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Transportation Research Procedia 82 (2025) 3521–3536

Transportation Research Procedia

www.elsevier.com/locate/procedia

World Conference on Transport Research - WCTR 2023 Montreal 17-21 July 2023

A study on the factors affecting the adoption of electric buses among the non-Public Transit users in Ahmedabad, India

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Abstract

The transportation sector has been aiming to reduce the carbon emissions by promoting the use of low emission vehicles. Although the Indian electric vehicle market is dominated by electric two-wheelers and three wheelers, various governmental schemes have boosted the inclusion of electric buses within the urban bus fleet. However, it is essential for the transport authorities to understand the acceptability of the electric buses among the commuters who are not using public transport currently. This paper aims at understanding the preferences of non-public transport users, to assess the probability of them shifting their modal choice towards public transport, and electric buses in particular, within the Indian context. The data has been collected through a Stated Choice experiment from 414 individuals in Ahmedabad. It has been observed that the low-income individuals are found to prefer public transit if the buses are electric with an affordable fare. The results indicate that electrification of urban bus fleet can improve the image of the existing bus services thereby facilitating modal shift towards public transit among the low-income individuals who have shifted to other modes of transport due to the deterioration of the service quality of the existing transit system.

Keywords: Electric bus; environment; discrete choice analysis; modal shift

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10.1016/j.trpro.2024.12.078

1. Introduction

Multiple global organisations such as the United Nations (UN), the Organisation for Economic Co-operation and Development (OECD), and Asian Development Bank (ADB) have been aiming at reducing carbon emissions through various proactive measures. Several attempts have been made in the transportation sector to encourage the use of low emission vehicles. India pledged to reduce its Greenhouse Gas (GHG) emission intensity by 33-35% of 2005 levels by 2030. In response to the ambitious target, India rolled out schemes to support the emerging electric mobility ecosystem. The Indian electric vehicle (EV) ecosystem is presently in a nascent phase. The electrification of vehicles is increasing promptly, driven by the improving vehicular efficiency, fast evolving battery technology, reducing cost of battery as well as ecological awareness. The government's push to ensure EV adoption through fiscal incentives and tax benefits has further boosted the market growth. Currently, the EV market is dominated by electric two-wheelers and three wheelers (Tarei et al., 2021).

The rolling out of Faster Adoption and Manufacturing of (Hybrid &) Electric Vehicles in India (FAME) scheme in 2015 gave a significant push to electrification. Further, in 2018, the Ministry of Power (MoP) published the guidelines for setting up public charging stations and delicensed the activity of selling power for EVs. Later, in 2019, the second phase of the FAME scheme provided an outlay of 100,000 million for investment in EVs. The second phase of FAME scheme sanctioned 5545 electric buses in 60+ Indian cities and out of which 2500 buses are contracted out.

Rapid progress regarding incorporation of EVs within the urban bus fleet has been observed in the state of Gujarat. Under the second phase of the FAME scheme, 850 electric buses have been sanctioned and 650 electric buses have already been procured for various cities like Ahmedabad, Rajkot, Surat and Vadodara. In this regard, Ahmedabad Municipal Corporation (AMC) has been spearheading the electric mobility agenda by introducing electric buses in Bus Rapid Transit System (BRTS) in Ahmedabad. In 2019, 100 electric buses were deployed on the BRTS corridors of the city. Another 40 buses were added in 2021 and 60 more buses have already been added recently. Apart from the incorporation of electric buses in the existing bus fleets, it is also important for the operators to formulate efficient strategies that can significantly improve the operational efficiency.

The successful implementation of electric buses depends on their acceptance by the public. This can happen in two possible ways. First, travellers currently using non-public transport modes can shift towards public transport (and electric buses in particular). Second, the introduction of electric buses and their higher level of service can induce new trips, e.g. as commuting is now more comfortable thanks to the electric buses, someone might choose to work from the office more days per week. In this study, we only focus on the first effect, i.e. the shift of demand from non-public transport modes towards electric buses. We do not focus on the second effect due to the difficulty identifying who would travel more, making it hard to reach and survey the relevant population. Furthermore, many of these new induced trips may be generated by individuals currently at home, whom we cannot reach easily. Finally, the most relevant environmental benefits come from the shift of trips from private modes to the electric buses, as the latter have lower emissions and negative externalities per passenger than car or motorcycle (Jakub et al. 2022).

The existing literature on electric buses mostly focus on vehicle technology (Li et al., 2016), battery technology (Masih-Tehrani et al., 2013), life cycle assessment (Jakub et al., 2022), charging infrastructure (Xylia et al., 2017) and prediction of energy demand (Gallet et al., 2018). The literature on users' preferences towards the electric buses is quite limited. Lin and Tan (2017) formulated interval regression model to determine individuals' willingness to pay to support the adoption of electric buses in four Chinese cities. They found that young, wealthy individuals who give more value towards air quality reported a willingness to pay a higher fare. However, the study also observed that the respondents, in general, had limited awareness about the governmental policies for implementing electric buses to address the issue of energy security in China. Such observation affirms the need for imparting knowledge about low emission mobility through awareness campaigns to gain the support of the public. Although willingness to pay extra fares for the electric buses were observed among the respondents in Spain (Saz-Salazar et al., 2020), majority of the respondents in Ecuador expressed their unwillingness to increase the cost of the service (González et al., 2021).

Traditionally, market shares in various disciplines have broadly been investigated using the discrete choice experiments (DCE). Loría et al. (2019) conducted DCEs among the bus users in Aberdeen, Scotland as part of Aberdeen Hydrogen Bus Project (AHBP) which introduced the largest hydrogen powered fleet in Europe. The study examined the users' preferences for the different characteristics of bus travel, including different types of emissions. It was found that respondents place a higher value on reductions of local emissions over global emissions and were willing to pay a 63% higher fare for zero emissions. Prasetio et al. (2019a) also conducted Stated Preference (SP) surveys to develop a model with 19 significant parameters. Although the model was formulated for selected routes, the study highlighted that the travel choice of the users was significantly influenced by environmental factors like noise, vibration and emissions that indicated a probable modal shift to public transport among the users.

Recently, Sunitiyoso et al. (2022) also explored the preference of the commuters towards the electric buses using DCEs in Jakarta. The results highlighted the inclination of the commuters towards the electric buses compared to non-electric buses. Moreover, the study also observed that the awareness of the users regarding GHG emissions affected their mode choice decisions.

While the trip attributes like travel time, cost etc. are critical in analysing the mode choice of individuals, the assessment of the effect of environmental parameters on the adoption of electric buses can highlight the impact of these factors on the public transit ridership. This paper presents a DCE study on users' acceptance of electric buses in Indian cities and investigates the effect of various travel and environmental attributes on the individuals' decision to adopt electric buses. This study has been conducted among the individuals not using public transit currently for commuting, unlike Sunitiyos et al. (2022) who analysed the preferences of the commuting population irrespective of their travel mode in Jakarta, Indonesia. It must be noted that the individual decisions in Indian cities are considerably different from Jakarta due to variations in transit operations, socio-economic characteristics and overall awareness on the global concerns.

The objective of this study is to understand the preferences of non-public transport users, to assess the probability of them shifting their modal choice towards public transport, and electric buses in particular, within the Indian context. We also seek to assess the acceptability of the electric buses to evaluate the success of the implementation of such low emission vehicles in the urban bus fleet. In this regard, it is necessary to investigate the effect of both instrumental and environmental attributes on the adoption of the electric buses among the users.

2. Data

1. Study Area

Ahmedabad, the largest city of Gujarat, has witnessed almost a 60% increase in the total built-up area from 171.2 sq. kms in 2011 to 271.3 sq. kms. in 2021 due to rapid urbanisation induced by the exponential growth in industrial and commercial development. Almost half of the motorised trips in Ahmedabad are conducted using two-wheelers (CoE-UT, 2012). Although the proportion of four-wheeler trips is small at 4%, the preferences towards car ownership have increased rapidly thereby increasing the ownership rate from 47 cars to 73 cars per 1000 population over the past decade (RTO Ahmedabad, 2019). Besides, the mode share of the public transit has declined from 25% in 2012 to 13% in 2019. Such decline emphasises on the need to strengthen the service quality measures of the existing public transit system, i.e., Ahmedabad Municipal Transport Service (AMTS) and BRTS. Currently, Ahmedabad has initiated electrification of its bus fleet by acquiring 50 electric buses in 2019, and 90 buses in 2021. At present, 200 electric buses are operational on BRT routes. It is important to understand whether the electrification of buses in Ahmedabad can serve as an opportunity to increase the current transit mode share by adding a high-quality green fleet to supplement the existing services.

2. Survey design

Data was collected through a Stated Choice (SC) experiment. In it, participants faced four choice situations. In each choice situation participants had to imagine they needed to travel within the city, and could use only one of two possible transport modes, or not travel at all. The available modes were bus, and the mode participants were currently using: either auto-rickshaw, car, or motorcycle. There was no possibility to choose any mode other than bus or the currently used one so, for example, auto-rickshaw users could not choose to travel by car. Participants were instructed to choose independently in each choice situation, as if they were making different trips in different days.

The inclusion of only two alternatives was due to constraints while collecting data. Respondents were intercepted in the street while travelling, so the survey had to be short, and as cognitively undemanding as possible, while still collecting valuable information. As discussed by Caussade et al. (2005) , both the number of attributes and alternatives have a relevant impact on the cognitive effort required by respondents. In this case, we favoured a higher number of attributes over the number of alternatives, as this could provide us more insight on the most relevant factors determining travellers choice. Furthermore, as we use MNL models to analyse our data, we rely on the MNL property of independence of irrelevant alternatives (IIA), which prevents our estimates from biasing due to excluding irrelevant alternatives from the choice. As we know that the respondent would not choose other alternatives than the one they are already using under current conditions, the only relevant alternatives remain the current one, and the modified bus.

Figure 1 exhibits an example of a choice situation for an auto-rickshaw user. Such choice situations were also created for cars and motorcycles separately. The bus alternative was described by eleven attributes: access, waiting and travel time, number of transfers, level of crowding, whether the bus is electric or not, whether the bus uses the BRT lanes or not, availability of air conditioning (AC) on board, noise and emissions levels, and finally the cost or fare of the trip. Alternative modes were described by the same attributes, but with several attributes having fixed levels. For example, private modes (car and motorcycle) had zero access and waiting time, as well as zero transfers and the level of crowding was fixed to “you can seat”. The levels used for each alternative are described in Table 1.

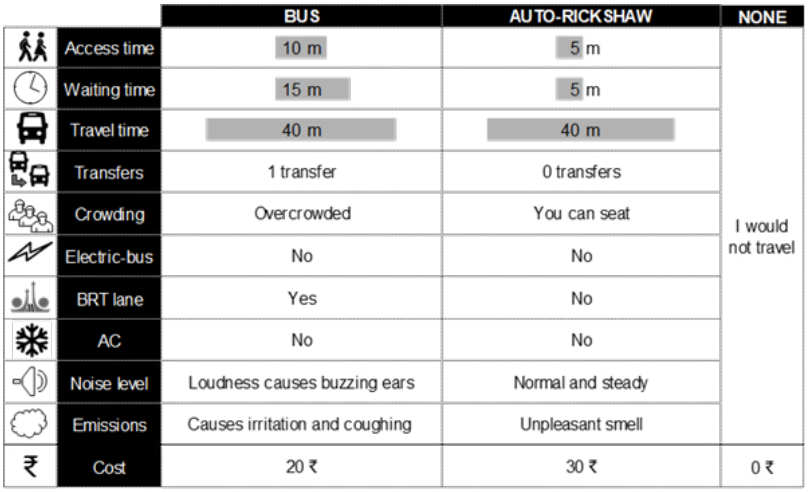

Fig 1: Example of choice situation for auto-rickshaw user

The experimental design, i.e., the combination of levels shown to participants in each choice scenario, was constructed following a D-efficient design, determined using the software Ngene (ChoiceMetrics 2012). D-efficient designs are experimental design whose aim is to minimise the trace of the expected covariance matrix of the estimated parameters. In other words, D-efficient designs select the explanatory variables (i.e., the experimental design) in such a way that the standard error of the estimated parameters is as small as possible.

To construct the efficient design three inputs must be defined: (i) the attributes (i.e., explanatory variables) and their possible levels, (ii) the type of model to be estimated, and (iii) some *a priori* or expected value of the parameters of the model. The first requirement (i) was determined by the attributes and their levels, as shown in Table 1. They were selected based on a review of Ahmedabad current transport system. For the second requirement (ii), a simple MNL model was assumed (see the Methodology section for details). While more complex models can be assumed, it is usually futile to do so, as the analyst does not know what the final shape of the model will be during the planning stage. Finally, the third (iii) requirement is a set of *a priori* values for the parameters of the assumed model. This is clearly the most difficult requirement, as the value of the parameters are unknown at the beginning of the study, because the whole objective of data collection is to determine the final value of the parameters. Therefore, to obtain *a priori* values, a small pilot study was performed.

The pilot study involved 18 respondents from each group of users (auto-rickshaw, car, and motorcycle), leading to a total of 54 respondents. The experimental design of the pilot was constructed using a D-efficient design with all prior values equal to zero. The estimated value of the parameters from the pilot study were used as prior values to generate the D-efficient design for the main data collection.

Table 1 - Attributes and their levels for each alternative

	Bus	Auto-rickshaw	Car	Motorcycle
Access time (min)	3, 5, 10	5	0	0
Waiting time (min)	5, 10, 15	5	0	0
In-vehicle time (min)	20, 30, 40, 45	10, 15, 20 25, 30, 35 40, 45, 50	10, 15, 20 25, 30, 35 40, 45, 50	10, 15, 20 25, 30, 35 40, 45, 50
Transfers	0, 1	0, 1	0	0
Crowding level	seating standing overcrowded	seating	seating	seating
Propulsion	electric, gas	gas	gas	gas
Uses BRT lane	yes, no	no	no	no
Air conditioning	yes, no	no	yes, no	no
Noise level	normal and steady loud bursts loud and buzzing ear	normal and steady loud bursts loud and buzzing ear	normal and steady loud bursts loud and buzzing ear	normal and steady loud bursts loud and buzzing ear
Emissions	non-noticeable unpleasant smell irritation & coughing	non-noticeable unpleasant smell irritation & coughing	non-noticeable unpleasant smell irritation & coughing	non-noticeable unpleasant smell irritation & coughing
Trip cost (₹)	10, 15, 20	15, 20, 30	30, 35, 40	10, 12, 15

3. *Sample description*

The main data collection effort recorded the responses of 414 individuals, 138 of each kind of user (auto-rickshaw, car, and motorcycle). Each respondent answered four choice scenarios, leading to a total of 1656 choices. The samples were recorded across various locations like transit stations and major activity nodes in Ahmedabad, highlighted in the figure 2.

Table 2 presents the main characteristics of the sample, segmented by kind of user. 62% of the sample is composed of males. 55% of the sample is between 26 and 45 years old. Only 1% of respondents come from single-person households, while 88% come from households with three or more members. 21% of the sample report household incomes lower than 30 thousand rupees, while 65% report a household income between 50 and 100 thousand rupees. Finally, 63% of the sample report 15 or more years of education.

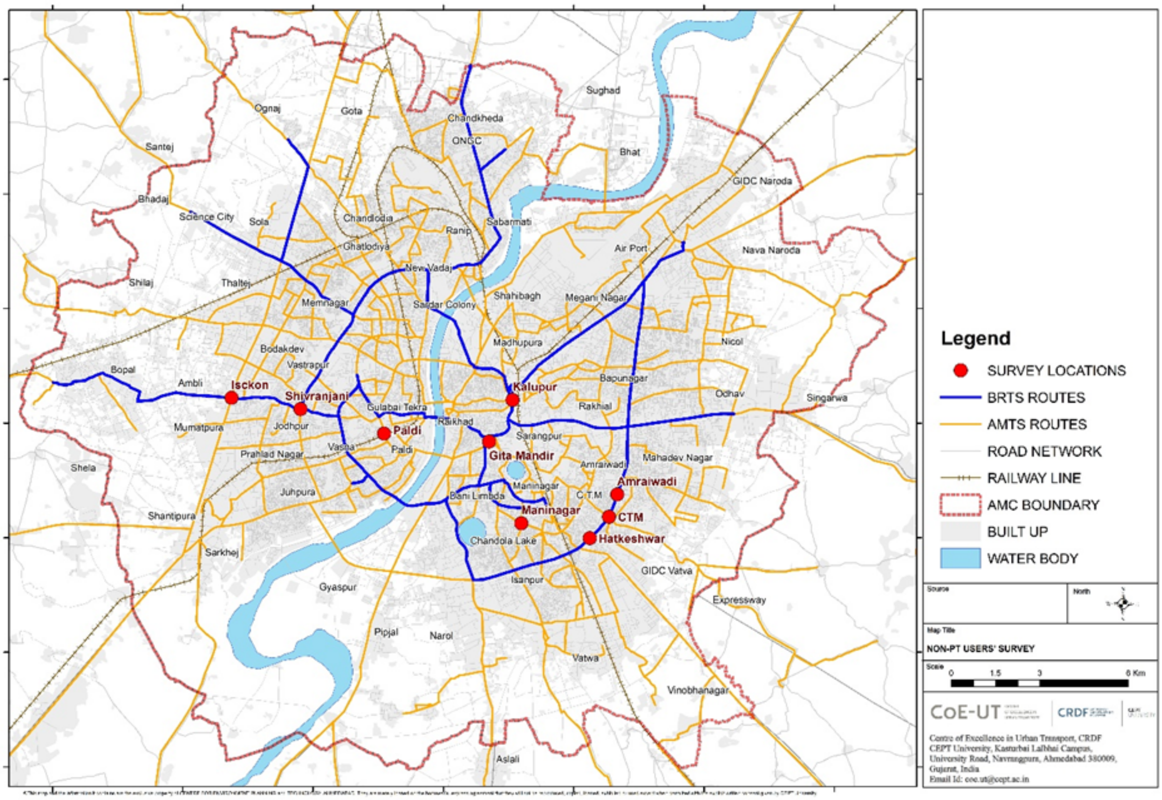

Fig 2: Locations for Stated Preference Survey

Table 2: Main characteristics of the sample

		Auto-rickshaws		Two-wheelers		Car		Total	
		n	%	*n*	%	*n*	%	*n*	%
Sex	Female	84	60.9	53	38.4	45	32.6	182	44.0
	Male	54	39.1	85	61.6	93	67.4	232	56.0
Age	18 – 25	35	25.4	34	24.6	18	13.0	87	21.0
	26 – 35	36	26.1	32	23.2	27	19.6	95	22.9
	36 – 45	36	26.1	44	31.9	59	42.8	139	33.6
	46 – 55	27	19.6	25	18.1	24	17.4	76	18.4
	56 – 60	4	2.9	3	2.2	10	7.2	17	4.1
Household size	1 person	1	0.7	1	0.7	1	0.7	3	0.7
	2 people	16	11.6	15	10.9	14	10.1	45	10.9
	3 people	38	27.5	44	31.9	21	15.2	103	24.9
	4 people	62	44.9	49	35.5	64	46.4	175	42.3
	5+ people	21	15.2	29	21.0	38	27.5	88	21.3
Number of cars	No cars	137	99.3	121	87.7	0	0.0	258	62.3
	1 car	0	0.0	15	10.9	137	99.3	152	36.7
	2 cars	0	0.0	2	1.4	1	0.7	3	0.7
	3+ cars	1	0.7	0	0.0	0	0.0	1	0.2
Number of motorcycles	No motorcycle	7	5.1	0	0.0	0	0.0	7	1.7
	1 motorcycle	92	66.7	82	59.4	84	60.9	258	62.3
	2 motorcycles	36	26.1	50	36.2	47	34.1	133	32.1
	3+ motorcycles	3	2.2	6	4.3	7	5.1	16	3.9
Monthly household income (K₹)	20 – 30	49	35.5	29	21.0	13	9.4	91	22.0
	30 – 40	1	0.7	0	0.0	0	0.0	1	0.2
	40 – 50	4	2.9	1	0.7	0	0.0	5	1.2
	50 – 75	55	39.9	47	34.1	43	31.2	145	35.0
	75 – 100	16	11.6	43	31.2	37	26.8	96	23.2
	100 – 150	4	2.9	4	2.9	11	8.0	19	4.6
	150+	9	6.5	14	10.1	34	24.6	57	13.8
Years of education	None	1	0.7	10	7.2	9	6.5	20	4.8
	Up to 5	2	1.4	1	0.7	1	0.7	4	1.0
	Up to 9	0	0.0	10	7.2	0	0.0	10	2.4
	Up to 10	40	29.0	27	19.6	23	16.7	90	21.7
	Up to 14	0	0.0	3	2.2	0	0.0	3	0.7
	Up to 15	36	26.1	44	31.9	65	47.1	145	35.0
	17 or more	59	42.8	43	31.2	40	29.0	142	34.3
	Total	138		138		138		414	

3. Methodology

1. *Modelling Framework*

Discrete choice models are based on Lancaster's theory of utility. According to Lancaster (1966), individuals obtain utility not from objects themselves, but from the combination of the object attributes and the individual preferences for those attributes. McFadden (1973) operationalised Lancaster's theory through the multinomial logit (MNL) model. Similar to the previous studies conducted on the users' preferences towards electric buses, this study also formulated an MNL model to investigate the influence of various trip and environmental attributes on the mode choice of the individuals. Let us consider an individual *n* choosing between a finite set of *J* alternatives in choice situation *t*. Then the utility that individual *n* will obtain from selecting alternative *j* in choice situation *t* can be described as in equation (1).

$$U_{ntj} = \beta_n' X_{tj} + \varepsilon_{ntj} \tag{1}$$

where $\beta_n' = [\beta_{n1}, \beta_{n2}, \ldots, \beta_{nK}]$ is a vector of values representing the preferences of individual *n* for the column vector $X_{tj}' = [x_{tj1}, x_{tj2}, \ldots, x_{tjK}]$ of the attributes of alternative *j* in choice scenario *t*. If $\beta_{nk}>0$, then individual *n* has a positive utility for the attribute *k*. If $\beta_{nk}<0$, it denotes that the utility of a specific mode reduces with respect to attribute *k*. And if $\beta_{nk}=0$, it means that individual *n* is indifferent to attribute *k*. Finally, ε_{ntj} is a random error term representing all attributes that are unobservable for the modeller, but not the decision maker.

By assuming ε_{njt} to follow an independent and identically distributed standard Gumbel distribution across n, j and *t*, and assuming that individuals choose the alternative with the highest utility, a closed-form formula for the probability of choosing an alternative can be derived (McFadden 1973).

$$P_{ni}(X|\beta) = P(U_{ni} > U_{nj}, \forall j \neq i) = \frac{e^{\beta_n' X_i}}{\sum_l e^{\beta_n' X_l}} \tag{2}$$

The values of the β parameters are estimated by maximising the value of the likelihood function, in other words, by searching for the most likely set of β that generated the data. However, due to numerical precision issues, it is often easier to maximise the log of the likelihood (i.e. the log-likelihood), as expressed in equation (3).

$$LogLikelihood(\beta) = \sum_{n}^{N} \sum_{t=1}^{T} log\left(P_{njt}(X|\beta)\right) \tag{3}$$

2. *Model Structure*

A Multinomial Logit (MNL) model was used to analyse the data. More complex models were tested (such as mixed MNL and latent class models) but without significant improvements on model fit. Therefore, the simpler yet informative MNL model described below was used. The deterministic utility functions for each mode (alternative) are presented below.

$$V_{auto} = \beta_{auto} + \alpha^{\lambda_{TT}} \beta_{TPub} \mathrm{GT_{auto}} + \beta_{trans} trans_{auto} + \beta_{cost} \alpha^{\lambda_{cost}} cost_{auto} \tag{4}$$

$$\begin{aligned} V_{bus} = \beta_{bus} + \alpha^{\lambda_{TT}} \beta_{TPub} GT_{bus} + \beta_{trans} trans_{bus} + \alpha\left(\beta_{\mathrm{crowd_1}} \mathrm{crowd_{1m}} + \beta_{\mathrm{crowd_2}} \mathrm{crowd_{2m}}\right) \\ + \alpha^{-1} \beta_{\mathrm{electric}} \mathrm{electric} + \beta_{cost} \alpha^{\lambda_{cost}} cost_{bus} \end{aligned} \tag{5}$$

$$V_{car} = \beta_{car} + \beta_{TPriv} TT_{car} + \beta_{cost} \alpha^{\lambda_{cost}} cost_{car} \tag{6}$$

$$V_{moto} = \beta_{moto} + \beta_{TPriv} TT_{moto} + \beta_{cost} \alpha^{\lambda_{cost}} cost_{moto} \tag{7}$$

where $\alpha = \frac{\mathrm{hh}Inc}{\overline{\mathrm{hh}Inc}}$, with *hhInc* being the household income and $\overline{hhInc}$ being the average household income in the sample, making α a relative measurement of income with respect to the average. GP_m and TT_m are the generalised and travel time of mode *m*, respectively (GP is defined in the next paragraph). $trans_m$ is the number of transfers within the same mode *m*. $cost_m$ is the cost or fare of using the mode *m*. $crowd_1$ and $crowd_2$ are dummies taking value 1 if the crowding level is "standing" or "overcrowded", respectively, and zero in other case. *electric* is another dummy taking value 1 if the bus is electric, as opposed to diesel powered, and takes value zero in all other cases. All β and λ values are parameters to be estimated.

The access, waiting and travel time of public modes are considered together through the generalised time, which is defined as a weighted sum of access (AT), waiting (WT) and travel time (TT) as follows: $GT_m = 1.49AT_m + 1.83WT_m + TT_m$. These values were obtained from the meta-analysis performed by Wardman et al. (2016). The weighting is exogenous to the estimation, meaning that those values did not come from the estimated data, but from the literature. Attempts to estimate original values from the data led to non-significant (i.e., zero) weights for access and waiting time. This was probably because most respondents are users of private modes (car and motorcycle), so they are not used to pay attention to access and waiting times. Nevertheless, using weights from the literature ensures that the model is still sensitive to these attributes.

In the utility functions, the time of public modes is scaled by $\alpha^{\lambda_{TT}}$. If $\lambda_{TT} > 0$, this formulation implies that the effect of time will be bigger in magnitude for individuals with higher income, and smaller for those with lower income (as compared to individuals with income equal to the average). Similarly, the effect of crowding is scaled by α, which is equivalent to the previous scaling factor, but assuming λ = 1, while the effect of *electric* is scaled by α^{-1}. This also has the effect of increasing the sensitivity to crowding for individuals with higher income and diminishing for individuals with lower income; while having the opposite effect for *electric*, i.e., individuals with higher income are less sensitive to electrified buses. Finally, the effect of cost is scaled by the factor $\alpha^{\lambda_{cost}}$. This time, we expect $\lambda_{cost} < 0$, which would decrease the sensitivity to cost for individuals with higher income and increase it for individuals with lower income.

As the data combines observations from three different subsamples (auto-rickshaw, car, and motorcycle users), deterministic utilities are scaled by factors μ_{auto}, μ_{car} and μ_{moto} in each case. The factor for auto-rickshaw users is set to one for identification purposes.

3. Average Marginal Effects

Marginal effect can be defined as the partial effect of a covariate x_k on the dependent variable (in our case, the probability of choosing a mode). In non-linear models such as the MNL, the value of the marginal effect depends not only on the value of x_k, but also of all other explanatory variables. To obtain a single number measuring the effect of changes in x_k, we instead calculate the average marginal effect (AME), which represents the expected value of the marginal effect of x_k on the sample. Following Wooldridge (2010) we calculate the AME of continuous variables (e.g. travel time) using the expression in equation (8), and instead use equation (9) for categorical i.e., dummy variables (e.g. electric bus). All explanatory variables other than x_k remain at their observed value.

$$AME_{jk} = \frac{1}{NT}\sum_{n}\sum_{t}\hat{P}_{ntj}(x_{tjk} + \delta_k) - \hat{P}_{ntj}(x_{tjk}) \tag{8}$$

$$AME_{jk} = \frac{1}{NT}\sum_{n}\sum_{t}\hat{P}_{ntj}(x_{tjk} = 1) - \hat{P}_{ntj}(x_{tjk} = 0) \tag{9}$$

where NT is the total number of observations in the dataset, $\hat{P}_{ntj}(\dots)$ is the forecasted probability of alternative *j* being chosen in by individual *n* in choice scenario *t*. x_{tjk} is the value of explanatory variable *k* for alternative *j* in choice scenario *t*. δ_k is the change in explanatory variable k for which the AME is calculated (e.g. 1 additional minute). It is essential to compute the AMEs to understand the effect on the probability of individuals' mode choices due to a unit change in the attribute under consideration.

4. Results and Discussions

Table 3 presents the estimated value and t-ratios of each model parameter. It also presents fit indices in the form of the final loglikelihood, rho squared, Akaike and Bayesian information criterion. Only parameters reaching a t-ratio magnitude of at least 1.36 have been kept in the model, which is equivalent to a significance of 83%. Alternative specific constants (i.e., mode intercepts) are excluded from this rule, as they are necessary to avoid biasing other parameters.

Only two aggregated time coefficients have been estimated: one for public transport modes (bus and auto-rickshaw), and one for private modes (car and motorcycle). As discussed in the previous section (see eq. 4 and 5) access and waiting times have been considered with fixed weights with respect to travel time. In particular, access time is considered to be 1.49 times as onerous as travel time, while waiting time is 1.83 times as onerous. This is only relevant for public modes of transport, as private modes do not have access nor waiting time.

While the noise and gas emission levels were included in the survey design, their effects did not reach significance. In an effort to make these two attributes easier to grasp, they were described in relativistic terms. In particular, noise had three levels: "Normal and steady", "Normal with loud bursts", and "Loudness causes buzzing ears". One possible reason for these parameters to not have reached significance is that the interpretation of "normal" might have varied across individuals, preventing the model from capturing a significant effect. Similarly, emissions also have three levels: "Non-noticeable", "Unpleasant smell", and "Causes irritation and coughing". Once again, the definition of "unpleasant" and "irritation" could have varied across individuals, preventing the parameter for reaching significance.

Alternatively, it is also possible that most respondents simply do not consider noise and emissions as relevant attributes when selecting a mode of transport. This is in contrast to the observations made in Prasetio et al. (2019a) and Sunitiyoso et al. (2022), who do find significant effects.

Studies have highlighted that frequency of service and quality of infrastructure are perceived as major barriers to public transportation across Indian cities (Sinha et al., 2020; Soman et al., 2019). AMTS and BRTS are the major service provides for bus operations in Ahmedabad. While AMTS has a large network coverage, BRTS operating on limited routes have been able to deploy electric fleet currently (CoE UT, 2023). The specifications provided for electric buses with low floor height make them superior to the existing Diesel/CNG buses under operation in Ahmedabad (Khandekar et al., 2018). Such contrasting feature of the electric buses make them more attractive to the non-PT users who perceive quality of service as a major barrier to the adoption of public transportation (Sinha, 2019). Therefore, electric bus attribute, being perceived as fleet with improved service quality, has more importance to such respondents compared to the environmental attributes.

Finally, the survey also included the presence (or absence) of Air Conditioning (AC) in the bus and car, but its effect was not significant. This seems to indicate that most participants in the study do not value the presence of AC in any significant manner.

Table 3: Model parameters

Coefficient		Value	t-ratio
Mode	Bus	0.0000	(base)
	Auto-rickshaw	-0.0618	-0.32
	Car	0.2129	0.59
	Motorcycle	0.8044	1.27
Time	Public	-0.0112	-2.34
	Private	-0.0137	-1.79
	λ_{income}	1.2628	4.29
Transfers		-0.1579	-1.36
Crowding	Sitting	0.0000	(base)
	Standing	-0.2555	-1.79
	Overcrowded	-0.4941	-2.88
Electric	Bus	0.2115	2.46
Cost/Fare	Main effect	-0.0229	-2.10
	λ_{income}	-1.1356	-2.83
Scale	Auto-rickshaw	1.0000	(base)
	Car	0.9906	2.70
	Motorcycle	0.7487	2.22
Loglikelihood			-998.6
Number of parameters			14
Number of individuals			414
Number of observations			1656
ρ^2			0.130
Adjusted ρ^2			0.118
AIC			2025.3
BIC			2101.1

Most parameters in the model exhibit the expected sign and are significant with more than 95% confidence. The only exceptions are *transfers* (83% significance), *standing* and *time* for private modes (the last two with 93% significance).

As mentioned before, the model incorporates scale factors μ. Results indicate that responses by car and motorcycle users have a lower scale factor and therefore a higher level of noise in their responses, or heterogeneity in their preferences. However, it is not possible to disentangle one from the other.

As expected, sensitivity to *time*, *crowding*, *electric* buses, and *cost/fare* is mediated by income, with richer individuals being more sensitive to *time* and *crowding*, but less so to *electric* buses and *cost/fare*. The only exceptions are the travel time for private modes (car and motorcycle), which is not sensitive to income. This is probably because the income among owners of these modes is higher, and therefore their sensitivity is more homogeneous. Indeed, the average income among car and motorcycle users is 76 and 62 thousand rupees respectively, while for users of public transport the average income is only equal to almost 49 thousand rupees.

1. Average marginal effects

Table 4 shows the AME for covariates found significant in the model discussed above. The AME was estimated disaggregated by income level. This was achieved by assuming that the whole sample belonged to a given income level, and then predicting for all of them. This approach ensures that all AMEs are calculated with the same number of observations. Table 4 below presents the average marginal effects of changes in attributes on the probability of choosing that alternative, as well as its 95% confidence interval.

Since the AME is a difference between probabilities, they are expressed in percentage points. For example, an increase in auto-rickshaw's access time by 10 minutes induces an average decrease of 0.7% on the probability of choosing auto-rickshaw among people with low income, and this effect has a 95% confidence interval between -1.8% and -0.1%. Several cells in the table are empty. This means that the particular attribute doesn't influence that alternative. For example, the attributes like access and waiting time only influence public transport modes.

No cross-effects are reported in Table 4. For example, making the bus more crowded reduces the probability of choosing bus, but at the same time increases the probability of choosing other modes. Those cross-effects are not reported for two reasons: (i) Two alternatives were available to the respondents, so the prediction wouldn't be realistic, and (ii) Cross elasticities are not very informative in an MNL model due to the independence of irrelevant alternatives (IIA) properties (Train, 2002, Section 3.1).

Sensitivity to travel time in public transport is higher for richer people, implying that travelling by public transport is more onerous for such groups compared to the lower income individuals. The same effect is not present among private modes, where the travel time in private modes is less onerous for individuals with higher income. This reflects the strong preference towards private modes among higher income individuals. In mathematical terms, this is caused by the public modes having very low utility for high income people, so even if the private modes become less attractive, the drop in probability is not so significant.

Transfers required to complete a specific trip influence only public mode. Auto-rickshaw endures slightly bigger penalties due to additional transfers when compared to bus, especially among high-income individuals. This is due to auto-rickshaw probably being used for shorter trips (maybe just the last mile), and their routes are more flexible (if they do have routes), making users less likely to transfer between auto-rickshaws. Sensitivity to transfers in bus diminishes for high income individuals, with respect to mid-income individuals. This is because the richer the individual, more averse they are to use the bus due to their perception of increased travel time in bus. The high penalty for travel time makes the bus so unattractive that additional transfers contribute little dis-utility as compared to the travel time, and therefore have a smaller effect. Another way to understand this is that for rich individuals the bus already has a very low probability of being chosen, so adding more transfers has little room to make the bus less attractive to this section of individuals. Indeed, the average probability of choosing bus is only 23% among the high-income individuals. The AME of transfers, however, does not reach a 95% level of confidence, as its Confidence Interval (CI) crosses over zero.

Crowding levels are also increasingly onerous for higher income individuals, though the effect of the "standing" level is not significant at 95% confidence with its CI slightly crossing above zero. Travelling on an overcrowded bus has a very strong negative effect, especially among middle and high-income individuals. In the case of mid-income individuals, it reduces the probability of taking the bus by 8.3%, over twice as much as standing in the bus while travelling, and it is equivalent to approximately 27 minutes of extra travel time.

The presence of electric buses has a positive effect on the probability of riding the bus, especially among low-income individuals (+10.3%). The impact of electric buses among the high-income individuals is quite less, at only +1.6%. The most probable reason for this is that especially low-income individuals associate electric buses with an improved level of service, e.g., less noise and emissions, or maybe even air conditioning.

Table 4 - Average Marginal Effects (%) of different covariates with respect to income

AME	Income	Auto-Rickshaws			Two-Wheelers			Car			Bus		
		lower	*mean*	*upper*	*lower*	*mean*	*upper*	*lower*	*mean*	*upper*	*lower*	*mean*	*upper*
Access time (+10 min)	Low	-1.8	-0.7	-0.1	-	-	-	-	-	-	-1.6	-0.6	-0.1
	Middle	-5.6	-3.0	-0.4	-	-	-	-	-	-	-5.1	-2.6	-0.4
	High	-15.3	-8.2	-0.8	-	-	-	-	-	-	-7.5	-4.8	-0.8
Waiting time (+10 min)	Low	-2.1	-0.8	-0.2	-	-	-	-	-	-	-2.0	-0.7	-0.1
	Middle	-6.8	-3.6	-0.5	-	-	-	-	-	-	-6.2	-3.1	-0.5
	High	-19.0	-10.1	-1.0	-	-	-	-	-	-	-9.0	-5.8	-1.0
Travel time (+10 min)	Low	-1.2	-0.5	-0.1	-5.5	-2.3	-0.1	-3.7	-1.4	-0.1	-1.1	-0.4	-0.1
	Middle	-3.8	-2.0	-0.3	-6.1	-2.2	-0.1	-6.8	-3.1	-0.2	-3.4	-1.7	-0.3
	High	-10.1	-5.4	-0.6	-3.6	-1.3	-0.1	-4.9	-2.1	-0.1	-5.3	-3.4	-0.5
Transfers (+1)	Low	-6.4	-2.7	1.8	-	-	-	-	-	-	-6.2	-2.4	1.5
	Middle	-8.5	-3.6	2.4	-	-	-	-	-	-	-8.6	-3.1	1.9
	High	-8.1	-3.3	2.0	-	-	-	-	-	-	-6.3	-2.2	1.5
Crowding (standing)	Low	-	-	-	-	-	-	-	-	-	-2.0	-1.1	0.0
	Middle	-	-	-	-	-	-	-	-	-	-7.4	-4.1	0.1
	High	-	-	-	-	-	-	-	-	-	-14.2	-7.7	0.1
Crowding (over-crowded)	Low	-	-	-	-	-	-	-	-	-	-3.7	-2.2	-0.9
	Middle	-	-	-	-	-	-	-	-	-	-13.2	-8.3	-3.6
	High	-	-	-	-	-	-	-	-	-	-24.0	-14.3	-5.8
Electric	Low	-	-	-	-	-	-	-	-	-	1.6	10.3	20.1
	Middle	-	-	-	-	-	-	-	-	-	0.8	5.1	10.1
	High	-	-	-	-	-	-	-	-	-	0.2	1.6	3.1
Cost/fare (+5₹)	Low	-11.0	-7.5	-1.9	-15.0	-7.1	-0.4	-5.8	-3.9	-1.1	-11.0	-7.0	-1.9
	Middle	-6.0	-3.4	-0.6	-5.4	-2.3	-0.1	-5.8	-3.1	-0.6	-4.7	-2.9	-0.5
	High	-3.5	-1.3	-0.1	-1.7	-0.6	0.0	-1.8	-0.8	-0.1	-2.1	-0.9	-0.1

Finally, as expected, the higher the income the less sensitive individuals are to price. For low-income individuals an increase of 5₹ has an equivalent effect on the probability of riding the bus to three additional transfers. For high-income people, on the other hand, a 5₹ increase has a smaller effect than one additional transfer.

2. *Willingness to pay*

The willingness to pay correspond to the marginal rate of substitution between an attribute and money. In other words, it represents the compensation (or price reduction) an individual requires for enduring an undesirable attribute; or their willingness to pay (or willingness to accept a higher cost) for a desirable attribute. Table 5 presents these values for low-, middle- and high-income participants (using the average income of each group to calculate each WTP value).

As can be seen in Table 5, the WTP always increases with income. This is because the sensitivity to price decreases with income, and therefore a bigger amount of money is necessary to compensate for a change in the level of utility.

Cost/fare is the most relevant attribute among low-income individuals. This is reflected on how they are willing to pay only 7₹ or less for 10-minutes reductions in travel time, and only 2₹ for reducing one transfer, sitting instead of travelling in an overcrowded bus, or riding an electric bus.

Table 5 - Willingness to pay (with 95% confidence interval)

WTP	Income	Public			Private		
		lower	mean	upper	lower	mean	upper
Access	Low	-21	-11	0	-30	-13	4
time	Middle	-64	-34	-4	-90	-42	7
(₹/Hour)	High	-205	-91	23	-273	-111	51
Waiting	Low	-26	-13	0	-37	-16	5
time	Middle	-78	-42	-5	-111	-51	9
(₹/Hour)	High	-252	-112	29	-336	-136	63
Travel	Low	-14	-7	0	-20	-9	2
time	Middle	-43	-23	-3	-60	-28	5
(₹/Hour)	High	-138	-61	16	-183	-75	34
Transfers	Low	-4	-2	1	-	-	-
(₹/transfer)	Middle	-14	-5	3	-	-	-
	High	-41	-14	13	-	-	-
Crowding	Low	-2	-1	0	-	-	-
(standing)	Middle	-16	-7	2	-	-	-
(₹/seat)	High	-118	-44	30	-	-	-
Crowding	Low	-3	-2	0	-	-	-
(over-	Middle	-27	-13	0	-	-	-
crowded)	High	-209	-85	38	-	-	-
Electric	Low	0	2	5	-	-	-
	Middle	0	7	15	-	-	-
	High	-8	19	47	-	-	-

For middle- and high-income participants travel time is the most relevant attribute. They are willing to pay 23₹ and 61₹ respectively for 10 minutes reduction in travel time in public transport. Travel time is followed by crowding and transfers in terms of importance. Their willingness to pay for electric buses, on the other hand, is not very high, at only 7₹ and 19₹ per trip for mid- and high-income individuals.

1. Conclusion

Recently, several attempts across the globe are being made to adopt renewable sources of energy in the transportation sector not only to mitigate challenges related to climate change but also to ensure the accessibility to energy while improving the energy security. With several national, state and local level programs, the EV ecosystem in India has strengthened and adoption of EVs is improving across different states. Amongst the cities electrifying their PT systems, Ahmedabad has one of the largest electric bus fleets. This research aimed at exploring the preferences towards electric buses among the non-PT users.

According to the observations, the individuals with higher income are more sensitive to the time attribute inclusive of access and waiting time and the crowding level inside the bus. On the other hand, low-income individuals are found to prefer public transit if the buses are electric with an affordable fare. However, the environmental attributes like noise and emission levels are not found to have significant effect on the mode choice behaviour of the non-PT users. In this regard, additional surveys have been conducted to understand the perceptions about the electric buses among the existing PT users. It has been observed that nearly 86% of the existing users have higher preference towards the electric buses. While majority of the PT users perceive the noise in electric buses to be lesser compared to the traditional diesel buses, such users are also aware about the zero emission levels of the electric buses.

The motorised mode share of PT in Ahmedabad has dropped from 25% in 2012 to 13% in 2019, with passengers shifting to private and intermediate public transport modes. This is because city bus services have not kept pace with the increasing population and travel demand in the city – bus numbers are much lower than the desirable standards, most of the routes have very high headways increasing the wait times and bus routes have not been restructured based on changes in the travel patterns. Ahmedabad Municipal Transport Service (AMTS) and BRTS services operate independently as a result of which last mile connectivity for BRTS is poor. Coupled with lack of integration of bus fares, this has resulted in a decline in passenger ridership and a shift to personalised modes of transport. This is consistent with the results obtained from the analysis where the non-PT users have been found to give more emphasis on the trip specific attributes like time, fare, transfers and service quality attributes like crowding. Although electric buses have been observed to have significant effect on the mode choice, the non-PT users mostly tend to associate the electric buses with buses of superior quality. The deterioration in service quality may also be attributed as a reason for non-PT users not giving more value to environmental attributes. The results, therefore, implies that the PT operators can facilitate the modal shift among the low-income individuals by improving the service quality of the existing transit system. It has also been observed that middle- and high-income individuals are highly sensitive to travel time and are less sensitive to fare compared to the low-income individuals. Besides, the high-income individuals are less sensitive to the electric buses implying the indifference towards the electric buses due to their dependency on the automobiles. In general, such individuals are less likely to opt for public transport even if it is an electric bus.

With the above context, certain policies may be recommended for the implementation of electric buses in the PT system. Although the non-PT users seem to be indifferent to environmental factors, electric buses are preferred over the conventional diesel buses similar to the existing PT users. Therefore, the urban authorities may consider the prioritisation of replacement of the traditional diesel buses with the electric buses. In this regard, the city of Ahmedabad can formulate a long-term plan for carrying forward a public transport electrification strategy. The city may also consider facilitation of electric vehicles in other modes of transport to reduce emissions. Based on the observations related to individuals' response to existing service quality levels, the city authorities are also required to ensure reliable transit service with improved journey time while reducing the headway to ensure lower waiting times and reduction in the crowding level during peak times. Implementation of such policies would require the development of a long-term strategy focusing on target PT mode shares, fleet requirement estimation, level of bus electrification and drawing out an electrification plan.

As any other study, ours has some limitations. First, the data collection method (intercepting travellers in the street) limited the complexity of the choice tasks, mainly in terms of number of alternatives. Future data collection efforts could offer a wider and more representative set of alternatives to respondents. Second, although factors influencing the mode choice behaviour of the non-PT users have been identified in this study, it is also important to consider the attitudinal factors of the individuals to understand their attitudes towards the electric buses. Such attitudinal factors have not been considered in the model. Moreover, it is also essential to get an overview about the individuals' responses towards current environmental issues. Such overview is required to extract further information on the contrasting observation made for the environmental factors selected for this study. Future studies may also explore various scenarios to assess the implications of electrification of the existing PT system in Ahmedabad.

Acknowledgements

The present study is a part of the ongoing research project titled, “Strategy and Action Plan for electrification of PT or IPT in Indian Cities”. We are grateful to the UKPACT Green Recovery Challenge Fund without whose financial support we would not have been able to conduct this research.

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