males for workplace and highway is estimated by keeping leisure place as a base category and is found to be negative ($\beta^{w}_{male} = -0.25\ and\ \beta^{h}_{male} = -0.21$), implying females are more likely than males to choose workplaces and highways for charging their vehicles. Although this might be counter intuitive, a similar finding has been reported in some of the earlier studies (Philipsen et al., 2016, 2015). This could potentially be because of a strong perceived association between charging stations and refuelling stations and hint towards the fact that people cannot dissociate charging stations from refuelling stations which are generally along the highways. A stronger preference for highway charging stations by females could be because of familiarity with refuelling stations and a general wish for similar charging facilities (Halbey et al., 2015). In terms of age, highway is taken as the reference category and the coefficients of leisure and workplace are estimated and found to be negative ($\beta^{l}_{age} = -0.018\ and\ \beta^{w}_{age} = -0.013$), implying a reduced affinity towards leisure and workplace compared to highways with the increase in age. Similarly, the model also indicates that the utility of leisure ($\beta^{l}_{inc} = -0.014$) and highway ($\beta^{h}_{inc} = -0.010$) decreases in comparison to workplace as the income of the choice-maker increases. The model also indicates that buyers with higher knowledge of electric vehicles have lower preference for charging stations at workplaces and highways as compared to buyers with low and medium knowledge about electric vehicles. Similarly, as the average daily distance travelled by a person increases, the utility of leisure decreases ($\beta^{l}_{dist} = -0.005$), and the utility of the workplace increases ($\beta^{w}_{dist} = 0.010$) with respect to the on-highway charging stations.

### 5.2. *Integrated choice and latent variable model*

This section discusses the results obtained from the integrated choice and latent variable modelling. In this model knowledge about electric vehicles is considered as a latent variable. Respondents were asked to self-assess their knowledge about electric vehicles and rate it on a scale of 1- 5. In addition, respondents were also asked to show their agreement to some of statements (as shown in Figure 3) on a scale of 1 – 5. In the first step confirmatory factor analysis (CFA) was conducted to test for the reliability and validity of the indicators. CFA revealed all indicators to have a factor loading of more than 0.5 on the latent factor. Furthermore, the reliability of the latent construct was evaluated using both Cronbach's alpha and composite reliability. Both indicators surpassed the established threshold of 0.7, thus confirming satisfactory reliability levels (Ab Hamid et al., 2017; Ursachi et al., 2015). Average variance extracted was found to be more than 0.5, thus confirming convergent validity. The goodness of fit measures such as TLI, CFI, RMSEA, and SRMR were also found to be satisfactory.

Similar to the estimation of MMNL models, a number of ICLV models were also estimated. Similar to the approach followed in the previous section on the estimation of MMNL models, we estimate two sets of models. The first set of models assume charging time to have the same disutility at all three locations and the second set of models assume charging time at workplace and leisure places to have different disutility as compared to the charging time at highway. We used 1500, 2000 and 2500 MLHS draws to estimate mixed logit models, and the results from 2500 draws are reported below. All the alternative specific coefficients are first assumed to be deterministic and socio-demographic variables are specified only in the measurement model. The results are reported in ICLV Model A-1 (Table A-9). In the subsequent models, socio-demographic variables are specified in discrete choice model as well as the latent variable model. That is, the socio-demographic variables affect the utility of the charging location directly as well as through the latent variable. Furthermore, we also estimate models assuming alternative specific coefficients to be random. The results are presented in ICLV Model A-3 (Table A-9). Similar to the MMNL model presented in the previous section, charging time, waiting time and emissions are assumed to follow the negative log-normal distribution and distance to the nearest charging station is assumed to follow the zero-bounded triangular distribution. A similar approach has been followed for the other set of models where charging time at workplace and leisure places to have different disutility as compared to the charging time at highway. These results are presented in Table A-12. Comparing the log-likelihood values, it can be found that ICLV Model A-3 and ICLV Model A-6 (Table A-9 and Table A-12) are the best-fit models and are presented in Table 4, Table 5, and Table 6 as ICLV Model 1 and ICLV Model 2 respectively.



**Table 4:** Results from ICLV model

| Variables | ICLV Model 1 | ICLV Model 2 |
|---|---|---|
| | **Coefficient** | **Coefficient** |
| ASC: Leisure | $1.42^{***}$ | $1.44^{***}$ |
| ASC: Workplace | $0.95^{***}$ | $0.93^{***}$ |
| ***Charging station attributes*** | | |
| Charging cost (INR) | $\beta_{cc} = -0.01^{***}$ | $\beta_{cc} = -0.01^{***}$ |
| Charging time (hours) | $\mu_{ln,ct} = -5.25^{***}$ | $\mu_{ln,ct}^{lw} = -7.74^{***}$ |
| | $\sigma_{ln,ct} = 2.04^{***}$ | $\sigma_{ln,ct}^{lw} = 3.30^{***}$ |
| | | $b_{tr,ct}^{h} = -0.07^{***}$ |
| Waiting time (hours) | $\mu_{ln,wt} = -1.23^{***}$ | $\mu_{ln,wt} = -1.43^{***}$ |
| | $\sigma_{ln,wt} = 1.10^{***}$ | $\sigma_{ln,wt} = 1.32^{***}$ |
| Distance to the nearest charging station (kms) | $b_{tr,dist} = -0.23^{***}$ | $b_{tr,dist} = -0.23^{***}$ |
| Emissions | $\mu_{ln,em} = -4.40^{***}$ | $\mu_{ln,em} = -4.39^{***}$ |
| | $\sigma_{ln,em} = 2.20^{***}$ | $\sigma_{ln,em} = 2.02^{***}$ |
| ***Influence of knowledge*** | | |
| Knowledge: Workplace | $\lambda_{know} = -0.41^{***}$ | $\lambda_{know} = -0.41^{***}$ |

| | | |
|---|---|---|
| Knowledge: Highway | $\lambda_{know} = -0.04^{n.s.}$ | $\lambda_{know} = -0.03^{n.s.}$ |
| ***Influence of socio-demographics and electric vehicle ownership*** | | |
| Male: Workplace | $\beta^{w}_{male} = -0.20^{***}$ | $\beta^{w}_{male} = -0.20^{***}$ |
| Male: Highway | $\beta^{h}_{male} = -0.17^{**}$ | $\beta^{h}_{male} = -0.22^{**}$ |
| Age: Leisure (Years) | $\beta^{l}_{age} = -0.016^{***}$ | $\beta^{l}_{age} = -0.018^{***}$ |
| Age: Workplace (Years) | $\beta^{w}_{age} = -0.010^{**}$ | $\beta^{w}_{age} = -0.012^{***}$ |
| Income: Leisure (10000s INR) | $\beta^{l}_{inc} = -0.010^{***}$ | $\beta^{l}_{inc} = -0.010^{***}$ |
| Income: Highway (10000s INR) | $\beta^{h}_{inc} = -0.005^{n.s.}$ | $\beta^{h}_{inc} = -0.006^{n.s.}$ |
| ***Travel variables*** | | |
| Daily distance: Leisure (kms) | $\beta^{l}_{dist} = -0.006^{***}$ | $\beta^{l}_{dist} = -0.008^{***}$ |
| Daily distance: Workplace (kms) | $\beta^{w}_{dist} = 0.009^{***}$ | $\beta^{w}_{dist} = 0.007^{***}$ |
| EV ownership: Workplace | $\beta^{w}_{VO} = 0.34^{***}$ | $\beta^{w}_{VO} = 0.33^{***}$ |
| EV ownership: Highway | $\beta^{h}_{VO} = 0.21^{***}$ | $\beta^{h}_{VO} = 0.23^{***}$ |
| Log-likelihood (Choice Model) | $-5130$ | $-5120$ |

Note: *** denotes significance at a p-value less than 0.01; ** denotes significance at a p-value less than 0.05 and * denotes significance at a p-value less than 0.10; n.s. denotes that the parameter is not statistically significant

**Table 4:** Results of structural equation of the structural equation model

| | **ICLV Model Coefficients** | |
|---|---|---|
| | **Knowledge** | |
| | **ICLV Model 1** | **ICLV Model 2** |
| Gender: Male | $0.196^{***}$ | $0.197^{***}$ |
| Age | $0.004^{n.s.}$ | $0.004^{n.s.}$ |
| Income | $-0.013^{***}$ | $-0.012^{***}$ |
| Electric Vehicle Ownership | $0.179^{**}$ | $0.177^{**}$ |
| Standard deviation | $0.850^{***}$ | $0.850^{***}$ |

Note: *** denotes significance at a p-value less than 0.01; ** denotes significance at a p-value less than 0.05 and n.s. denotes that the parameter is not statistically significant

**Table 5:** Results of measurement equation of the structural equation model

| **ICLV Model 1** | **ICLV Model 2** |
|---|---|
| Coefficients of Latent Variables | |
| $d_{know_1} = 1$ | $d_{know_1} = 1$ |
| $d_{know_2} = 2.95^{***}$ | $d_{know_2} = 2.92^{***}$ |
| $d_{know_3} = 2.06^{***}$ | $d_{know_3} = 2.06^{***}$ |
| $d_{know_4} = 1.70^{***}$ | $d_{know_4} = 1.70^{***}$ |
| $d_{know_5} = 1.55^{***}$ | $d_{know_5} = 1.56^{***}$ |
| $d_{know_6} = 1.31^{***}$ | $d_{know_6} = 1.32^{***}$ |
| Thresholds of indicator 1 | |
| $\mu_{know_{11}} = -3.97^{***}$ | $\mu_{know_{11}} = -3.97^{***}$ |
| $\mu_{know_{12}} = -1.31^{***}$ | $\mu_{know_{12}} = -1.31^{***}$ |
| $\mu_{know_{13}} = 1.37^{***}$ | $\mu_{know_{13}} = 1.37^{***}$ |
| $\mu_{know_{14}} = 2.80^{***}$ | $\mu_{know_{14}} = 2.80^{***}$ |
| Thresholds of indicator 2 | |
| $\mu_{know_{21}} = -6.12^{***}$ | $\mu_{know_{21}} = -6.07^{***}$ |
| $\mu_{know_{22}} = -5.07^{***}$ | $\mu_{know_{22}} = -5.04^{***}$ |
| $\mu_{know_{23}} = -2.83^{***}$ | $\mu_{know_{23}} = -2.80^{***}$ |

| | | | |
|---|---|---|---|
| $\mu_{know_{24}}$ | $= -\ 0.47^{n.s.}$ | $\mu_{know_{24}}$ | $= -\ 0.45^{n.s.}$ |
| Thresholds of indicator 3 | | | |
| $\mu_{know_{31}}$ | $= -\ 6.52^{***}$ | $\mu_{know_{31}}$ | $= -\ 6.51^{***}$ |
| $\mu_{know_{32}}$ | $= -\ 5.11^{***}$ | $\mu_{know_{32}}$ | $= -\ 5.10^{***}$ |
| $\mu_{know_{33}}$ | $= -\ 2.62^{***}$ | $\mu_{know_{33}}$ | $= -\ 2.61^{***}$ |
| $\mu_{know_{34}}$ | $= -\ 0.34^{n.s.}$ | $\mu_{know_{34}}$ | $= -\ 0.33^{n.s.}$ |
| Thresholds of indicator 4 | | | |
| $\mu_{know_{41}}$ | $= -\ 4.13^{***}$ | $\mu_{know_{41}}$ | $= -\ 4.13^{***}$ |
| $\mu_{know_{42}}$ | $= -\ 2.57^{***}$ | $\mu_{know_{42}}$ | $= -\ 2.56^{***}$ |
| $\mu_{know_{43}}$ | $= -\ 1.00^{***}$ | $\mu_{know_{43}}$ | $= -\ 0.99^{***}$ |
| $\mu_{know_{44}}$ | $=\ 0.81^{***}$ | $\mu_{know_{44}}$ | $=\ 0.82^{***}$ |
| Thresholds of indicator 5 | | | |
| $\mu_{know_{51}}$ | $= -\ 4.65^{***}$ | $\mu_{know_{51}}$ | $= -\ 4.66^{***}$ |
| $\mu_{know_{52}}$ | $= -\ 3.46^{***}$ | $\mu_{know_{52}}$ | $= -\ 3.47^{***}$ |
| $\mu_{know_{53}}$ | $= -\ 2.37^{***}$ | $\mu_{know_{53}}$ | $= -\ 2.38^{***}$ |
| $\mu_{know_{54}}$ | $= -\ 0.15^{n.s.}$ | $\mu_{know_{54}}$ | $= -\ 0.14^{n.s.}$ |
| Thresholds of indicator 6 | | | |
| $\mu_{know_{61}}$ | $= -\ 4.45^{***}$ | $\mu_{know_{61}}$ | $= -\ 4.45^{***}$ |
| $\mu_{know_{62}}$ | $= -\ 2.89^{***}$ | $\mu_{know_{62}}$ | $= -\ 2.89^{***}$ |
| $\mu_{know_{63}}$ | $= -\ 1.78^{***}$ | $\mu_{know_{63}}$ | $= -\ 1.78^{***}$ |
| $\mu_{know_{64}}$ | $= -\ 0.05^{n.s.}$ | $\mu_{know_{64}}$ | $= -\ 0.04^{n.s.}$ |

Note: *** denotes significance at a p-value less than 0.01; ** denotes significance at a p-value less than 0.05 and n.s. denotes that the parameter is not statistically significant

The alternative specific coefficients as obtained from ICLV models are almost similar to the coefficients estimated from the MMNL models. In terms of the latent variable, we observe that the coefficient of knowledge for highway is not statistically significant indicating same preference for a charging station at a highway or a leisure place among the potential buyers, *ceteris paribus*. On the other hand, the coefficient of knowledge for workplace is found to be negative ($\lambda_{know} = -0.41$). This implies a reduced preference for a workplace charging station as compared to a charging station at a leisure place with increasing knowledge about electric vehicles, *ceteris paribus.* The estimates for other socio-demographic variables are similar to the ones obtained in the MMNL model in the previous section.

The results from the structural component of the model indicate that the binary variable male gender exerts a statistically significant positive impact on knowledge. This indicates that males display a higher knowledge and understanding of electric vehicles. A potential reason for this can be that males have been found to be technologically more enthusiastic and hence more open to accepting a new technology (Bhat and Verma, 2023; Lee et al., 2010; Müller-Seitz et al., 2009). Income is found to have statistically significant negative impact on knowledge of electric vehicles whereas age is not found have a statistically significant impact on the knowledge about electric vehicles. As expected, electric vehicle ownership is found to have a statistically significant influence on knowledge about electric vehicles.

## 6. Conclusions, policy implications, and future scope

The increasing prevalence of electric vehicles underscores the pivotal role that well-planned charging infrastructure plays in fostering their widespread adoption. This study focused on understanding consumer preferences for charging locations, delving into the nuanced impact of crucial attributes like charging time, waiting time, cost, distance to charging station, and emissions. Recognizing the significant investment in developing charging infrastructure networks, this study provides valuable insights for stakeholders, aiding in their comprehension of the preferences of potential electric vehicle users. Beyond practical applications, our findings align with existing academic literature that emphasizes the importance of optimizing charging infrastructure planning. Importantly, the results gleaned from our research can serve as useful inputs for charging station optimisation models, contributing to the more effective and strategic planning of charging stations. Our estimation of discrete choice models reveals negative parameter estimates for various attributes, signalling a decrease in utility as factors like charging time, waiting time, cost, distance to charging station, and emissions increase. Noteworthy is the identification of gender-based differences in charging preferences, with females displaying a stronger inclination towards workplace and highway charging stations. Additionally, our models highlight the influence of daily travel distance on the choice of charging locations. MMNL models and ICLV models were estimated with two different specifications. The first specification was estimated by keeping the coefficient of charging time the same for all the alternatives. The second specification had the charging time coefficient kept the same for workplace and leisure places and a different coefficient for highways. The disutility associated with the charging time at a charging station located on a highway was higher than that associated with charging time at a workplace or a leisure place. By offering nuanced insights into consumer behaviour and preferences, this study contributes valuable information that can inform more effective planning and implementation of charging infrastructure for electric vehicles.

This study has some important policy implications that can help stakeholders and policymakers decide the pathway to expanding the public charging infrastructure. It is, however, crucial to approach the generalisation of research findings with caution, considering the inherent variations among countries in terms of culture and geography. The influence of certain factors, like the accessibility and density of charging infrastructure, may hold greater significance in developing economies. Consequently, applying the research model to diverse geographical contexts may lead to varied outcomes. Firstly, this study finds a significant disparity between the disutility of charging time at the workplace or the leisure place and the highway. Hence, slow chargers can be installed at work and leisure places such as cinemas, shopping malls, and recreational centres where people spend quite some time. However, fast charging stations should be made available along the highways. This study also finds the disutility associated with waiting time to be higher than that of charging time. More charging pods should be provided at the same charging station to reduce waiting time and queue lengths. Moreover, charging time (depending on the charger type) can directly influence the waiting time. Hence providing a mix of charger types (fast and slow) at charging stations can also be critical in increasing the usability of public charging infrastructure in terms of charging time and cost. Secondly, electric vehicles and charging infrastructure have been known as a chicken and egg problem wherein the potential vehicle buyers are worried about the lack of infrastructural network, and the service providers are concerned about the lower demand. Increasing charging stations network density improves the accessibility of public charging infrastructure, which, per this study, increases the usability of the infrastructure. For installing more charging stations, the land requirement increases. Hence, relaxation in land taxation, rents, and planning support can help SMEs install charging stations judiciously per user requirements. Government subsidies on instalments and interest-free electricity lines can help owners lower the charging costs, attracting more users. Thirdly, the infrastructural network for electric vehicles in Indian metropolitan cities has been growing extensively. These include both charging and battery-swapping stations, which private companies mainly operate. However, electric vehicle infrastructure network is still not treated in the same way as conventional refuelling stations and are hence allowed to operate only for limited hours in a day as per the Shops and Commercial Establishments Act 1961. The charging stations should be allowed to operate round the clock to ensure staggered charging patterns among the users. This would ensure reduced waiting times and higher usability. This policy would also help in staggering the load on the grid. Fourth, electric vehicles have been marketed as "green vehicles" and appeal more to environmentally friendly buyers. The fuel source used to derive the energy to charge the electric vehicles significantly impacts determining how green these vehicles are. This study finds that increasing emissions decreases the utility of public charging infrastructure. Using non-renewable sources for powering the charging infrastructure has a negative impact on the perceived value of a charging station. So, along with introducing public charging stations, the government should promote and market using renewable energy to power them. Lastly, as observed from the results, females prefer workplaces more to charge their vehicles than males. Hence, firms with a good proportion of female employees should focus on installing charging stations at the workplace and making these charging stations more female-friendly by providing better security and ease of use. Better facilities, and improved safety, such as CCTV surveillance, police patrolling, and separate sitting areas for males and females, may encourage females to use leisure places more.

Although the results are essential, there is a need for additional research to understand the requirements and preferences of electric vehicle charging stations. First, this research relies on data gathered from potential purchasers of electric four-wheelers, as explained in earlier sections. The absence of demographic information for this particular group makes it challenging to assess the sample's representativeness. Furthermore, the dataset comprises a small proportion of current electric vehicle owners, primarily due to the limited prevalence of electric vehicles in the Indian market. Subsequent studies could benefit from focusing on actual electric vehicle owners when the market share of such vehicles is more substantial, as opposed to potential users. Second, this study does not take into consideration the primary destination choice when considering the charging station location. The relation between primary destination choice and preference for charging location can be explored in future studies. Third, other charging station attributes, such as ease of access and extra facilities, are some factors that have not been considered in the model and can be included in future studies to understand user preferences better.

**Conflict of interests**

The authors declare that they have no conflict of interest.

**Appendix**

**Table A-1:** MNL model with coefficient of charging time at workplace, leisure and highway assumed to be the same

| Variables | MNL Model A-1 | MNL Model A-2 | MNL Model A-3 |
|---|---|---|---|
| | Coefficient | Coefficient | Coefficient |
| ASC: Leisure | $0.66^{***}$ | $1.12^{***}$ | $1.43^{***}$ |
| ASC: Workplace | $1.03^{***}$ | $1.27^{***}$ | $1.07^{***}$ |
| ***Charging station Attributes*** | | | |
| Charging cost (INR) | $\beta_{cc} = -0.01^{***}$ | $\beta_{cc} = -0.01^{***}$ | $\beta_{cc} = -0.01^{***}$ |
| Charging time (INR) | $\beta_{ct} = -0.03^{***}$ | $\beta_{ct} = -0.03^{***}$ | $\beta_{ct} = -0.03^{***}$ |
| Waiting time (hours) | $\beta_{wt} = -0.52^{***}$ | $\beta_{wt} = -0.52^{***}$ | $\beta_{wt} = -0.52^{***}$ |
| Distance to the nearest charging station (kms) | $\beta_{dist} = -0.11^{***}$ | $\beta_{dist} = -0.11^{***}$ | $\beta_{dist} = -0.11^{***}$ |
| Emissions | $\beta_{em} = -0.07^{*}$ | $\beta_{em} = -0.07^{*}$ | $\beta_{em} = -0.07^{*}$ |
| ***Socio-demographic variables*** | | | |
| Male: Workplace | -- | $\beta_{male}^{w} = -0.21^{***}$ | $\beta_{male}^{w} = -0.25^{***}$ |
| Male: Highway | -- | $\beta_{male}^{h} = -0.14^{**}$ | $\beta_{male}^{h} = -0.16^{**}$ |
| Age: Leisure (Years) | -- | $\beta_{age}^{l} = -0.014^{***}$ | $\beta_{age}^{l} = -0.015^{***}$ |
| Age: Workplace (Years) | -- | $\beta_{age}^{w} = -0.011^{**}$ | $\beta_{age}^{w} = -0.011^{**}$ |
| Income: Leisure (10000s INR) | -- | $\beta_{inc}^{l} = -0.013^{***}$ | $\beta_{inc}^{l} = -0.014^{***}$ |
| Income: Highway (10000s INR) | -- | $\beta_{inc}^{h} = -0.008^{**}$ | $\beta_{inc}^{h} = -0.008^{**}$ |
| Knowledge Medium: Workplace | -- | $\beta_{knowM}^{w} = -0.02^{n.s.}$ | $\beta_{knowM}^{w} = -0.06^{n.s.}$ |
| Knowledge High: Workplace | -- | $\beta_{knowH}^{w} = -0.08^{n.s.}$ | $\beta_{knowH}^{w} = -0.30^{***}$ |
| Knowledge Medium: Highway | -- | $\beta_{knowM}^{h} = 0.01^{n.s.}$ | $\beta_{knowM}^{h} = -0.01^{n.s.}$ |
| Knowledge High: Highway | -- | $\beta_{knowH}^{h} = -0.15^{n.s.}$ | $\beta_{knowH}^{h} = -0.27^{***}$ |
| ***Travel variables*** | | | |
| Daily distance: Leisure (kms) | -- | -- | $\beta_{dist}^{l} = -0.008^{***}$ |
| Daily distance: Workplace (kms) | -- | -- | $\beta_{dist}^{w} = 0.006^{***}$ |
| EV ownership: Workplace | -- | -- | $\beta_{VO}^{w} = 0.29^{***}$ |
| EV ownership: Highway | -- | -- | $\beta_{VO}^{h} = 0.20^{***}$ |
| Log-likelihood | $-5205$ | $-5181$ | $-5151$ |

**Note:** $^{***}$ denotes significance at a p-value less than 0.01; $^{**}$ denotes significance at a p-value less than 0.05 and $^{*}$denotes significance at a p-value less than 0.10; $^{n.s.}$ denotes that the parameter is not statistically significant

**Table A-2:** MNL model with coefficient of charging time at workplace and leisure assumed to be different from highway

| Variables | MNL Model A-4 | MNL Model A-5 | MNL Model A-6 |
|---|---|---|---|
| | Coefficient | Coefficient | Coefficient |
| ASC: Leisure | $0.61^{***}$ | $1.07^{***}$ | $1.38^{***}$ |
| ASC: Workplace | $0.97^{***}$ | $1.22^{***}$ | $1.03^{***}$ |
| ***Charging station Attributes*** | | | |
| Charging cost (INR) | $\beta_{cc}=-0.01^{***}$ | $\beta_{cc}=-0.01^{***}$ | $\beta_{cc}=-0.01^{***}$ |
| Charging time (hours) | $\beta_{ct}^{lw}=-0.03^{***}$ | $\beta_{ct}^{lw}=-0.03^{***}$ | $\beta_{ct}^{lw}=-0.03^{***}$ |
| | $\beta_{ct}^{h}=-0.04^{***}$ | $\beta_{ct}^{h}=-0.04^{***}$ | $\beta_{ct}^{h}=-0.04^{***}$ |
| Waiting time (hours) | $\beta_{wt}=-0.52^{***}$ | $\beta_{wt}=-0.52^{***}$ | $\beta_{wt}=-0.52^{***}$ |
| Distance to the nearest charging station (kms) | $\beta_{dist}=-0.11^{***}$ | $\beta_{dist}=-0.11^{***}$ | $\beta_{dist}=-0.11^{***}$ |
| Emissions | $\beta_{em}=-0.07^{***}$ | $\beta_{em}=-0.07^{***}$ | $\beta_{em}=-0.07^{***}$ |
| ***Socio-demographic variables*** | | | |
| Male: Workplace | -- | $\beta_{male}^{w}=-0.21^{***}$ | $\beta_{male}^{w}=-0.25^{***}$ |
| Male: Highway | -- | $\beta_{male}^{h}=-0.14^{**}$ | $\beta_{male}^{h}=-0.16^{**}$ |
| Age: Leisure (Years) | -- | $\beta_{age}^{l}=-0.014^{***}$ | $\beta_{age}^{l}=-0.015^{***}$ |
| Age: Workplace (Years) | -- | $\beta_{age}^{w}=-0.011^{**}$ | $\beta_{age}^{w}=-0.011^{**}$ |
| Income: Leisure (10000s INR) | -- | $\beta_{inc}^{l}=-0.013^{***}$ | $\beta_{inc}^{l}=-0.014^{***}$ |
| Income: Highway (10000s INR) | -- | $\beta_{inc}^{h}=-0.008^{**}$ | $\beta_{inc}^{h}=-0.008^{**}$ |
| Knowledge Medium: Workplace | -- | $\beta_{knowM}^{w}=-0.02^{n.s.}$ | $\beta_{knowM}^{w}=-0.06^{n.s.}$ |
| Knowledge High: Workplace | -- | $\beta_{knowH}^{w}=-0.07^{n.s.}$ | $\beta_{knowH}^{w}=-0.30^{***}$ |
| Knowledge Medium: Highway | -- | $\beta_{knowM}^{h}=\ 0.01^{n.s.}$ | $\beta_{knowM}^{h}=-0.01^{n.s.}$ |
| Knowledge High: Highway | -- | $\beta_{knowH}^{h}=-0.15^{n.s.}$ | $\beta_{knowH}^{h}=-0.27^{***}$ |
| ***Travel variables*** | | | |
| Daily distance: Leisure (kms) | -- | -- | $\beta_{dist}^{l}=-0.008^{***}$ |
| Daily distance: Workplace (kms) | -- | -- | $\beta_{dist}^{w}=\ 0.006^{***}$ |
| EV ownership: Workplace | -- | -- | $\beta_{VO}^{w}=\ 0.28^{***}$ |
| EV ownership: Highway | -- | -- | $\beta_{VO}^{h}=\ 0.19^{***}$ |
| Log-likelihood | $-5202$ | $-5177$ | $-5147$ |

**Note:** $^{***}$ denotes significance at a p-value less than 0.01; $^{**}$ denotes significance at a p-value less than 0.05 and $^{*}$ denotes significance at a p-value less than 0.10; $^{n.s.}$ denotes that the parameter is not statistically significant

**Table A-3:** MMNL model with all service variables assumed to follow negative log-normal distributions and coefficient of charging time at workplace, leisure and highway assumed to be the same

| Variables | MMNL Model A-1 | MMNL Model A-2 | MMNL Model A-3 | MMNL Model A-4 |
|---|---|---|---|---|
| | **Coefficient** | **Coefficient** | **Coefficient** | **Coefficient** |
| ASC: Leisure | $0.68^{***}$ | $1.15^{***}$ | $1.48^{***}$ | $1.46^{***}$ |
| ASC: Workplace | $1.05^{***}$ | $1.30^{***}$ | $1.09^{***}$ | $1.07^{***}$ |
| ***Charging station Attributes*** | | | | |
| Charging cost (INR) | $\beta_{cc} = -0.01^{***}$ | $\beta_{cc} = -0.01^{***}$ | $\beta_{cc} = -0.01^{***}$ | $\beta_{cc} = -0.01^{***}$ |
| Charging time (hours) | $\mu_{ct} = -4.95^{***}$ | $\mu_{ct} = -5.01^{***}$ | $\mu_{ct} = -5.17^{***}$ | $\mu_{ct} = -5.14^{***}$ |
| | $\sigma_{ln,ct} = 1.84^{***}$ | $\sigma_{ln,ct} = 1.88^{***}$ | $\sigma_{ln,ct} = 2.02^{***}$ | $\sigma_{ln,ct} = 1.99^{***}$ |
| Waiting time (hours) | $\mu_{ln,wt} = -1.05^{***}$ | $\mu_{ln,wt} = -1.14^{***}$ | $\mu_{ln,wt} = -1.25^{***}$ | $\mu_{ln,wt} = -1.21^{***}$ |
| | $\sigma_{ln,wt} = 0.94^{**}$ | $\sigma_{ln,wt} = 1.04^{**}$ | $\sigma_{ln,wt} = 1.15^{***}$ | $\sigma_{ln,wt} = 1.14^{***}$ |
| Distance to the nearest charging station (kms) | $\mu_{ln,dist} = -2.16^{***}$ | $\mu_{ln,dist} = -2.15^{***}$ | $\mu_{ln,dist} = -2.14^{***}$ | $\beta_{dist} = -0.12^{***}$ |
| | $\sigma_{ln,dist} = 0.09^{n.s.}$ | $\sigma_{ln,dist} = 0.01^{n.s.}$ | $\sigma_{ln,dist} = 0.02^{n.s.}$ | |
| Emissions | $\mu_{ln,em} = -3.99^{***}$ | $\mu_{ln,em} = -3.95^{***}$ | $\mu_{ln,em} = -4.37^{***}$ | $\mu_{ln,em} = -4.39^{***}$ |
| | $\sigma_{ln,em} = 1.75^{*}$ | $\sigma_{ln,em} = 1.70^{*}$ | $\sigma_{ln,em} = 2.03^{***}$ | $\sigma_{ln,em} = 2.04^{***}$ |
| ***Socio-demographic variables*** | | | | |
| Male: Workplace | -- | $\beta^{w}_{male} = -0.21^{***}$ | $\beta^{w}_{male} = -0.25^{***}$ | $\beta^{w}_{male} = -0.26^{***}$ |
| Male: Highway | -- | $\beta^{h}_{male} = -0.15^{**}$ | $\beta^{h}_{male} = -0.17^{**}$ | $\beta^{h}_{male} = -0.17^{**}$ |
| Age: Leisure (Years) | -- | $\beta^{l}_{age} = -0.017^{***}$ | $\beta^{l}_{age} = -0.015^{***}$ | $\beta^{l}_{age} = -0.015^{***}$ |
| Age: Workplace (Years) | -- | $\beta^{w}_{age} = -0.010^{**}$ | $\beta^{w}_{age} = -0.011^{***}$ | $\beta^{w}_{age} = -0.011^{***}$ |
| Income: Leisure (10000s INR) | -- | $\beta^{l}_{inc} = -0.013^{**}$ | $\beta^{l}_{inc} = -0.14^{***}$ | $\beta^{l}_{inc} = -0.002^{***}$ |
| Income: Highway (10000s INR) | -- | $\beta^{h}_{inc} = -0.009^{**}$ | $\beta^{h}_{inc} = -0.009^{***}$ | $\beta^{h}_{inc} = -0.001^{***}$ |
| Knowledge Medium: Workplace | -- | $\beta^{w}_{knowM} = -0.02^{n.s.}$ | $\beta^{w}_{knowM} = -0.06^{n.s.}$ | $\beta^{w}_{knowM} = -0.02^{n.s.}$ |
| Knowledge High: Workplace | -- | $\beta^{w}_{knowH} = -0.07^{n.s.}$ | $\beta^{w}_{knowH} = -0.31^{***}$ | $\beta^{w}_{knowH} = -0.07^{n.s.}$ |
| Knowledge Medium: Highway | -- | $\beta^{h}_{knowM} = 0.01^{n.s.}$ | $\beta^{h}_{knowM} = 0.02^{n.s.}$ | $\beta^{h}_{knowM} = 0.01^{n.s.}$ |
| Knowledge High: Highway | -- | $\beta^{h}_{knowH} = -0.15^{n.s.}$ | $\beta^{h}_{knowH} = -0.27^{***}$ | $\beta^{h}_{knowH} = -0.15^{n.s.}$ |
| ***Travel variables*** | | | | |
| Daily distance: Leisure (kms) | -- | -- | $\beta^{l}_{dist} = -0.008^{***}$ | $\beta^{l}_{dist} = -0.006^{***}$ |
| Daily distance: Workplace (kms) | -- | -- | $\beta^{w}_{dist} = 0.007^{***}$ | $\beta^{w}_{dist} = 0.007^{***}$ |
| EV ownership: Workplace | -- | -- | $\beta^{w}_{VO} = 0.30^{***}$ | $\beta^{w}_{VO} = 0.31^{***}$ |
| EV ownership: Highway | -- | -- | $\beta^{h}_{VO} = 0.21^{***}$ | $\beta^{h}_{VO} = 0.22^{***}$ |
| Log-likelihood | $-5201$ | $-5179$ | $-5144$ | $-5144$ |

**Note:** $^{***}$ denotes significance at a p-value less than 0.01; $^{**}$ denotes significance at a p-value less than 0.05 and $^{*}$ denotes significance at a p-value less than 0.10; $^{n.s.}$ denotes that the parameter is not statistically significant

**Table A-4:** MMNL model with all service variables assumed to follow negative log-normal distributions and coefficient of charging time at workplace and leisure assumed to be different from highway

| Variables | MMNL Model A-5 | MMNL Model A-6 | MMNL Model A-7 | MMNL Model A-8 |
|---|---|---|---|---|
| | **Coefficient** | **Coefficient** | **Coefficient** | **Coefficient** |
| ASC: Leisure | $0.62^{***}$ | $1.12^{***}$ | $1.43^{***}$ | $1.24^{***}$ |
| ASC: Workplace | $0.99^{***}$ | $1.26^{***}$ | $1.04^{***}$ | $1.15^{***}$ |
| ***Charging station Attributes*** | | | | |
| Charging cost (INR) | $\beta_{cc} = -0.01^{***}$ | $\beta_{cc} = -0.01^{***}$ | $\beta_{cc} = -0.01^{***}$ | $\beta_{cc} = -0.01^{***}$ |
| Charging time (hours) | $\mu_{ln,ct}^{lw} = -6.82^{***}$ | $\mu_{ln,ct}^{lw} = -7.35^{***}$ | $\mu_{ln,ct}^{lw} = -7.68^{***}$ | $\mu_{ln,ct}^{lw} = -7.67^{***}$ |
| | $\sigma_{ln,ct}^{lw} = 2.79^{***}$ | $\sigma_{ln,ct}^{lw} = 3.07^{***}$ | $\sigma_{ln,ct}^{lw} = 3.27^{***}$ | $\sigma_{ln,ct}^{lw} = 3.27^{***}$ |
| | $\mu_{ln,ct}^{h} = -3.36^{***}$ | $\mu_{ln,ct}^{h} = -3.33^{***}$ | $\mu_{ln,ct}^{h} = -3.36^{***}$ | $\beta_{ct}^{h} = -0.03^{***}$ |
| | $\sigma_{ln,ct}^{h} = 0.35^{n.s.}$ | $\sigma_{ln,ct}^{h} = 0.01^{n.s.}$ | $\sigma_{ln,ct}^{h} = 0.03^{n.s.}$ | |
| Waiting time (hours) | $\mu_{ln,wt} = -1.17^{***}$ | $\mu_{ln,wt} = -1.34^{***}$ | $\mu_{ln,wt} = -1.46^{***}$ | $\mu_{ln,wt} = -1.44^{***}$ |
| | $\sigma_{ln,wt} = 1.03^{**}$ | $\sigma_{ln,wt} = 1.19^{**}$ | $\sigma_{ln,wt} = 1.30^{**}$ | $\sigma_{ln,wt} = 1.29^{***}$ |
| Distance to the nearest charging station (kms) | $\mu_{ln,dist} = -2.17^{***}$ | $\mu_{ln,dist} = -2.15^{***}$ | $\mu_{ln,dist} = -2.15^{***}$ | $\beta_{dist} = -0.12^{***}$ |
| | $\sigma_{ln,dist} = 0.07^{n.s.}$ | $\sigma_{ln,dist} = 0.03^{n.s.}$ | $\sigma_{ln,dist} = 0.01^{n.s.}$ | |
| Emissions | $\mu_{ln,em} = -3.65^{***}$ | $\mu_{ln,em} = -3.79^{***}$ | $\mu_{ln,em} = -4.33^{***}$ | $\mu_{ln,em} = -4.32^{***}$ |
| | $\sigma_{ln,em} = 1.49^{*}$ | $\sigma_{ln,em} = 1.58^{**}$ | $\sigma_{ln,em} = 2.01^{***}$ | $\sigma_{ln,em} = 2.00^{***}$ |
| ***Socio-demographic variables*** | | | | |
| Male: Workplace | -- | $\beta_{male}^{w} = -0.21^{***}$ | $\beta_{male}^{w} = -0.25^{***}$ | $\beta_{male}^{w} = -0.25^{***}$ |
| Male: Highway | -- | $\beta_{male}^{h} = -0.19^{**}$ | $\beta_{male}^{h} = -0.21^{**}$ | $\beta_{male}^{h} = -0.21^{***}$ |
| Age: Leisure (Years) | -- | $\beta_{age}^{l} = -0.017^{***}$ | $\beta_{age}^{l} = -0.017^{***}$ | $\beta_{age}^{l} = -0.017^{***}$ |
| Age: Workplace (Years) | -- | $\beta_{age}^{w} = -0.013^{**}$ | $\beta_{age}^{w} = -0.013^{***}$ | $\beta_{age}^{w} = -0.013^{***}$ |
| Income: Leisure (10000s INR) | -- | $\beta_{inc}^{l} = -0.013^{***}$ | $\beta_{inc}^{l} = -0.014^{***}$ | $\beta_{inc}^{l} = -0.002^{***}$ |
| Income: Highway (10000s INR) | -- | $\beta_{inc}^{h} = -0.009^{**}$ | $\beta_{inc}^{h} = -0.010^{***}$ | $\beta_{inc}^{h} = -0.001^{***}$ |
| Knowledge Medium: Workplace | -- | $\beta_{knowM}^{w} = -0.01^{n.s.}$ | $\beta_{knowM}^{w} = -0.06^{n.s.}$ | $\beta_{knowM}^{w} = -0.02^{n.s.}$ |
| Knowledge High: Workplace | -- | $\beta_{knowH}^{w} = -0.07^{n.s.}$ | $\beta_{knowH}^{w} = -0.31^{***}$ | $\beta_{knowH}^{w} = -0.07^{n.s.}$ |
| Knowledge Medium: Highway | -- | $\beta_{knowM}^{h} = 0.01^{n.s.}$ | $\beta_{knowM}^{h} = 0.02^{n.s.}$ | $\beta_{knowM}^{h} = 0.01^{n.s.}$ |
| Knowledge High: Highway | -- | $\beta_{knowH}^{h} = -0.16^{n.s.}$ | $\beta_{knowH}^{h} = -0.24^{**}$ | $\beta_{knowH}^{h} = -0.15^{n.s.}$ |
| ***Travel variables*** | | | | |
| Daily distance: Leisure (kms) | -- | -- | $\beta_{dist}^{l} = -0.005^{***}$ | $\beta_{dist}^{l} = -0.004^{***}$ |
| Daily distance: Workplace (kms) | -- | -- | $\beta_{dist}^{w} = 0.010^{***}$ | $\beta_{dist}^{w} = 0.010^{***}$ |
| EV ownership: Workplace | -- | -- | $\beta_{VO}^{w} = 0.29^{***}$ | $\beta_{VO}^{w} = 0.30^{***}$ |
| EV ownership: Highway | -- | -- | $\beta_{VO}^{h} = 0.24^{***}$ | $\beta_{VO}^{h} = 0.24^{***}$ |
| Log-likelihood | −5198 | −5171 | −5136 | −5136 |

**Note:** $^{***}$ denotes significance at a p-value less than 0.01; $^{**}$ denotes significance at a p-value less than 0.05 and $^{*}$ denotes significance at a p-value less than 0.10; $^{n.s.}$ denotes that the parameter is not statistically significant

**Table A-5:** MMNL model with all service variables assumed to follow negative triangular distributions and coefficient of charging time at workplace, leisure and highway assumed to be the same

| Variables | MMNL Model A-9 | MMNL Model A-10 | MMNL Model A-11 |
|---|---|---|---|
| | Coefficient | Coefficient | Coefficient |
| ASC: Leisure | $0.66^{***}$ | $1.12^{***}$ | $1.43^{***}$ |
| ASC: Workplace | $1.03^{***}$ | $1.27^{***}$ | $1.08^{***}$ |
| ***Charging station Attributes*** | | | |
| Charging cost (INR) | $\beta_{cc} = -0.01^{***}$ | $\beta_{cc} = -0.01^{***}$ | $\beta_{cc} = -0.01^{***}$ |
| Charging time (hours) | $b_{tr,ct} = -0.06^{***}$ | $b_{tr,ct} = -0.06^{***}$ | $b_{tr,ct} = -0.06^{***}$ |
| Waiting time (hours) | $b_{tr,wt} = -1.05^{***}$ | $b_{tr,wt} = -1.05^{***}$ | $b_{tr,wt} = -1.06^{***}$ |
| Distance to the nearest charging station (kms) | $b_{tr,dist} = -0.22^{***}$ | $b_{tr,dist} = -0.23^{***}$ | $b_{tr,dist} = -0.23^{***}$ |
| Emissions | $b_{tr,em} = -0.14^{***}$ | $b_{tr,em} = -0.14^{***}$ | $b_{tr,em} = -0.15^{***}$ |
| ***Socio-demographic variables*** | | | |
| Male: Workplace | -- | $\beta^{w}_{male} = -0.21^{***}$ | $\beta^{w}_{male} = -0.25^{***}$ |
| Male: Highway | -- | $\beta^{h}_{male} = -0.14^{**}$ | $\beta^{h}_{male} = -0.16^{**}$ |
| Age: Leisure (Years) | -- | $\beta^{l}_{age} = -0.014^{***}$ | $\beta^{l}_{age} = -0.015^{***}$ |
| Age: Workplace (Years) | -- | $\beta^{w}_{age} = -0.011^{**}$ | $\beta^{w}_{age} = -0.011^{**}$ |
| Income: Leisure (10000s INR) | -- | $\beta^{l}_{inc} = -0.013^{***}$ | $\beta^{l}_{inc} = -0.014^{***}$ |
| Income: Highway (10000s INR) | -- | $\beta^{h}_{inc} = -0.008^{**}$ | $\beta^{h}_{inc} = -0.008^{**}$ |
| Knowledge Medium: Workplace | -- | $\beta^{w}_{knowM} = -0.02^{n.s.}$ | $\beta^{w}_{knowM} = -0.06^{n.s.}$ |
| Knowledge High: Workplace | -- | $\beta^{w}_{knowH} = -0.08^{n.s.}$ | $\beta^{w}_{knowH} = -0.30^{***}$ |
| Knowledge Medium: Highway | -- | $\beta^{h}_{knowM} = 0.01^{n.s.}$ | $\beta^{h}_{knowM} = 0.01^{n.s.}$ |
| Knowledge High: Highway | -- | $\beta^{h}_{knowH} = -0.15^{n.s.}$ | $\beta^{h}_{knowH} = -0.27^{***}$ |
| ***Travel variables*** | | | |
| Daily distance: Leisure (kms) | -- | -- | $\beta^{l}_{dist} = -0.008^{***}$ |
| Daily distance: Workplace (kms) | -- | -- | $\beta^{w}_{dist} = 0.006^{***}$ |
| EV ownership: Workplace | -- | -- | $\beta^{w}_{VO} = 0.29^{***}$ |
| EV ownership: Highway | -- | -- | $\beta^{h}_{VO} = 0.20^{***}$ |
| Log-likelihood | $-5205$ | $-5182$ | $-5150$ |

**Note:** $^{***}$ denotes significance at a p-value less than 0.01; $^{**}$ denotes significance at a p-value less than 0.05 and $^{*}$ denotes significance at a p-value less than 0.10; $^{n.s.}$ denotes that the parameter is not statistically significant

**Table A-6:** MMNL model with all service variables assumed to follow negative triangular distributions and coefficient of charging time at workplace and leisure assumed to be different from highway

| Variables | MMNL Model A-12 Coefficient | MMNL Model A-13 Coefficient | MMNL Model A-14 Coefficient |
|---|---|---|---|
| ASC: Leisure | $0.61^{***}$ | $0.99^{***}$ | $1.38^{***}$ |
| ASC: Workplace | $0.97^{***}$ | $1.16^{***}$ | $1.03^{***}$ |
| ***Charging station Attributes*** | | | |
| Charging cost (INR) | $\beta_{cc} = -0.01^{***}$ | $\beta_{cc} = -0.01^{***}$ | $\beta_{cc} = -0.01^{***}$ |
| Charging time (hours) | $b_{tr,ct}^{lw} = -0.06^{***}$ | $b_{tr,ct}^{lw} = -0.06^{***}$ | $b_{tr,ct}^{lw} = -0.06^{***}$ |
| | $b_{tr,ct}^{h} = -0.08^{***}$ | $b_{tr,ct}^{h} = -0.08^{***}$ | $b_{tr,ct}^{h} = -0.08^{***}$ |
| Waiting time (hours) | $b_{tr,wt} = -1.05^{***}$ | $b_{tr,wt} = -1.05^{***}$ | $b_{tr,wt} = -1.06^{***}$ |
| Distance to the nearest charging station (kms) | $b_{tr,dist} = -0.22^{***}$ | $b_{tr,dist} = -0.23^{***}$ | $b_{tr,dist} = -0.23^{***}$ |
| Emissions | $b_{tr,em} = -0.14^{***}$ | $b_{tr,em} = -0.14^{***}$ | $b_{tr,em} = -0.15^{***}$ |
| ***Socio-demographic variables*** | | | |
| Male: Workplace | -- | $\beta_{male}^{w} = -0.21^{***}$ | $\beta_{male}^{w} = -0.25^{***}$ |
| Male: Highway | -- | $\beta_{male}^{h} = -0.14^{**}$ | $\beta_{male}^{h} = -0.16^{**}$ |
| Age: Leisure (Years) | -- | $\beta_{age}^{l} = -0.014^{***}$ | $\beta_{age}^{l} = -0.015^{***}$ |
| Age: Workplace (Years) | -- | $\beta_{age}^{w} = -0.011^{**}$ | $\beta_{age}^{w} = -0.011^{**}$ |
| Income: Leisure (10000s INR) | -- | $\beta_{inc}^{l} = -0.013^{***}$ | $\beta_{inc}^{l} = -0.014^{***}$ |
| Income: Highway (10000s INR) | -- | $\beta_{inc}^{h} = -0.008^{**}$ | $\beta_{inc}^{h} = -0.008^{**}$ |
| Knowledge Medium: Workplace | -- | $\beta_{knowM}^{w} = -0.02^{n.s.}$ | $\beta_{knowM}^{w} = -0.06^{n.s.}$ |
| Knowledge High: Workplace | -- | $\beta_{knowH}^{w} = -0.07^{n.s.}$ | $\beta_{knowH}^{w} = -0.30^{***}$ |
| Knowledge Medium: Highway | -- | $\beta_{knowM}^{h} = 0.01^{n.s.}$ | $\beta_{knowM}^{h} = 0.02^{n.s.}$ |
| Knowledge High: Highway | -- | $\beta_{knowH}^{h} = -0.15^{n.s.}$ | $\beta_{knowH}^{h} = -0.27^{***}$ |
| ***Travel variables*** | | | |
| Daily distance: Leisure (kms) | -- | -- | $\beta_{dist}^{l} = -0.008^{***}$ |
| Daily distance: Workplace (kms) | -- | -- | $\beta_{dist}^{w} = 0.006^{***}$ |
| EV ownership: Workplace | -- | -- | $\beta_{VO}^{w} = 0.28^{***}$ |
| EV ownership: Highway | -- | -- | $\beta_{VO}^{h} = 0.19^{***}$ |
| Log-likelihood | −5204 | −5181 | −5149 |

**Note:** $^{***}$ denotes significance at a p-value less than 0.01; $^{**}$ denotes significance at a p-value less than 0.05 and $^{*}$ denotes significance at a p-value less than 0.10; $^{n.s.}$ denotes that the parameter is not statistically significant

**Table A-7:** MMNL model with charging time, waiting time and emissions assumed to follow negative log-normal distributions and accessibility assumed to follow triangular distribution and coefficient of charging time at workplace, leisure and highway assumed to be the same

| Variables | MMNL Model A-15 | MMNL Model A-16 | MMNL Model A-17 | MMNL Model A-18 |
|---|---|---|---|---|
| | Coefficient | Coefficient | Coefficient | Coefficient |
| ASC: Leisure | $0.68^{***}$ | $1.15^{***}$ | $1.48^{***}$ | $1.49^{***}$ |
| ASC: Workplace | $1.05^{***}$ | $1.29^{***}$ | $1.09^{***}$ | $1.09^{***}$ |
| ***Charging station Attributes*** | | | | |
| Charging cost (INR) | $\beta_{cc} = -0.01^{***}$ | $\beta_{cc} = -0.01^{***}$ | $\beta_{cc} = -0.01^{***}$ | $\beta_{cc} = -0.01^{***}$ |
| Charging time (hours) | $\mu_{ln,ct} = -4.94^{***}$ | $\mu_{ln,ct} = -5.01^{***}$ | $\mu_{ln,ct} = -5.17^{***}$ | $\mu_{ln,ct} = -5.12^{***}$ |
| | $\sigma_{ln,ct} = 1.84^{***}$ | $\sigma_{ln,ct} = 1.88^{***}$ | $\sigma_{ln,ct} = 2.01^{***}$ | $\sigma_{ln,ct} = 2.01^{***}$ |
| Waiting time (hours) | $\mu_{ln,wt} = -1.09^{***}$ | $\mu_{ln,wt} = -1.16^{***}$ | $\mu_{ln,wt} = -1.23^{***}$ | $\mu_{ln,wt} = -1.23^{***}$ |
| | $\sigma_{ln,wt} = 0.98^{***}$ | $\sigma_{ln,wt} = 1.06^{***}$ | $\sigma_{ln,wt} = 1.13^{***}$ | $\sigma_{ln,wt} = 1.13^{***}$ |
| Distance to the nearest charging station (kms) | $b_{tr,dist} = -0.23^{***}$ | $b_{tr,dist} = -0.23^{***}$ | $b_{tr,dist} = -0.24^{***}$ | $b_{tr,dist} = -0.23^{***}$ |
| Emissions | $\mu_{ln,em} = -4.07^{***}$ | $\mu_{ln,em} = -4.43^{***}$ | $\mu_{ln,em} = -4.48^{***}$ | $\mu_{ln,em} = -4.39^{***}$ |
| | $\sigma_{ln,em} = 1.82^{*}$ | $\sigma_{ln,em} = 1.89^{***}$ | $\sigma_{ln,em} = 2.10^{***}$ | $\sigma_{ln,em} = 2.05^{***}$ |
| ***Socio-demographic variables*** | | | | |
| Male: Workplace | -- | $\beta^{w}_{male} = -0.21^{***}$ | $\beta^{w}_{male} = -0.25^{***}$ | $\beta^{w}_{male} = -0.25^{***}$ |
| Male: Highway | -- | $\beta^{h}_{male} = -0.15^{**}$ | $\beta^{h}_{male} = -0.17^{**}$ | $\beta^{h}_{male} = -0.17^{**}$ |
| Age: Leisure (Years) | -- | $\beta^{l}_{age} = -0.017^{***}$ | $\beta^{l}_{age} = -0.015^{***}$ | $\beta^{l}_{age} = -0.015^{***}$ |
| Age: Workplace (Years) | -- | $\beta^{w}_{age} = -0.010^{**}$ | $\beta^{w}_{age} = -0.011^{***}$ | $\beta^{w}_{age} = -0.011^{***}$ |
| Income: Leisure (10000s INR) | -- | $\beta^{l}_{inc} = -0.013^{***}$ | $\beta^{l}_{inc} = -0.014^{***}$ | $\beta^{l}_{inc} = -0.014^{***}$ |
| Income: Highway (10000s INR) | -- | $\beta^{h}_{inc} = -0.009^{**}$ | $\beta^{h}_{inc} = -0.009^{***}$ | $\beta^{h}_{inc} = -0.009^{***}$ |
| Knowledge Medium: Workplace | -- | $\beta^{w}_{knowM} = -0.02^{n.s.}$ | $\beta^{w}_{knowM} = -0.06^{n.s.}$ | -- |
| Knowledge High: Workplace | -- | $\beta^{w}_{knowH} = -0.07^{n.s.}$ | $\beta^{w}_{knowH} = -0.31^{***}$ | $\beta^{w}_{knowH} = -0.30^{***}$ |
| Knowledge Medium: Highway | -- | $\beta^{h}_{knowM} = 0.01^{n.s.}$ | $\beta^{h}_{knowM} = 0.01^{n.s.}$ | -- |
| Knowledge High: Highway | -- | $\beta^{h}_{knowH} = -0.15^{n.s.}$ | $\beta^{h}_{knowH} = -0.27^{***}$ | $\beta^{h}_{knowH} = -0.26^{***}$ |
| ***Travel variables*** | | | | |
| Daily distance: Leisure (kms) | -- | -- | $\beta^{l}_{dist} = -0.008^{***}$ | $\beta^{l}_{dist} = -0.008^{***}$ |
| Daily distance: Workplace (kms) | -- | -- | $\beta^{w}_{dist} = 0.007^{***}$ | $\beta^{w}_{dist} = 0.007^{***}$ |
| EV ownership: Workplace | -- | -- | $\beta^{w}_{VO} = 0.31^{***}$ | $\beta^{w}_{VO} = 0.30^{***}$ |
| EV ownership: Highway | -- | -- | $\beta^{h}_{VO} = 0.21^{***}$ | $\beta^{h}_{VO} = 0.21^{***}$ |
| Log-likelihood | −5201 | −5180 | −5143 | −5143 |

**Note:** $^{***}$ denotes significance at a p-value less than 0.01; $^{**}$ denotes significance at a p-value less than 0.05 and $^{*}$ denotes significance at a p-value less than 0.10; $^{n.s.}$ denotes that the parameter is not statistically significant

**Table A-8:** MMNL model with charging time, waiting time and emissions assumed to follow negative log-normal distributions and accessibility assumed to follow triangular distribution and coefficient of charging time at workplace and leisure assumed to be different from highway

| Variables | MMNL Model A-19 | MMNL Model A-20 | MMNL Model A-21 | MMNL Model A-22 |
|---|---|---|---|---|
| | Coefficient | Coefficient | Coefficient | Coefficient |
| ASC: Leisure | $0.63^{***}$ | $1.12^{***}$ | $1.43^{***}$ | $1.45^{***}$ |
| ASC: Workplace | $0.99^{***}$ | $1.26^{***}$ | $1.05^{***}$ | $1.02^{***}$ |
| ***Charging station Attributes*** | | | | |
| Charging cost (INR) | $\beta_{cc} = -0.01^{***}$ | $\beta_{cc} = -0.01^{***}$ | $\beta_{cc} = -0.01^{***}$ | $\beta_{cc} = -0.01^{***}$ |
| Charging time (hours) | $\mu_{ln,ct}^{lw} = -6.91^{***}$<br>$\sigma_{ln,ct}^{lw} = 2.84^{***}$<br>$\mu_{ln,ct}^{h} = -3.32^{***}$<br>$\sigma_{ln,ct}^{h} = 0.04^{n.s.}$ | $\mu_{ln,ct}^{lw} = -7.34^{***}$<br>$\sigma_{ln,ct}^{lw} = 3.07^{***}$<br>$\mu_{ln,ct}^{h} = -3.34^{***}$<br>$\sigma_{ln,ct}^{h} = 0.13^{n.s.}$ | $\mu_{ln,ct}^{lw} = -7.65$<br>$\sigma_{ln,ct}^{lw} = 3.24^{***}$<br>$\mu_{ln,ct}^{h} = -3.37^{***}$<br>$\sigma_{ln,ct}^{h} = 0.11^{n.s.}$ | $\mu_{ln,ct}^{lw} = -7.74^{***}$<br>$\sigma_{ln,ct}^{lw} = 3.30^{***}$<br>$b_{tr,ct}^{h} = -0.07^{***}$ |
| Waiting time (hours) | $\mu_{ln,wt} = -1.19^{***}$<br>$\sigma_{ln,wt} = 1.06^{***}$ | $\mu_{ln,wt} = -1.33^{***}$<br>$\sigma_{ln,wt} = 1.18^{***}$ | $\mu_{ln,wt} = -1.42^{***}$<br>$\sigma_{ln,wt} = 1.27^{***}$ | $\mu_{ln,wt} = -1.40^{***}$<br>$\sigma_{ln,wt} = 1.25^{***}$ |
| Distance to the nearest charging station (kms) | $b_{tr,dist} = -0.23^{***}$ | $b_{tr,dist} = -0.23^{***}$ | $b_{tr,dist} = -0.23^{***}$ | $b_{tr,dist} = -0.23^{***}$ |
| Emissions | $\mu_{ln,em} = -3.82^{***}$<br>$\sigma_{ln,em} = 1.61^{***}$ | $\mu_{ln,em} = -4.04^{***}$<br>$\sigma_{ln,em} = 1.76^{*}$ | $\mu_{ln,em} = -4.34^{***}$<br>$\sigma_{ln,em} = 2.02^{***}$ | $\mu_{ln,em} = -4.31^{***}$<br>$\sigma_{ln,em} = 2.00^{***}$ |
| ***Socio-demographic variables*** | | | | |
| Male: Workplace | -- | $\beta_{male}^{w} = -0.21^{***}$ | $\beta_{male}^{w} = -0.25^{***}$ | $\beta_{male}^{w} = -0.25^{***}$ |
| Male: Highway | -- | $\beta_{male}^{h} = -0.19^{**}$ | $\beta_{male}^{h} = -0.21^{**}$ | $\beta_{male}^{h} = -0.21^{***}$ |
| Age: Leisure (Years) | -- | $\beta_{age}^{l} = -0.02^{***}$ | $\beta_{age}^{l} = -0.017^{***}$ | $\beta_{age}^{l} = -0.018^{***}$ |
| Age: Workplace (Years) | -- | $\beta_{age}^{w} = -0.01^{**}$ | $\beta_{age}^{w} = -0.013^{***}$ | $\beta_{age}^{w} = -0.013^{***}$ |
| Income: Leisure (10000s INR) | -- | $\beta_{inc}^{l} = -0.020^{**}$ | $\beta_{inc}^{l} = -0.014^{***}$ | $\beta_{inc}^{l} = -0.014^{***}$ |
| Income: Highway (10000s INR) | -- | $\beta_{inc}^{h} = -0.013^{**}$ | $\beta_{inc}^{h} = -0.010^{***}$ | $\beta_{inc}^{h} = -0.010^{***}$ |
| Knowledge Medium: Workplace | -- | $\beta_{knowM}^{w} = -0.02^{n.s.}$ | $\beta_{knowM}^{w} = -0.06^{n.s.}$ | -- |
| Knowledge High: Workplace | -- | $\beta_{knowH}^{w} = -0.07^{n.s.}$ | $\beta_{knowH}^{w} = -0.31^{***}$ | $\beta_{knowH}^{w} = -0.27^{***}$ |
| Knowledge Medium: Highway | -- | $\beta_{knowM}^{h} = 0.01^{n.s.}$ | $\beta_{knowM}^{h} = 0.02^{n.s.}$ | -- |
| Knowledge High: Highway | -- | $\beta_{knowH}^{h} = -0.16^{n.s.}$ | $\beta_{knowH}^{h} = -0.24^{**}$ | $\beta_{knowH}^{h} = -0.22^{**}$ |
| ***Travel variables*** | | | | |
| Daily distance: Leisure (kms) | -- | -- | $\beta_{dist}^{l} = -0.005^{**}$ | $\beta_{dist}^{l} = -0.005^{**}$ |
| Daily distance: Workplace (kms) | -- | -- | $\beta_{dist}^{w} = 0.010^{***}$ | $\beta_{dist}^{w} = 0.010^{***}$ |
| EV ownership: Workplace | -- | -- | $\beta_{VO}^{w} = 0.29^{***}$ | $\beta_{VO}^{w} = 0.29^{***}$ |
| EV ownership: Highway | -- | -- | $\beta_{VO}^{h} = 0.24^{***}$ | $\beta_{VO}^{h} = 0.23^{***}$ |
| Log-likelihood | $-5198$ | $-5174$ | $-5135$ | $-5135$ |

**Note:** $^{***}$ denotes significance at a p-value less than 0.01; $^{**}$ denotes significance at a p-value less than 0.05 and $^{*}$ denotes significance at a p-value less than 0.10; $^{n.s.}$ denotes that the parameter is not statistically significant

**Table A-9:** ICLV model with coefficient of charging time at workplace, leisure and highway assumed to be the same

| Variables | ICLV Model A-1<br>Coefficient | ICLV Model A-2<br>Coefficient | ICLV Model A-3<br>Coefficient |
|---|---|---|---|
| ASC: Leisure | $0.78^{***}$ | $1.46^{***}$ | $1.52^{***}$ |
| ASC: Workplace | $0.87^{***}$ | $1.00^{***}$ | $1.00^{***}$ |
| ***Charging station attributes*** | | | |
| Charging cost (INR) | $\beta_{cc} = -0.01^{***}$ | $\beta_{cc} = -0.01^{***}$ | $\beta_{cc} = -0.01^{***}$ |
| Charging time (hours) | $\beta_{ct} = -0.03^{***}$ | $\beta_{ct} = -0.03^{***}$ | $\mu_{ln,ct} = -5.25^{***}$<br>$\sigma_{ln,ct} = 2.04^{***}$ |
| Waiting time (hours) | $\beta_{wt} = -0.52^{***}$ | $\beta_{wt} = -0.52^{***}$ | $\mu_{ln,wt} = -1.23^{***}$<br>$\sigma_{ln,wt} = 1.10^{***}$ |
| Distance to the nearest charging station (kms) | $\beta_{dist} = -0.11^{***}$ | $\beta_{dist} = -0.11^{***}$ | $b_{tr,dist} = -0.23^{***}$ |
| Emissions | $\beta_{em} = -0.07^{*}$ | $\beta_{em} = -0.07^{*}$ | $\mu_{ln,em} = -4.40^{***}$<br>$\sigma_{ln,em} = 2.20^{***}$ |
| ***Influence of Knowledge*** | | | |
| Knowledge: Workplace | $\lambda_{know} = -0.40^{***}$ | $\lambda_{know} = -0.42^{***}$ | $\lambda_{know} = -0.41^{***}$ |
| Knowledge: Highway | $\lambda_{know} = -0.06^{n.s.}$ | $\lambda_{know} = -0.03^{n.s.}$ | $\lambda_{know} = -0.04^{n.s.}$ |
| ***Influence of socio-demographics and electric vehicle ownership*** | | | |
| Male: Workplace | -- | $\beta^{w}_{male} = -0.20^{***}$ | $\beta^{w}_{male} = -0.20^{***}$ |
| Male: Highway | -- | $\beta^{h}_{male} = -0.17^{**}$ | $\beta^{h}_{male} = -0.17^{**}$ |
| Age: Leisure (Years) | -- | $\beta^{l}_{age} = -0.016^{***}$ | $\beta^{l}_{age} = -0.016^{***}$ |
| Age: Workplace (Years) | -- | $\beta^{w}_{age} = -0.010^{**}$ | $\beta^{w}_{age} = -0.010^{***}$ |
| Income: Leisure (10000s INR) | -- | $\beta^{l}_{inc} = -0.009^{***}$ | $\beta^{l}_{inc} = -0.010^{***}$ |
| Income: Highway (10000s INR) | -- | $\beta^{h}_{inc} = -0.004^{n.s.}$ | $\beta^{h}_{inc} = -0.005^{n.s.}$ |
| ***Travel variables*** | | | |
| Daily distance: Leisure (kms) | $\beta^{l}_{dist} = -0.006^{***}$ | $\beta^{l}_{dist} = -0.006^{***}$ | $\beta^{l}_{dist} = -0.006^{***}$ |
| Daily distance: Workplace (kms) | $\beta^{w}_{dist} = 0.008^{***}$ | $\beta^{w}_{dist} = 0.008^{***}$ | $\beta^{w}_{dist} = 0.009^{***}$ |
| EV ownership: Workplace | -- | $\beta^{w}_{VO} = 0.32^{***}$ | $\beta^{w}_{VO} = 0.34^{***}$ |
| EV ownership: Highway | -- | $\beta^{h}_{VO} = 0.19^{**}$ | $\beta^{h}_{VO} = 0.21^{***}$ |
| Log-likelihood (Choice model) | $-5153$ | $-5136$ | $-5130$ |

**Note:** $^{***}$ denotes significance at a p-value less than 0.01; $^{**}$ denotes significance at a p-value less than 0.05 and $^{*}$ denotes significance at a p-value less than 0.10; $^{n.s.}$ denotes that the parameter is not statistically significant

**Table A-10:** Results of structural equation of the structural equation model

| Variables | ICLV Model Coefficients | | |
|---|---|---|---|
| | Knowledge | | |
| | ICLV Model A-1 | ICLV Model A-2 | ICLV Model A-3 |
| Gender: Male | $0.207^{***}$ | $0.195^{***}$ | $0.196^{***}$ |
| Age | $0.003^{n.s.}$ | $0.004^{n.s.}$ | $0.004^{n.s.}$ |
| Income | $-0.013^{***}$ | $-0.012^{***}$ | $-0.012^{***}$ |
| Electric Vehicle Ownership | $0.164^{**}$ | $0.189^{**}$ | $0.179^{**}$ |
| Standard deviation | $0.837^{***}$ | $0.844^{***}$ | $0.850^{***}$ |

**Note:** $^{***}$ denotes significance at a p-value less than 0.01; $^{**}$ denotes significance at a p-value less than 0.05 and $^{*}$ denotes significance at a p-value less than 0.10; $^{n.s.}$ denotes that the parameter is not statistically significant

**Table A-11:** Results of measurement equation of the structural equation model

| ICLV Model A-1 | ICLV Model A-2 | ICLV Model A-3 |
|---|---|---|
| Coefficients of Latent Variables | | |
| $d_{know_1} = 1$ | $d_{know_1} = 1$ | $d_{know_1} = 1$ |
| $d_{know_2} = 2.96^{***}$ | $d_{know_2} = 2.95^{***}$ | $d_{know_2} = 2.95^{***}$ |
| $d_{know_3} = 2.09^{***}$ | $d_{know_3} = 2.09^{***}$ | $d_{know_3} = 2.06^{***}$ |
| $d_{know_4} = 1.73^{***}$ | $d_{know_4} = 1.72^{***}$ | $d_{know_4} = 1.70^{***}$ |
| $d_{know_5} = 1.58^{***}$ | $d_{know_5} = 1.56^{***}$ | $d_{know_5} = 1.55^{***}$ |
| $d_{know_6} = 1.34^{***}$ | $d_{know_6} = 1.32^{***}$ | $d_{know_6} = 1.31^{***}$ |
| Thresholds of indicator 1 | | |
| $\mu_{know_{11}} = -\ 3.99^{***}$ | $\mu_{know_{11}} = -\ 3.96^{***}$ | $\mu_{know_{11}} = -\ 3.97^{***}$ |
| $\mu_{know_{12}} = -\ 1.34^{***}$ | $\mu_{know_{12}} = -\ 1.30^{***}$ | $\mu_{know_{12}} = -\ 1.31^{***}$ |
| $\mu_{know_{13}} = 1.33^{***}$ | $\mu_{know_{13}} = 1.37^{***}$ | $\mu_{know_{13}} = 1.37^{***}$ |
| $\mu_{know_{14}} = 2.78^{***}$ | $\mu_{know_{14}} = 2.81^{***}$ | $\mu_{know_{14}} = 2.80^{***}$ |
| Thresholds of indicator 2 | | |
| $\mu_{know_{21}} = -\ 6.17^{***}$ | $\mu_{know_{21}} = -\ 6.08^{***}$ | $\mu_{know_{21}} = -\ 6.12^{***}$ |
| $\mu_{know_{22}} = -\ 5.13^{***}$ | $\mu_{know_{22}} = -\ 5.04^{***}$ | $\mu_{know_{22}} = -\ 5.07^{***}$ |
| $\mu_{know_{23}} = -\ 2.89^{***}$ | $\mu_{know_{23}} = -\ 2.80^{***}$ | $\mu_{know_{23}} = -\ 2.83^{***}$ |
| $\mu_{know_{24}} = -\ 0.55^{n.s.}$ | $\mu_{know_{24}} = -\ 0.45^{n.s.}$ | $\mu_{know_{24}} = -\ 0.47^{n.s.}$ |
| Thresholds of indicator 3 | | |
| $\mu_{know_{31}} = -\ 6.58^{***}$ | $\mu_{know_{31}} = -\ 6.53^{***}$ | $\mu_{know_{31}} = -\ 6.52^{***}$ |
| $\mu_{know_{32}} = -\ 5.18^{***}$ | $\mu_{know_{32}} = -\ 5.11^{***}$ | $\mu_{know_{32}} = -\ 5.11^{***}$ |
| $\mu_{know_{33}} = -\ 2.69^{***}$ | $\mu_{know_{33}} = -\ 2.62^{***}$ | $\mu_{know_{33}} = -\ 2.62^{***}$ |
| $\mu_{know_{34}} = -\ 0.40^{n.s.}$ | $\mu_{know_{34}} = -\ 0.34^{n.s.}$ | $\mu_{know_{34}} = -\ 0.34^{n.s.}$ |
| Thresholds of indicator 4 | | |
| $\mu_{know_{41}} = -\ 4.19^{***}$ | $\mu_{know_{41}} = -\ 4.13^{***}$ | $\mu_{know_{41}} = -\ 4.13^{***}$ |
| $\mu_{know_{42}} = -\ 2.62^{***}$ | $\mu_{know_{42}} = -\ 2.56^{***}$ | $\mu_{know_{42}} = -\ 2.57^{***}$ |
| $\mu_{know_{43}} = -\ 1.05^{***}$ | $\mu_{know_{43}} = -\ 0.99^{***}$ | $\mu_{know_{43}} = -\ 1.00^{***}$ |
| $\mu_{know_{44}} = 0.76^{***}$ | $\mu_{know_{44}} = 0.82^{***}$ | $\mu_{know_{44}} = 0.81^{***}$ |
| Thresholds of indicator 5 | | |
| $\mu_{know_{51}} = -\ 4.71^{***}$ | $\mu_{know_{51}} = -\ 4.65^{***}$ | $\mu_{know_{51}} = -\ 4.65^{***}$ |
| $\mu_{know_{52}} = -\ 3.52^{***}$ | $\mu_{know_{52}} = -\ 3.46^{***}$ | $\mu_{know_{52}} = -\ 3.46^{***}$ |
| $\mu_{know_{53}} = -\ 2.43^{***}$ | $\mu_{know_{53}} = -\ 2.37^{***}$ | $\mu_{know_{53}} = -\ 2.37^{***}$ |
| $\mu_{know_{54}} = -\ 0.20^{n.s.}$ | $\mu_{know_{54}} = -\ 0.14^{n.s.}$ | $\mu_{know_{54}} = -\ 0.15^{n.s.}$ |
| Thresholds of indicator 6 | | |
| $\mu_{know_{61}} = -\ 4.50^{***}$ | $\mu_{know_{61}} = -\ 4.45^{***}$ | $\mu_{know_{61}} = -\ 4.45^{***}$ |
| $\mu_{know_{62}} = -\ 2.94^{***}$ | $\mu_{know_{62}} = -\ 2.89^{***}$ | $\mu_{know_{62}} = -\ 2.89^{***}$ |
| $\mu_{know_{63}} = -\ 1.83^{***}$ | $\mu_{know_{63}} = -\ 1.78^{***}$ | $\mu_{know_{63}} = -\ 1.78^{***}$ |
| $\mu_{know_{64}} = -\ 0.09^{n.s.}$ | $\mu_{know_{64}} = -\ 0.05^{n.s.}$ | $\mu_{know_{64}} = -\ 0.05^{n.s.}$ |

**Note:** $^{***}$ denotes significance at a p-value less than 0.01 and $^{n.s.}$ denotes that the parameter is not statistically significant

**Table A-12:** ICLV model with coefficient of charging time at workplace and leisure assumed to be different from highway

| Variables | ICLV Model A-4 | ICLV Model A-5 | ICLV Model A-6 |
|---|---|---|---|
| | **Coefficient** | **Coefficient** | **Coefficient** |
| ASC: Leisure | $0.74^{***}$ | $1.42^{***}$ | $1.44^{***}$ |
| ASC: Workplace | $0.83^{***}$ | $0.95^{***}$ | $0.93^{***}$ |
| ***Charging station attributes*** | | | |
| Charging cost (INR) | $\beta_{cc} = -0.01^{***}$ | $\beta_{cc} = -0.01^{***}$ | $\beta_{cc} = -0.01^{***}$ |
| Charging time (hours) | $\beta^{lw}_{ct} = -0.03^{***}$ | $\beta^{lw}_{ct} = -0.03^{***}$ | $\mu^{lw}_{ln,ct} = -7.74^{***}$ <br> $\sigma^{lw}_{ln,ct} = 3.30^{***}$ |
| | $\beta^{h}_{ct} = -0.04^{***}$ | $\beta^{h}_{ct} = -0.04^{***}$ | $b^{h}_{tr,ct} = -0.07^{***}$ |
| Waiting time (hours) | $\beta_{wt} = -0.52^{***}$ | $\beta_{wt} = -0.52^{***}$ | $\mu_{ln,wt} = -1.43^{***}$ <br> $\sigma_{ln,wt} = 1.32^{***}$ |
| Distance to the nearest charging station (kms) | $\beta_{dist} = -0.11^{***}$ | $\beta_{dist} = -0.11^{***}$ | $b_{tr,dist} = -0.23^{***}$ |
| Emissions | $\beta_{em} = -0.07^{*}$ | $\beta_{em} = -0.07^{*}$ | $\mu_{ln,em} = -4.39^{***}$ <br> $\sigma_{ln,em} = 2.02^{***}$ |
| ***Influence of knowledge*** | | | |
| Knowledge: Workplace | $\lambda_{know} = -0.40^{***}$ | $\lambda_{know} = -0.42^{***}$ | $\lambda_{know} = -0.41^{***}$ |
| Knowledge: Highway | $\lambda_{know} = -0.06^{n.s.}$ | $\lambda_{know} = -0.03^{n.s.}$ | $\lambda_{know} = -0.03^{n.s.}$ |
| ***Influence of socio-demographics and electric vehicle ownership*** | | | |
| Male: Workplace | -- | $\beta^{w}_{male} = -0.20^{***}$ | $\beta^{w}_{male} = -0.20^{***}$ |
| Male: Highway | -- | $\beta^{h}_{male} = -0.17^{**}$ | $\beta^{h}_{male} = -0.22^{**}$ |
| Age: Leisure (Years) | -- | $\beta^{l}_{age} = -0.015^{***}$ | $\beta^{l}_{age} = -0.018^{***}$ |
| Age: Workplace (Years) | -- | $\beta^{w}_{age} = -0.010^{**}$ | $\beta^{w}_{age} = -0.012^{***}$ |
| Income: Leisure (10000s INR) | -- | $\beta^{l}_{inc} = -0.009^{***}$ | $\beta^{l}_{inc} = -0.010^{***}$ |
| Income: Highway (10000s INR) | -- | $\beta^{h}_{inc} = -0.004^{n.s.}$ | $\beta^{h}_{inc} = -0.006^{n.s.}$ |
| ***Travel variables*** | | | |
| Daily distance: Leisure (kms) | $\beta^{l}_{dist} = -0.006^{***}$ | $\beta^{l}_{dist} = -0.008^{***}$ | $\beta^{l}_{dist} = -0.008^{***}$ |
| Daily distance: Workplace (kms) | $\beta^{w}_{dist} = 0.008^{***}$ | $\beta^{w}_{dist} = 0.007^{***}$ | $\beta^{w}_{dist} = 0.007^{***}$ |
| EV ownership: Workplace | -- | $\beta^{w}_{VO} = 0.32^{***}$ | $\beta^{w}_{VO} = 0.33^{***}$ |
| EV ownership: Highway | -- | $\beta^{h}_{VO} = 0.19^{***}$ | $\beta^{h}_{VO} = 0.23^{***}$ |
| Log-likelihood | $-5149$ | $-5131$ | $-5120$ |

**Note:** $^{***}$ denotes significance at a p-value less than 0.01; $^{**}$ denotes significance at a p-value less than 0.05 and $^{*}$ denotes significance at a p-value less than 0.10; $^{n.s.}$ denotes that the parameter is not statistically significant

**Table A-13:** Results of structural equation of the structural equation model

| Variables | ICLV Model Coefficients | | |
|---|---|---|---|
| | Knowledge | | |
| | **ICLV Model A-4** | **ICLV Model A-5** | **ICLV Model A-6** |
| Gender: Male | $0.207^{***}$ | $0.195^{***}$ | $0.197^{***}$ |
| Age | $0.004^{n.s.}$ | $0.004^{n.s.}$ | $0.004^{n.s.}$ |
| Income | $-0.013^{***}$ | $-0.012^{***}$ | $-0.012^{***}$ |
| Electric Vehicle Ownership | $0.154^{**}$ | $0.179^{**}$ | $0.177^{**}$ |
| Standard deviation | $0.839^{***}$ | $0.844^{***}$ | $0.850^{***}$ |

**Note:** $^{***}$ denotes significance at a p-value less than 0.01; $^{**}$ denotes significance at a p-value less than 0.05 and $^{*}$ denotes significance at a p-value less than 0.10; $^{n.s.}$ denotes that the parameter is not statistically significant

**Table A-14:** Results of measurement equation of the structural equation model

| ICLV Model A-4 | ICLV Model A-5 | ICLV Model A-6 |
|---|---|---|
| Coefficients of Latent Variables | | |
| $d_{know_1} = 1$ | $d_{know_1} = 1$ | $d_{know_1} = 1$ |
| $d_{know_2} = 2.98^{***}$ | $d_{know_2} = 2.99^{***}$ | $d_{know_2} = 2.92^{***}$ |
| $d_{know_3} = 2.08^{***}$ | $d_{know_3} = 2.09^{***}$ | $d_{know_3} = 2.06^{***}$ |
| $d_{know_4} = 1.72^{***}$ | $d_{know_4} = 1.72^{***}$ | $d_{know_4} = 1.70^{***}$ |
| $d_{know_5} = 1.58^{***}$ | $d_{know_5} = 1.56^{***}$ | $d_{know_5} = 1.56^{***}$ |
| $d_{know_6} = -1.34^{***}$ | $d_{know_6} = 1.32^{***}$ | $d_{know_6} = 1.32^{***}$ |
| Thresholds of indicator 1 | | |
| $\mu_{know_{11}} = -3.99^{***}$ | $\mu_{know_{11}} = -3.96^{***}$ | $\mu_{know_{11}} = -3.97^{***}$ |
| $\mu_{know_{12}} = -1.34^{***}$ | $\mu_{know_{12}} = -1.30^{***}$ | $\mu_{know_{12}} = -1.31^{***}$ |
| $\mu_{know_{13}} = 1.33^{***}$ | $\mu_{know_{13}} = 1.37^{***}$ | $\mu_{know_{13}} = 1.37^{***}$ |
| $\mu_{know_{14}} = 2.78^{***}$ | $\mu_{know_{14}} = 2.81^{***}$ | $\mu_{know_{14}} = 2.80^{***}$ |
| Thresholds of indicator 2 | | |
| $\mu_{know_{21}} = -6.20^{***}$ | $\mu_{know_{21}} = -6.10^{***}$ | $\mu_{know_{21}} = -6.07^{***}$ |
| $\mu_{know_{22}} = -5.15^{***}$ | $\mu_{know_{22}} = -5.06^{***}$ | $\mu_{know_{22}} = -5.04^{***}$ |
| $\mu_{know_{23}} = -2.90^{***}$ | $\mu_{know_{23}} = -2.82^{***}$ | $\mu_{know_{23}} = -2.80^{***}$ |
| $\mu_{know_{24}} = -0.55^{n.s.}$ | $\mu_{know_{24}} = -0.46^{n.s.}$ | $\mu_{know_{24}} = -0.45^{n.s.}$ |
| Thresholds of indicator 3 | | |
| $\mu_{know_{31}} = -6.59^{***}$ | $\mu_{know_{31}} = -6.52^{***}$ | $\mu_{know_{31}} = -6.51^{***}$ |
| $\mu_{know_{32}} = -5.16^{***}$ | $\mu_{know_{32}} = -5.10^{***}$ | $\mu_{know_{32}} = -5.10^{***}$ |
| $\mu_{know_{33}} = -2.69^{***}$ | $\mu_{know_{33}} = -2.62^{***}$ | $\mu_{know_{33}} = -2.61^{***}$ |
| $\mu_{know_{34}} = -0.40^{n.s.}$ | $\mu_{know_{34}} = -0.34^{n.s.}$ | $\mu_{know_{34}} = -0.33^{n.s.}$ |
| Thresholds of indicator 4 | | |
| $\mu_{know_{41}} = -4.18^{***}$ | $\mu_{know_{41}} = -4.12^{***}$ | $\mu_{know_{41}} = -4.13^{***}$ |
| $\mu_{know_{42}} = -2.61^{***}$ | $\mu_{know_{42}} = -2.56^{***}$ | $\mu_{know_{42}} = -2.56^{***}$ |
| $\mu_{know_{43}} = -1.05^{***}$ | $\mu_{know_{43}} = -0.99^{***}$ | $\mu_{know_{43}} = -0.99^{***}$ |
| $\mu_{know_{44}} = 0.76^{***}$ | $\mu_{know_{44}} = 0.82^{***}$ | $\mu_{know_{44}} = 0.82^{***}$ |
| Thresholds of indicator 5 | | |
| $\mu_{know_{51}} = -4.70^{***}$ | $\mu_{know_{51}} = -4.65^{***}$ | $\mu_{know_{51}} = -4.66^{***}$ |
| $\mu_{know_{52}} = -3.51^{***}$ | $\mu_{know_{52}} = -3.46^{***}$ | $\mu_{know_{52}} = -3.47^{***}$ |
| $\mu_{know_{53}} = -2.42^{***}$ | $\mu_{know_{53}} = -2.37^{***}$ | $\mu_{know_{53}} = -2.38^{***}$ |
| $\mu_{know_{54}} = -0.20^{n.s.}$ | $\mu_{know_{54}} = -0.14^{n.s.}$ | $\mu_{know_{54}} = -0.14^{n.s.}$ |
| Thresholds of indicator 6 | | |
| $\mu_{know_{61}} = -4.50^{***}$ | $\mu_{know_{61}} = -4.45^{***}$ | $\mu_{know_{61}} = -4.45^{***}$ |
| $\mu_{know_{62}} = -2.94^{***}$ | $\mu_{know_{62}} = -2.89^{***}$ | $\mu_{know_{62}} = -2.89^{***}$ |
| $\mu_{know_{63}} = -1.83^{***}$ | $\mu_{know_{63}} = -1.78^{***}$ | $\mu_{know_{63}} = -1.78^{***}$ |
| $\mu_{know_{64}} = -0.09^{n.s.}$ | $\mu_{know_{64}} = -0.05^{n.s.}$ | $\mu_{know_{64}} = -0.04^{n.s.}$ |

**Note:** $^{***}$ denotes significance at a p-value less than 0.01 and $^{n.s.}$ denotes that the parameter is not statistically significant

**References**


Ab Hamid, M.R., Sami, W., Mohmad Sidek, M.H., 2017. Discriminant Validity Assessment: Use of Fornell & Larcker criterion versus HTMT Criterion. J Phys Conf Ser 890, 012163. https://doi.org/10.1088/1742-6596/890/1/012163

Bansal, P., Kumar, R.R., Raj, A., Dubey, S., Graham, D.J., 2021. Willingness to pay and attitudinal preferences of Indian consumers for electric vehicles. Energy Econ 100, 105340. https://doi.org/10.1016/J.ENECO.2021.105340

Baresch, M., Moser, S., 2019. Allocation of e-car charging: Assessing the utilization of charging infrastructures by location. Transp Res Part A Policy Pract 124, 388–395. https://doi.org/10.1016/J.TRA.2019.04.009

Ben-Akiva, M., Mcfadden, D., Train, K., Walker, J., Bhat, C., Bierlaire, M., Polytechnique, E., De Lausanne, F., Boersch-Supan, A., Brownstone, D., Bunch, D.S., Daly, A., Europe, R., De Palma, A., Munizaga, M.A., 2002. Hybrid Choice Models: Progress and Challenges. Mark Lett 13, 163–175.

Bhat, F.A., Verma, A., 2023. Consumer intention to accept electric two-wheelers in India: a valence theory approach to unveil the role of identity and utility. Transportation (Amst) 1–41. https://doi.org/10.1007/S11116-023-10430-Z

Bhat, F.A., Verma, A., 2022. A Bibliometric Analysis and Review of Adoption Behaviour of Electric Vehicles. Transportation in Developing Economies 2022 9:1 9, 1–30. https://doi.org/10.1007/S40890-022-00175-2

Bhat, F.A., Verma, M., Verma, A., 2022. Measuring and Modelling Electric Vehicle Adoption of Indian Consumers. Transportation in Developing Economies 8, 6. https://doi.org/10.1007/s40890-021-00143-2

CarDekho, 2023. CarDekho: New Cars, Car Prices, Buy & Sell Used Cars in India [WWW Document]. URL https://www.cardekho.com/ (accessed 7.9.23).

Chakraborty, R., Chakravarty, S., 2023. Factors affecting acceptance of electric two-wheelers in India: A discrete choice survey. Transp Policy (Oxf) 132, 27–41. https://doi.org/10.1016/J.TRANPOL.2022.12.015

Charly, A., Thomas, N.J., Foley, A., Caulfield, B., 2023. Identifying optimal locations for community electric vehicle charging. https://doi.org/10.1016/j.scs.2023.104573

Chhikara, R., Garg, R., Chhabra, S., Karnatak, U., Agrawal, G., 2021. Factors affecting adoption of electric vehicles in India: An exploratory study. Transp Res D Transp Environ 100. https://doi.org/10.1016/j.trd.2021.103084

Chu, W., Im, M., Song, M.R., Park, J., 2019. Psychological and behavioral factors affecting electric vehicle adoption and satisfaction: A comparative study of early adopters in China and Korea. Transp Res D Transp Environ 76, 1–18. https://doi.org/10.1016/J.TRD.2019.09.009

Dong, J., Liu, C., Lin, Z., 2014. Charging infrastructure planning for promoting battery electric vehicles: An activity-based approach using multiday travel data. Transp Res Part C Emerg Technol 38, 44–55. https://doi.org/10.1016/j.trc.2013.11.001

Eswar, M., Roy, A.K., 2018. Urbanisation in Karnataka: Trend and Spatial Pattern. Journal of Regional Development and Planning 5, 5–20. https://doi.org/10.1080/17441730902790024

Fotouhi, Z., Hashemi, M.R., Narimani, H., Bayram, I.S., 2019. A general model for EV drivers' charging behavior. IEEE Trans Veh Technol 68, 7368–7382. https://doi.org/10.1109/TVT.2019.2923260

Franke, T., Krems, J.F., 2013. Understanding charging behaviour of electric vehicle users. Transp Res Part F Traffic Psychol Behav 21, 75–89. https://doi.org/10.1016/j.trf.2013.09.002

Fuller, R., Landrigan, P.J., Balakrishnan, K., Bathan, G., Bose-O'Reilly, S., Brauer, M., Caravanos, J., Chiles, T., Cohen, A., Corra, L., Cropper, M., Ferraro, G., Hanna, J., Hanrahan, D., Hu, H., Hunter, D., Janata, G., Kupka, R., Lanphear, B., Lichtveld, M., Martin, K., Mustapha, A., Sanchez-Triana, E., Sandilya, K., Schaefli, L., Shaw, J., Seddon, J., Suk, W., Téllez-Rojo, M.M., Yan, C., 2022. Pollution and health: a progress update. Lancet Planet Health 6, e535–e547. https://doi.org/10.1016/S2542-5196(22)00090-0

Funke, S.Á., Sprei, F., Gnann, T., Plötz, P., 2019. How much charging infrastructure do electric vehicles need? A review of the evidence and international comparison. Transp Res D Transp Environ 77, 224–242. https://doi.org/10.1016/j.trd.2019.10.024

Giansoldati, M., Rotaris, L., Scorrano, M., Danielis, R., 2020. Does electric car knowledge influence car choice? Evidence from a hybrid choice model. Research in Transportation Economics 80, 100826. https://doi.org/10.1016/J.RETREC.2020.100826

Globisch, J., Plötz, P., Dütschke, E., Wietschel, M., 2019. Consumer preferences for public charging infrastructure for electric vehicles. Transp Policy (Oxf) 81, 54–63. https://doi.org/10.1016/J.TRANPOL.2019.05.017

Gong, S., Ardeshiri, A., Hossein Rashidi, T., 2020. Impact of government incentives on the market penetration of electric vehicles in Australia. Transp Res D Transp Environ 83. https://doi.org/10.1016/j.trd.2020.102353

Government of Karnataka, 2023a. evJagruthi [WWW Document]. URL https://evjagruthi.karnataka.gov.in/ (accessed 8.12.23).

Government of Karnataka, 2023b. Electric Vehicle Charging Infrastructure [WWW Document]. URL https://bescom.karnataka.gov.in/new-page/Electric%20Vehicle%20Charging%20Infrastructure/en (accessed 8.11.23).

Government of Karnataka, 2017. Karnataka Electric Vehicle and Energy Storage Policy.

Guo, C., Yang, J., Yang, L., 2018. Planning of electric vehicle charging infrastructure for urban areas with tight land supply. Energies (Basel) 11. https://doi.org/10.3390/en11092314

Halbey, J., Kowalewski, S., Ziefle, M., 2015. Going on a road-trip with my electric car: Acceptance criteria for long-distance-use of electric vehicles. Lecture Notes in Computer Science (including subseries Lecture Notes in Artificial Intelligence and Lecture Notes in Bioinformatics) 9188, 473–484. https://doi.org/10.1007/978-3-319-20889-3_44/FIGURES/2

Hardman, S., Jenn, A., Tal, G., Axsen, J., Beard, G., Daina, N., Figenbaum, E., Jakobsson, N., Jochem, P., Kinnear, N., Plötz, P., Pontes, J., Refa, N., Sprei, F., Turrentine, T., Witkamp, B., 2018. A review of consumer preferences of and interactions with electric vehicle charging infrastructure. Transp Res D Transp Environ 62, 508–523. https://doi.org/10.1016/j.trd.2018.04.002

He, J., Yang, H., Tang, T.-Q., Huang, H.-J., 2017. An optimal charging station location model with the consideration of electric vehicle's driving range. https://doi.org/10.1016/j.trc.2017.11.026

He, S.Y., Kuo, Y.H., Wu, D., 2016. Incorporating institutional and spatial factors in the selection of the optimal locations of public electric vehicle charging facilities: A case study of Beijing, China. Transp Res Part C Emerg Technol 67, 131–148. https://doi.org/10.1016/J.TRC.2016.02.003

Hensher, D.A., Greene, W.H., 2003. The mixed logit model: The state of practice. Transportation (Amst) 30, 133–176. https://doi.org/10.1023/A:1022558715350/METRICS

Hess, S., Bierlaire, M., Polak, J.W., 2005. Estimation of value of travel-time savings using mixed logit models. Transp Res Part A Policy Pract 39, 221–236. https://doi.org/10.1016/J.TRA.2004.09.007

Hess, S., Palma, D., 2019. Apollo: A flexible, powerful and customisable freeware package for choice model estimation and application. Journal of Choice Modelling 32, 100170. https://doi.org/10.1016/J.JOCM.2019.100170

IBM Corp., 2019. IBM SPSS Statistics for Windows, Version 26.0.

IEA, 2022. Global EV Outlook. Paris.

IEA, 2020a. CO2 Emissions from Fuel Combustion: Overview, IEA, Paris.

IEA, 2020b. Tracking Transport 2020, IEA, Paris.

Jia, J., Liu, C., Wan, T., 2019. Planning of the charging station for electric vehicles utilizing cellular signaling data. Sustainability (Switzerland) 11. https://doi.org/10.3390/su11030643

Jochem, P., Babrowski, S., Fichtner, W., 2015. Assessing CO2 emissions of electric vehicles in Germany in 2030. Transp Res Part A Policy Pract 78, 68–83. https://doi.org/10.1016/j.tra.2015.05.007

Karolemeas, C., Tsigdinos, S., Tzouras, P.G., Nikitas, A., Bakogiannis, E., 2021. Determining Electric Vehicle Charging Station Location Suitability: A Qualitative Study of Greek Stakeholders Employing Thematic Analysis and Analytical Hierarchy Process. Sustainability 2021, Vol. 13, Page 2298 13, 2298. https://doi.org/10.3390/SU13042298

Kessels, R., Goos, P., Vandebroek, M., 2006. A Comparison of Criteria to Design Efficient Choice Experiments. https://doi.org/10.1509/jmkr.43.3.409 43, 409–419. https://doi.org/10.1509/JMKR.43.3.409

Kidiyoor, S., 2022. Bengaluru's number of vehicles doubles in a decade, but BMTC fleet size remains stagnant. The Hindu.

Landrigan, P.J., Fuller, R., Acosta, N.J.R., Adeyi, O., Arnold, R., Basu, N. (Nil), Baldé, A.B., Bertollini, R., Bose-O'Reilly, S., Boufford, J.I., Breysse, P.N., Chiles, T., Mahidol, C., Coll-Seck, A.M., Cropper, M.L., Fobil, J., Fuster, V., Greenstone, M., Haines, A., Hanrahan, D., Hunter, D., Khare, M., Krupnick, A., Lanphear, B., Lohani, B., Martin, K., Mathiasen, K. v., McTeer, M.A., Murray, C.J.L., Ndahimananjara, J.D., Perera, F., Potočnik, J., Preker, A.S., Ramesh, J., Rockström, J., Salinas, C., Samson, L.D., Sandilya, K., Sly, P.D., Smith, K.R., Steiner, A., Stewart, R.B., Suk, W.A., van Schayck, O.C.P., Yadama, G.N., Yumkella, K., Zhong, M., 2018. The Lancet Commission on pollution and health. The Lancet 391, 462–512. https://doi.org/10.1016/S0140-6736(17)32345-0/ATTACHMENT/BFCFD5A0-F041-4475-B3E9-13C53824D76B/MMC1.PDF

Lee, H.J., Cho, H.J., Xu, W., Fairhurst, A., 2010. The influence of consumer traits and demographics on intention to use retail self-service checkouts. Marketing Intelligence and Planning 28, 46–58. https://doi.org/10.1108/02634501011014606/FULL/PDF

Ministry of Power, 2022. Charging Infrastructure for Electric Vehicles (EV) – the revised consolidated Guidelines & Standards. New Delhi.

Morikawa, T., Ben-Akiva, M., McFadden, D., 2002. Discrete choice models incorporating revealed preferences and psychometric data. Advances in Econometrics 16, 29–55. https://doi.org/10.1016/S0731-9053(02)16003-8/FULL/XML

Morrissey, P., Weldon, P., O'Mahony, M., 2016. Future standard and fast charging infrastructure planning: An analysis of electric vehicle charging behaviour. Energy Policy 89, 257–270. https://doi.org/10.1016/J.ENPOL.2015.12.001

Müller-Seitz, G., Dautzenberg, K., Creusen, U., Stromereder, C., 2009. Customer acceptance of RFID technology: Evidence from the German electronic retail sector. Journal of Retailing and Consumer Services 16, 31–39. https://doi.org/10.1016/J.JRETCONSER.2008.08.002

Napoli, G., Polimeni, A., Micari, S., Andaloro, L., Antonucci, V., 2020. Optimal allocation of electric vehicle charging stations in a highway network: Part 1. Methodology and test application. J Energy Storage 27. https://doi.org/10.1016/j.est.2019.101102

Patt, A., Aplyn, D., Weyrich, P., van Vliet, O., 2019. Availability of private charging infrastructure influences readiness to buy electric cars. Transp Res Part A Policy Pract 125, 1–7. https://doi.org/10.1016/J.TRA.2019.05.004

Philipsen, R., Schmidt, T., Van Heek, J., Ziefle, M., 2016. Fast-charging station here, please! User criteria for electric vehicle fast-charging locations. Transp Res Part F Traffic Psychol Behav 40, 119–129. https://doi.org/10.1016/j.trf.2016.04.013

Philipsen, R., Schmidt, T., Ziefle, M., 2015. A Charging Place to Be - Users' Evaluation Criteria for the Positioning of Fast-charging Infrastructure for Electro Mobility. Procedia Manuf 3, 2792–2799. https://doi.org/10.1016/j.promfg.2015.07.742

Preacher, K.J., Coffman, D.L., 2006. Computing power and minimum sample size for RMSEA [Computer software] [WWW Document]. URL http://www.quantpsy.org/rmsea/rmsea.htm (accessed 6.6.23).

Qian, L., Grisolía, J.M., Soopramanien, D., 2019. The impact of service and government-policy attributes on consumer preferences for electric vehicles in China. Transp Res Part A Policy Pract 122, 70–84. https://doi.org/10.1016/j.tra.2019.02.008

Qiao, D., Wang, G., Xu, M., 2023. Fast-charging station location problem: A two-phase approach with mathematical program with equilibrium constraints considering charging choice behaviour. Sustain Cities Soc 96, 104678. https://doi.org/10.1016/J.SCS.2023.104678

Rose, J.M., Bliemer, Mi.C.J., 2009. Constructing efficient stated choice experimental designs. Transp Rev 29, 587–617. https://doi.org/10.1080/01441640902827623

Roychowdhury, A., Dubey, G., 2018. The urban commute: And how it contributes to pollution and energy consumption, New Delhi, India: Centre for Science and Environment.

Ruoso, A.C., Ribeiro, J.L.D., 2022. An assessment of barriers and solutions for the deployment of electric vehicles in the Brazilian market. Transp Policy (Oxf) 127, 218–229. https://doi.org/10.1016/J.TRANPOL.2022.09.004

S. A. Funke, P. Plotz, 2017. A techno-economic analysis of fast charging needs in Germany for different ranges of battery electric vehicles, in: European Battery, Hybrid and Fuel Cell Electric Vehicle Congress . pp. 1–7.

Shahraki, N., Cai, H., Turkay, M., Xu, M., 2015. Optimal locations of electric public charging stations using real world vehicle travel patterns. Transp Res D Transp Environ 41, 165–176. https://doi.org/10.1016/j.trd.2015.09.011

She, Z.Y., Qing Sun, Ma, J.J., Xie, B.C., 2017. What are the barriers to widespread adoption of battery electric vehicles? A survey of public perception in Tianjin, China. Transp Policy (Oxf) 56, 29–40. https://doi.org/10.1016/J.TRANPOL.2017.03.001

Simsekoglu, Ö., 2018. Socio-demographic characteristics, psychological factors and knowledge related to electric car use: A comparison between electric and conventional car drivers. Transp Policy (Oxf) 72, 180–186. https://doi.org/10.1016/J.TRANPOL.2018.03.009

Sun, X.H., Yamamoto, T., Morikawa, T., 2016. Fast-charging station choice behavior among battery electric vehicle users. Transp Res D Transp Environ 46, 26–39. https://doi.org/10.1016/j.trd.2016.03.008

Sun, X.H., Yamamoto, T., Morikawa, T., 2015. Charge timing choice behavior of battery electric vehicle users. Transp Res D Transp Environ 37, 97–107. https://doi.org/10.1016/J.TRD.2015.04.007

Sun, Z., Gao, W., Li, B., Wang, L., 2020. Locating charging stations for electric vehicles. Transp Policy (Oxf) 98, 48–54. https://doi.org/10.1016/j.tranpol.2018.07.009

The Hindu, 2022. 1,000 EV charging stations in Karnataka soon: Energy Minister [WWW Document]. URL https://www.thehindu.com/news/national/karnataka/1000-ev-charging-stations-in-karnataka-soon-energy-minister/article65391413.ece (accessed 8.12.23).

Train, K., 2003. Discrete Choice Methods with Simulation. Cambridge University Press, Cambridge.

Ursachi, G., Horodnic, I.A., Zait, A., 2015. How Reliable are Measurement Scales? External Factors with Indirect Influence on Reliability Estimators. Procedia Economics and Finance 20, 679–686. https://doi.org/10.1016/S2212-5671(15)00123-9

Walker, J.L., Wang, Y., Thorhauge, M., Ben-Akiva, M., 2018. D-efficient or deficient? A robustness analysis of stated choice experimental designs. Theory Decis 84, 215–238. https://doi.org/10.1007/s11238-017-9647-3

World Population Review, 2023. Bangalore Population [WWW Document]. URL https://worldpopulationreview.com/world-cities/bangalore-population (accessed 6.1.23).

**Preferences for public electric vehicle charging infrastructure locations:** A discrete choice analysis

**Research Highlights**

1. A first of its kind study to explore the preferences for the locations of electric vehicle charging stations.
2. Explores the influence of charging station attributes on the choice of charging station location.
3. Waiting time has higher disutility as compared to charging time.
4. Charging time at highways is perceived to be more onerous than charging time at workplaces or leisure places.