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Evaluation of Prospective Users' Choice Decision toward Electric Two-Wheelers Using a Stated Preference Survey: An Indian Perspective

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Abstract: Electric two-wheelers (E2W) can help de-carbonize transport in Indian cities. To promote E2W as an attractive alternative compared to the conventional two-wheelers, an investigation on prospective users' choice decisions is necessary. This paper proposed a comprehensive methodology to evaluate the prospective users' choice decision toward electric two-wheelers and related attributes in the Indian context. In this paper, attributes such as Operating Cost (OC) savings, top speed, range, charging duration, acceleration, and purchase cost were considered to design a Stated Preference (SP) survey to collect data from prospective E2W users in Hyderabad, India. Concurrently, multinomial logit (MNL) and random parameter logit (RPL) models are developed, and the willingness-to-pay (WTP) associated with each of the identified attributes was estimated. Additionally, the effect of socio-economic characteristics on prospective users' choice decision was also assessed. Subsequently, a sensitivity analysis was carried out to estimate the relative influence of the attributes on an individual's choice decision in terms of the shift in probability to choose alternatives with better attribute levels than the base alternative. The results revealed that top speed was perceived as the most important attribute influencing an individual's choice decision, followed by acceleration and charging duration. Age, income, and journey time significantly influenced an individual's perception toward E2W and related attributes in the Indian context.

Keywords: electric two-wheelers (E2W); stated preference (SP) survey; multinomial logit (MNL); random parameter logit (RPL); willingness-to-pay (WTP); sensitivity analysis



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1. Background and Motivation

The rapid urbanization coupled with subsequent motorization in recent decades is responsible for increasing the level of vehicle emitted greenhouse gas (GHG) compounds into the ambient air. This phenomenon has contributed adversely to the environment in terms of global warming and subsequent climate change, which is one of the significant threats to human society worldwide [1]. As per the Global Ambient Air Quality Database, nine out of 10 humans breathe polluted air, leading to seven million deaths each year worldwide, of which many are in Asian and African countries [2]. To address this ongoing global crisis, in the Paris Agreement, a set of goals has been specified by the United Nations to all the member nations to restrict the rise in global temperature well below 2 degrees Celsius compared to pre-industrial levels [3]. This reduction in ambient temperature level could be achieved by adopting alternative technology in the sectors with significant contributions toward global climate change. Among various sectors contributing to global warming, the transport sector is considered as one of the major sources of GHG emission [4,5]. The US transportation sector produces approximately 28% of all US global warming emissions [6], whereas the Indian transport sector contributes almost 60% of the total GHG emission from various activities in India [7]. This finding indicates that vehicular GHG emission plays

an extremely detrimental role toward poor air quality, leading to 1.67 million deaths due to outdoor pollution in India in 2019 [8]. To address this concern, the promotion of less-polluting modes with alternative technology is necessary for a sustainable transportation system. Motorized two-wheelers are observed to be the most used and most polluting modes among different transportation modes [9]. Therefore, the promotion and use of electric two-wheelers (E2Ws) as an alternative to conventional motorized two-wheelers would substantially improve the air quality and improve the overall quality of Indian urban residents' life.

Motorized two-wheelers play a vital role in meeting commuters' travel requirements, so they have been the most preferred commuting mode in India. The reliability and maneuverability offered by motorized two-wheelers play an essential role in their increased patronage in the country. Motorized two-wheelers provide a faster journey with relatively lower operating costs due to the lower fuel consumption per passenger-kilometer than other motor vehicles [10]. Apart from the travel dynamics, the urban characteristics of Indian cities with a higher population density and narrow streets with frequent congestions have led commuters to choose motorized two-wheelers as a convenient option for point-to-point transport due to their size and ease of maneuvering [11]. With 169 million units, motorcycles accounted for almost 73% of all registered motor vehicles in India in 2016 [12]. As per the data, one km of motorized two-wheeler travel in 2021 would be responsible for emitting 628 mg of CO, 416 mg of HC, 122 mg of NO_x, 36.33 g of CO₂, and 23 mg of PM_{2.5} [13], indicating the severe degradation of air quality due to increased number of motorized two-wheelers in India. Excessive dependence on motorized two-wheelers for regular commuting has led to severe air pollution generated due to increased fossil fuel consumption [14]. The current fleet size of motorized two-wheelers is contributing to the substantial increase in the concentration of harmful greenhouse gas (GHG) compounds such as CO, CO₂, SO₂, and other Chlorofluorocarbon (CFC) compounds [15]. In addition, about 50% of the gasoline produced from crude oil is consumed by the motorcycle fleet alone [15]. Hence, the motorized two-wheelers contribute to significant energy wastage and poor air quality, leading to a significant reduction in the quality of life of urban Indian residents. Hence, it is essential to promote clean-fueled vehicles such as E2Ws, which rely on electricity for their propulsion to eventually restrict the GHG emissions associated with gasoline to power motorized two-wheelers [16]. In this regard, an emission model by Amjad et al. [15] forecasts that a total of 48% reduction in CO₂ emission could be attained in India by replacing all gasoline-powered motorized two-wheelers with E2Ws, even considering the emission due to electricity generation. The replacement would eventually facilitate 2.25–37.59 billion liters of annual gasoline savings for India in 10 years. The annual savings on the expenditure on gasoline would account for a savings of US\$50 billion for crude oil imports [15].

The government of India has also recognized the advantages of promoting E2Ws and has implemented the FAME (Faster Adoption and Manufacturing of (Hybrid) and Electric Vehicles) scheme in 2017. Under the FAME scheme, the government of India has allocated an estimated sum of US\$1.3 billion for providing subsidies toward purchasing electric vehicles. Despite the subsidies, India's overall share of E2Ws is still below 1% [17]. The low share of E2Ws in the Indian context indicates that the prospective user's requirements with respect to a two-wheeler have not been incorporated, which needs to be investigated in detail.

For the stated purpose, a detailed investigation of the prospective user's perception toward factors associated with the electric two-wheelers (E2W) in the Indian context is taken up in this paper. An individual's perception toward a particular attribute or a transport mode can be evaluated in terms of the perceived benefit associated with that particular attribute/mode. The perceived benefit associated with improvement in each factor can also be expressed in monetary terms or willingness-to-pay (WTP) value. The WTP or perceived benefits related to different factors provide a clear direction of focus, which is necessary for a specific improvement strategy [18]. The WTP or perceived benefit associated with each E2W

specific attribute is utilized in this paper to estimate the welfare change expected from them. The rationale of using WTP is to determine how the existing motorized two-wheeler users value various attributes toward their decision-making process concerning using an E2W as the most and least beneficial attributes that could be identified. User benefit assessment involves the development of travel behavior models by analyzing stated choice data, as was done in previous studies in the context of bicycle infrastructure [19,20], bus-service attributes [21,22], metro-facility attributes [23,24], and stated choice electric vehicles [25,26]. This research carries out an in-depth investigation on E2W related improvement strategies through the explicit incorporation of user benefit with this background. To examine the influence of various socio-economic and trip-related characteristics on respondent's perception and overall valuation, the presence of heterogeneity with respect to (1) age, (2) monthly family income, and (3) average journey time for a typical commuting trip is studied in detail. Hyderabad, an Indian metropolitan motorized two-wheeler-dominated city, is selected as the case study area in this research. A brief review of the existing literature on the research topic and the identified scopes for this paper are presented in the next section.

2. Literature Review and Research Scope

Existing studies on the E2Ws choice or acceptance are broadly based on two types of surveys: (a) Revealed Preference (RP) survey and (b) Stated Preference (SP) survey. RP survey-based studies correlate the existing E2W user's behavior toward various attributes, whereas studies based on an SP survey would permit the researchers to evaluate hypothetical or non-existent options [27]. As E2W is a very new mode to the Indian market, investigating E2W operational characteristics by providing hypothetical/stated options is thought to be a better strategy. A brief review of SP survey-based studies investigating commuter perception toward E2W and related attributes are briefly summarized in this section. Among such studies, Chiu and Tzeng [14] designed a stated-choice experiment and used the multinomial logit (MNL) model to identify a set of key attributes influencing E2Ws in Taiwan. They found speed as a crucial attribute toward choosing motorized two-wheelers. They also suggested that critical infrastructures such as charging facilities and mechanical services were essential for commuters' broader acceptance of E2Ws. They found that males' and females' perceptions toward such choice decisions vary significantly. In another Taiwan-based research study, Sung et al. [28] employed a Bayesian learning model to understand the consumers' choice behavior for E2Ws. They found the quality of E2Ws to be a guiding attribute. Furthermore, attributes such as recharging time and charging point location were observed significantly to affect the respondents' choices. They also inferred that educated male users with higher household income and small gasoline motorized two-wheelers are the primary target groups for E2Ws. In their research, Sun and Zhang [29] have employed the dogit model with parameterized captivity functions to analyze the different policy level interventions and technological innovations of E2Ws in Laos. It was found that the range, distance to charging points, operation cost, and diffusion rate were the major influential factors. Users were willing to pay an additional 1.27 times their monthly income to increase the range by 50 km. Another research by Jones et al. [30] analyzed the impact of economic incentives and technological improvements on adopting E2Ws among Vietnamese commuters by formulating a mixed logit model based on Stated Preference data. They proposed that policy interventions with respect to reduction in the sales tax could be used as a useful tool to increase the electric motorcycle purchase in the Vietnamese context. Specifically, the elimination of sales tax on E2W and a higher sales tax on motorized two-wheelers would significantly improve the E2W market share. Zhou et al. [31] has also conducted an SP survey and employed a binary logistic regression model to identify the critical E2W performance-related factors based on the Chinese commuters' perception and found that the factors such as environmental concern, low charging cost, license number, and high-income levels have significant positive effects on the purchase intention of the commuters.

In another recent research in Taiwan, Lee et al. [32] developed a multinomial logit model for incorporating the commuters' choice behavior for exploring the key attributes affecting their choice for an electric motorcycle. It was found that a long battery recharging time, lower accessibility to the recharging stations, and a high purchase price were key deterrents, and government incentives were a significant motivators toward purchasing E2W. Zhu et al. [33] used the Contingent Valuation Method (CVM) to identify the critical influencing factors based on the willingness-to-buy (WTB) and willingness-to-pay (WTP) for E2Ws by the Chinese commuters. It was found that the respondent's sale price, charging fee, repair fee, and tax incentives associated with E2W were valued more than the product features of E2W, such as driving speed and load capacity. Furthermore, the respondents' income levels had a significant influence. Guerra [11] collected stated-choice data and developed a mixed logit model with random coefficients to measure E2Ws' potential to replace gasoline motorized two-wheelers in Indonesia. It was found that price and performance were significant attributes. Moreover, the commuters were willing to pay an extra 7–13% extra for E2Ws with a 10 km longer range, 10 km/h faster speed, and an hour shorter charge time. Table 1 presents a summary of existing SP survey-based research studies investigating user perception toward E2W.

A review of the existing literature investigating commuters' attitude/perception toward key determinants of E2W choice provides a proper understanding of the present work. However, several areas require further research attention, especially in India, where E2W is not a very popular mode. Firstly, the review indicates that most of the existing studies are conducted in the countries such as China, Taiwan, or Vietnam, where E2W is already an established alternative mode of transport. However, E2W is still at its' nascent stage in India, requiring a detailed investigation, especially from the proposed user's perspective. Moreover, due to significant differences in transport and urban characteristics, the factors used in such studies may not be directly transferrable to India. Hence, there is a need to use a set of factors hypothesized to influence the proposed commuter's E2W choice in the typical Indian context and subsequently quantify the roles of various such attributes on Indian commuter's choice decision making. Secondly, the use of WTP estimates to evaluate the non-commuters' choice behavior is rather limited in the existing research literature. Thirdly, only a few studies have explored the influence of socio-economic and trip-specific characteristics toward the E2W in general and E2W-specific operational characteristics in particular. Such investigation becomes more important for Indian scenarios, where the identification and segmentation of the future market of E2W are very important.

To address these aforementioned aspects and augment the literature in this context, this research conducts a detailed investigation of the users' perception on different attributes by employing multinomial logit (MNL) and random parameter logit (RPL) models for the data collected through a Stated Preference (SP) survey on the potential users of E2Ws in the Indian context. The existing conventional motorized two-wheeler users interested in purchasing the E2W in the near future are considered as the respondents of this research. Heterogeneity toward the valuation of different E2W-specific attributes is evaluated with respect to socio-economic characteristics such as age, monthly family income, and trip characteristics such as average commute journey time. Finally, a sensitivity analysis is conducted to examine the impact of improving various E2W operational attributes on future users' choice behavior. The following section presents the attribute selection and the attribute levels considered in this research.

Table 1. Summary of existing Stated Preference (SP) survey-based research studies.

S.No	Source	Country	Attributes	Choice Alternatives for the Survey	Model
1	Chiu et al. (1999) [14]	Taiwan	Purchase price, maximum speed, emission level, operating cost, cruise range	(A) Electric motorized two-wheelers (B) Low-engine-volume gasoline motorcycle (C) High-engine-volume gasoline motorcycle	Multinomial logit model (MNL)
2	Sung (2010) [28]	Taiwan	Price, top speed, maximum driving range, operating cost, recharging time, recharging method	(A) Gasoline motorcycle (B) Electric motorcycle	Bayesian learning process model
3	Jones et al. (2013) [30]	Vietnam	Price, range, refuel/recharge time, operating cost, maintenance cost, acceleration, speed, license requirement, sales tax	(A) Standard gas motorcycle (B) Large gas motorcycle (C) Electric scooter	Mixed logit model
4	Sun and Zhang (2013) [29]	Laos	Engine displacement for electric motorcycle (EM), efficiency of conventional motorcycle (CM), efficiency of EM, maximum speed, cruising range, charge time, battery life, diffusion rate, distance to the charge station, warning sound, future monthly income level, vehicle body price for CM, vehicle body price for EM, subsidy for EM, life cycle cost for ten years	(A) Conventional motorcycle (B) Electric motorcycle (C) No buying	Dogit model with parameterized captivity functions
5	Lee et al. (2016) [32]	Taiwan	Maximum speed, hill-climbing, acceleration, weight, range, refueling time, fuel availability	(A) Internal Combustion (IC) engine motorcycle (B) Electric motorcycle (C) Hydrogen fuel motorcycle	Multinomial logit model (MNL)
6	Zhou et al. (2016) [31]	China	Cognitive level, environmental consciousness, fuel price, charge cost, family size, license number, income	(A) Electric motorcycle	Binary logistic regression model
7	Guerra (2019) [11]	Indonesia	Purchase price, maximum speed, range, charging duration,	(A) Conventional Motorcycle (B) Electric Motorcycle (C) No Motorcycle	Mixed logit model with random coefficients
8	Zhu et al. (2019) [33]	China	Charging fees, environmental benefits, safety, education level, family members, motorcycle number, income level	(A) Electric motorcycle alternative 1 (B) Electric Motorcycle alternative 2	Binary logistic regression model

Selection of Attributes and the Levels

Based on the tabular summary of existing SP survey-based research (Table 1), an exhaustive set of attributes could be observed. While it is possible to include many attributes that can be included in a single design, researchers suggested an upper limit of six or seven attributes, if possible lower, for reducing user fatigue [34]. In their ongoing research, authors [35] have demonstrated a rational approach for selecting an exclusive set of attributes influencing E2W use in a typical Indian context. They have used several extensively adopted multi-attribute decision making (MADM) techniques to prioritize

a key set of E2W specific operational variables among the exhaustive set of attributes based on user perception. Based on the methodology, attributes such as purchase cost, OC (Operating Cost) savings, range, top speed, charging time, and acceleration were selected for the SP survey and subsequent valuation. Subsequently, the attribute levels were decided based on the actual market scenario, discussions with the experts, and attribute level selection guidelines [34]. The levels of the attributes are presented in Table 2, along with a brief description of the attributes. The levels are presented from a base condition to improved conditions for each attribute.

Table 2. Summary of attributes.

S.No	Attributes	Description	Level	Values
1	Purchase cost	The total cost paid for owning the electric two-wheeler	Level_1 (Base)	₹80,000 (US\$1087)
			Level_2	₹90,000 (US\$1222.8)
			Level_3	₹100,000 (US\$1358.7)
2	OC savings	The savings in the operating cost of electric two-wheelers in comparison to the average OC value of the existing electric two-wheelers	Level_1 (Base)	10%
			Level_2	30%
			Level_3	50%
3	Range	The maximum distance that can be traveled on a fully charged electric two-wheeler	Level_1 (Base)	120 km
			Level_2	150 km
			Level_3	180 km
4	Top speed	The highest speed that can be traveled on an electric two-wheeler	Level_1 (Base)	40 km/h
			Level_2	60 km/h
			Level_3	80 km/h
5	Charging infrastructure	The total time taken to charge the electric two-wheeler	Level_1 (Base)	5 h
			Level_2	4 h
			Level_3	3 h
6	Acceleration	The time taken by the electric two-wheeler to reach a speed from 0 to 60 km/h	Level_1 (Base)	4 s
			Level_2	7 s
			Level_3	10 s

3. Design of Stated Preference Survey Questionnaire

SP survey hypothetical alternatives are designed based on the identified attributes and their respective selected levels. Subsequently, the choice sets are designed. For six attributes with three levels each, a full factorial design would have generated $3^6 = 729$ choice options. However, it is not practical to include so many options in a choice experiment considering user fatigue. In this regard, fractional factorial designs such as efficient designs could be a more appropriate alternative [27]. An efficient design produces the parameter estimates associated with the least plausible standard [36]. In this paper, a D-optimal efficient design is adopted for obtaining the optimal number of choice sets. Such designs adopt D-optimality as the efficiency criteria that seek to minimize the dispersion matrix's determinant (D-error). The design with the lowest D-error is called D-optimal design [36]. In this paper, the N-Genie statistical package [37] is used to design the SP survey's optimal number of choice sets. While designing the D-optimal design, all attribute signs are considered based on the preliminary research references. The D-optimal design approach can generate a set of choice situations where the dominant alternatives are automatically avoided. Hence, such a design approach leads to a statistically better design. However, a further manual inspection of the choice situations was also carried out to remove the dominant alternatives (if any). In general, two broad types of choice experiments are conducted, namely, labeled or alternative-specific and unlabeled or generic experiments [38]. For an unlabeled or generic experiment, respondents are less inclined to consider the label and mainly focus on the choice attributes. One of the major aims of this paper is to evaluate the WTP associated with the attributes; an unlabeled choice experiment is adopted here.

An unlabeled D-optimal design has further produced 18 choice sets. The number of choice sets was limited to 18 and were randomly divided into three blocks, with each respondent receiving a questionnaire containing one random block. As a result, the number of choice sets for each respondent was limited to six. In each choice set, alternatives are presented in a generic/unlabeled form. For choice experiments, respondents were presented with two alternative E2W option with varying levels of attributes. Respondents were suggested to assume the E2W vehicle types to be similar except for the attribute levels defined during the survey. The used questionnaire was refined based on a previously conducted pilot study, which addressed any issues the respondents faced during the survey process. Two sample choice set representations are shown in Table 3, where the respondents were asked to select their most preferred alternative.

Table 3. Sample choice sets.

Attribute	Purchase Cost	OC Savings	Range	Top Speed	Charging Duration	Acceleration	Select Your Choice
Sample choice set-1							
Alternative A	₹90,000 (US\$1222.8)	30%	180 km	80 km/h	3 h	4 s	<input type="radio"/>
Alternative B	₹80,000 (US\$1087)	30%	120 km	40 km/h	5 h	10 s	<input type="radio"/>
Sample choice set-2							
Alternative A	₹80,000 (US\$1087)	10%	120 km	60 km/h	5 h	10 s	<input type="radio"/>
Alternative B	₹100,000 (US\$1358.7)	50%	180 km	60 km/h	3 h	4 s	<input type="radio"/>

4. Data Collection and Database Development Process

In this paper, Hyderabad, an Indian metropolitan city, has been selected as the case study to demonstrate the proposed methodology. Hyderabad is Telangana's state capital, functioning as the state's central administrative, industrial, and commercial hub. The population in Hyderabad was 9.48 million in 2018 and is projected to reach 12.71 million by the end of 2030 [39]. It was the 6th most populous city in India in 2011 [40] and is expected to become the 28th most populous city in the world by 2030 [41]. Hyderabad's traffic density has increased significantly with the increase of private vehicles and two-wheelers in recent years. There were over 5.3 million vehicles registered in Hyderabad in 2018, of which 4.3 million are two-wheelers [42], subsequently leading to increased air pollution in the city. Hence, the promotion of E2W can substantially influence the overall quality of life of urban commuters in Hyderabad. For this research purpose, existing two-wheelers were considered the future/prospective users of E2W, and their perception toward E2W in general and related attributes was collected and modelled.

For the data collection process, the survey questionnaire was composed of three sections. First, users' socio-economic (age, gender, monthly family income, two-wheeler ownership, etc.) and trip-specific information (daily journey time using two-wheelers, average daily travel expenditure), etc. were collected. The second component of the survey questions was provided to make users aware of the E2W in general, the survey attributes, and their respective levels in specific for an increased familiarity of the respondents. In the final component of the survey, respondents were provided with six-choice sets, where each choice set corresponds to a pair of E2W alternatives (Table 3). Using a three-stage questionnaire, the data were collected from Hyderabad using Computer-Assisted Personal Interview (CAPI) [43,44]. The convenient sampling method was adopted for data collection. For the research, the target group was the exiting conventional motorized two-wheeler users having a valid driver's license. For data collection, a group of enumerators was trained by the researchers. They were deployed at offices, shopping complexes, colleges, universities, and market locations for intercepting the respondents for the survey. Finally, a

total of 15 such major locations distributed across the various zones were identified. Then, during the weekdays from 08:00 a.m. to 05:00 p.m., a team of experienced survey enumerators and researchers were deployed at those identified locations to capture two-wheeler users' actual perceptions. Firstly, the research's target respondent was identified by asking a particular two-wheeler user about their awareness toward E2W and future intention toward procuring an E2W. The interested future owners were the target respondents in this research. Subsequently, the trained enumerators guided the respondents through the CAPI screens. Each survey took approximately 15 min to complete the response collection process. Initially, while collecting data, almost 700 existing motorized two-wheeler users were approached for the survey, among which a total of 584 responses were collected from the survey across various locations in Hyderabad. Among the collected dataset, some responses to the stated choice options were incomplete, and for some respondents, the socio-economic information was either missing or inconsistent. All such incomplete responses were removed, and finally, a total set of 480 complete responses was used for further analysis. The selection of an adequate and representative sample is an important task for any sample-based statistical analysis.

In this paper, the population of interest includes two-wheeler users in Hyderabad. However, Indian census data [40] do not provide any information on two-wheeler users' socio-demographic profile. Hence, the sample representativeness cannot be directly assessed. However, for a better understanding, the sample is compared with the Hyderabad population statistics [40]. Sample statistics indicate an age distribution of 82% and 18% of respondents belonging to age group up to 35 years and more than 35 years, respectively. On the other hand, the age distribution of the overall population of Hyderabad with respect to the latest Census Manual is 67% and 33% of residents up to age group 35 and more than 35, respectively [40]. This difference in sample and city profile could be attributed to two reasons. First, the city characteristics do not include only two-wheeler users but include all residents. Second, among the non-responsive samples, a significant number were relatively elder commuters (aged more than 35 years) who were relatively less interested in being interviewed by the survey team. As a result, the samples were found to be relatively skewed with younger respondents. Due to the unavailability of other socio-economic information in the census data, other socio-economic and trip characteristics could not be compared. However, this research's final comprehensive sample size (480) was found to be significantly more compared to the minimum sample size (385) required for adequately representing an infinite or unknown population. In this paper, by assuming a 95% confidence level, the minimum sample size necessary for an infinite population-based analysis can be estimated as 385 [45]. A similar sampling strategy was also adopted in some previous SP survey-based studies to estimate the potential demand of the E2Ws. A sample size of 500 [14] and 400 [30] respondents were used for modeling and subsequent interpretation with respect to E2W user characteristics in those studies. Hence, the sample size obtained in this survey was also found to be adequate in comparison with past studies. The summary of the descriptive statistics of the sample surveyed is presented in Table 4.

Table 4. Summary of the descriptive statistics.

Socio-Economic Variable	Classification	Total Number of Respondents	Percentage of Respondents (%)
Age (years)	≤35 years	394	82
	>35 years	86	18
Income (₹/month)	≤50,000 ₹/month (US\$679.3)	287	60
	>50,000 ₹/month (US\$679.3)	193	40
Education level	Below 12th grade	114	24
	Graduate	259	54
	Post graduate and above	107	22
Type of vehicle ownership	Two-wheeler	322	67
	Two-wheeler + Car	158	33
Number of trips per day (trips/day)	1	126	26
	2	155	32
	3	151	31
	>3	48	10
Average daily journey time (hours)	≤1 h/day	305	64
	>1 h/day	175	36
Number of household members	1 to 3	221	46
	5 to 6	193	40
	>6	66	14

5. Model Development

The collected travel behavior database was used to develop the MNL and RPL models for estimation of respondent's perceived benefit associated with E2W attributes. Subsequently, the marginal willingness-to-pay (WTP) results associated with the attributes were calculated. The following section presents the theoretical background of these econometric models.

5.1. Theoretical Background of the Multinomial Logit and Random Parameter Logit Models

The discrete choice models, such as MNL and RPL, are derived from the basis of the random utility maximization theory. The theory assumes that the decision-makers would choose a particular alternative that maximizes their perceived utility [46]. The utility of the alternatives can be estimated from the coefficient of the attributes derived from the MNL and RPL models. Hence, the development of the MNL and RPL models would help understand the purchase behavior of the non-users, which can act as a solid basis for developing a policy framework to support the promotion of the E2Ws in India.

5.1.1. Multinomial Logit Model

The utility of the alternatives as perceived by the decision-maker is derived from the MNL model, assuming the error term ε to be an independently and identically distributed extreme value. Train [46] provides a comprehensive description of the theoretical background and the MNL model's formulation. In the MNL model, the coefficient of the attributes is estimated from the maximum likelihood estimator (MLE) method. The utility $U_{i,n}$ as perceived by the decision-maker n , to choose an alternative i can be estimated with Equation (1). The deterministic component $V_{i,n}$ in the utility function is represented in Equation (2).

$$U_{i,n} = V_{i,n} + \varepsilon_{i,n}, \text{ for all } i \in C_n \quad (1)$$

$$V_{i,n} = \beta X_{i,n} \quad (2)$$

where $U_{i,n}$ is the utility, $V_{i,n}$ is the deterministic component, $\varepsilon_{i,n}$ is the random components, and C_n is the available choice set. $X_{i,n}$ is a vector representing the attributes of the alternatives and the socio-demographic attributes of the decision-maker n . In this paper, the choice set C_n includes two alternatives with six attributes, as shown in Table 3. β represents

the coefficients of the attributes that will be estimated. Subsequently, the probability $P_n(i)$ of the respondent n to choose the alternative i is derived from Equation (3) [46].

$$P_n(i) = \frac{e^{V_{i,n}}}{\sum e^{V_{j,n}}} \text{ for all } j \in C_n \quad (3)$$

The MNL model is considered as the foundation for the analysis of the discrete choices of the decision-maker. However, there are some limitations regarding the MNL model. First, the Independence of Irrelevant Alternatives (IIA) property of the MNL model assumes the error term $\varepsilon_{i,n}$ to be independently and identically distributed across all the choice alternatives. The IIA property assumes that regardless of the changes in attributes of the alternatives, the ratio of the probability of choice between two alternatives will always remain constant and is not even affected by the addition of new alternatives to the system [38,47]. However, the IIA property is not valid in the real application. The addition of the new alternatives to the system would directly impact the decision-makers' choice behaviors, which is often illustrated by the red bus/blue bus paradox [47]. Additionally, the other limitation of the MNL model is the assumption of the coefficient of the attributes to remain identical for all the decision-makers [19,46], which is a highly unlikely assumption. The RPL/mixed logit model addresses such shortcomings by allowing for random taste variation, unrestricted substitution patterns, and correlation in unobserved factors over time [46]. A brief theoretical background of the RPL model is provided in the subsequent section.

5.1.2. Random Parameter Logit Model

The MNL model considers only the observed preference heterogeneity among the decision-makers by interacting attributes of the alternatives with the decision-makers' characteristics [48]. However, certain specific assumptions are necessary to include the unobserved preference heterogeneity in the model. In this regard, Boyd and Mellman [49] has introduced the RPL model with certain modifications to the standard MNL model. The random parameters are included as a pre-specified parametric continuous mixing distribution function $f(\beta)$. The RPL model is the integral of the standard MNL model over a density of the parameters. The probability of the decision-maker i to choose the particular alternative is derived from Equation (4).

$$P_n(i) = \int \frac{e^{V_{ni}(\beta)}}{\sum e^{V_{nj}(\beta)}} f(\beta) d\beta \quad (4)$$

where $f(\beta)$ is a density function. $V_{ni}(\beta)$ is the observed preference heterogeneity. The probability $P_n(i)$ is a weighted average evaluated at different values of β , $V_{ni}(\beta) = \beta_n x_{ni}$, where x_{ni} is a vector of the attributes related to a particular alternative. The choice probability in RPL models does not have a closed-form solution; it is difficult to estimate the coefficients analytically. Hence, the simulated maximum likelihood using Halton draws [46] could be adopted to estimate the coefficient. Generally, a method of random draws using pseudo-random sequence is adopted for the random draws. However, Bhat [50] has suggested an alternative "quasi-random maximum likelihood" method, which adopts the uniformly distributed sequences rather than the random draws. Due to its conceptual simplicity, the Halton draws reduce the number of draws compared to the random draws, reducing the run time and the simulation errors associated with the draws. Halton draws can vary from 50 to 2000. However, Bhat [50] has adopted 125 random draws. In this paper, 500 Halton draws were selected during the simulation runs in NLogit. The next important step in estimating the coefficient of the attributes is the assumption of the probability distribution of the $f(\beta)$.

The coefficient estimates of the attributes derived from the RPL model will vary according to the assumed probability distribution of the $f(\beta)$. Different parametric distributions such as normal, log normal, uniform, and triangular distributions have been considered for

the $f(\beta)$. However, Louviere and Eagle [51] have specified that the normal distributions may provide incorrect results if the assumed distribution is not appropriate for the data. If the random parameters are assumed to follow a normal distribution, both positive and negative coefficient estimates would exist in the population. The normal distribution's unbounded nature indicates that all real numbers have a non-zero probability of being produced as a draw. Therefore, assuming that a given coefficient follows normal distribution is equivalent to making an a priori assumption that both negative and non-negative values may exist in the population [52]. The true distribution might contain all negative values but could have a mean closer to zero with a longer tail in the negative space. In such a scenario, the normal distribution's symmetrical nature could lead to a substantial portion of non-negative values, which may be impractical [52]. Among other distributions, log-normal has a limited application due to its long tail toward the unbounded side, and also, it has slow convergences in a certain set of scenarios [52]. The log-normal distribution is useful only when the coefficient is known to have the same set of signs for the entire population. Triangular or uniform distributions have been previously adopted for the parameters. The uniform distribution assumes β to be uniformly distributed between $(b - s)$ and $(b + s)$, where the mean (b) and spread (s) are estimated [46]. The triangular distribution has a positive density that starts at $(b - s)$ value and rises linearly to mean and then drops linearly to $(b + s)$ spread. Hence, the distribution is bounded on both sides, avoiding estimating the coefficient with the very large values by either normal or log-normal distribution. Furthermore, if the mean and spread are assumed to be equal, the same signs of the coefficients could be ensured by the respondents [46]. Considering all these aspects, for RPL models, $f(\beta)$ has been assumed to follow the constrained triangular distribution (assuming mean and spread to be equal) for estimating the coefficient estimates of the attributes. The major advantage of a constrained triangular distribution is that the WTP can be calculated as the ratio of the mean coefficient of any attribute to the mean coefficient of cost attribute, unlike other distribution assumptions. Standard deviation also has a significant role to play.

5.1.3. Heterogeneity Investigation with Respect to Socio-Economic and Trip Characteristics

The effect of prospective users' socio-economic and trip characteristics on WTP estimates was evaluated by introducing the heterogeneity around the means of random parameters in the RPL model. The individual heterogeneity of preferences is introduced in RPL models through interactions between the attributes and the prospective users' socio-economic and trip characteristics, which would help evaluate the effect of socio-economic or trip-related characteristics on user preferences [22]. The interactions would evaluate the effect of socio-economic characteristics of the users on their choice behavior. Heterogeneity may occur due to taste variation in how the respondents weigh the attributes [53]. In a discrete choice modeling framework, the incorporation of taste heterogeneity in terms of socio-economic or trip characteristics would help to explore the influence of different user groups on model estimates, whereas the exclusive estimation of mean estimates of the parameters would fail to investigate the variation of preferences among a different set of prospective users [54]. The expression of the unobserved component of utility being $\beta_n x_{nj}$, the expression for overall utility could be expressed as presented in Equation (2), where β_n varies across each individual respondent both randomly and systematically with observable variables z_n . Hence, when random parameters are assumed to be uncorrelated, the utility function of alternative i is expressed as presented in Equation (5) [27].

$$U_{nj} = \left(\beta + \Delta z_n + \sum \frac{1}{z} v_n \right) x_{nj} + \varepsilon_{nj} \quad (5)$$

$$U_{nj} = (\beta + \Delta z_n + \eta_n) x_{nj} + \varepsilon_{nj} \quad (6)$$

In case of the k^{th} attribute, the random coefficient could be expressed as presented in Equation (7).

$$\beta_{nk} = \beta + \delta_k z_n + \eta_n \quad (7)$$

η_n denotes the random parameter with stochastic properties. v_n is a primitive vector of uncorrelated random variables with known variances. The actual scale factors that provide the unknown standard deviation of the random parameters are arrayed on the diagonal of the diagonal matrix $(\Sigma^{\frac{1}{2}})$ [27]. The term $\delta_k z_n$ accommodates heterogeneity in the mean of the distribution of the random parameter.

The introduction of an interaction between the mean estimate of the random parameter and an observed covariate reveals the presence or absence of preference heterogeneity around the mean parameter estimate. If the interaction is not statistically significant, then it can be concluded that there is an absence of preference heterogeneity around the mean based on observed covariates. A statistically insignificant interaction does not indicate any preference heterogeneity around the mean; instead, it indicates that the model has not reported its presence. It means that the analyst relies entirely on the mean and standard deviation of the parameter estimate. The latter represents all sources of preference heterogeneity in the population sampled [27]. Therefore, in this paper, the heterogeneity around the mean parameter estimate of each attribute has been evaluated with respect to prospective users belonging to different categories such as age (≤ 35 years and > 35 years), monthly family income ($\leq 50,000$ ₹/month and $> 50,000$ ₹/month), and average daily journey time (≤ 1 h/day and > 1 h/day).

5.2. Multinomial Logit and Random Parameter Logit Model Estimation

In this work, MNL and RPL models were developed using the NLogit statistical package [55]. First, MNL and RPL models are developed for the complete dataset, and then WTP values are estimated. Second, the heterogeneity effect with respect to socio-economic parameters such as age, monthly family income, and trip-specific characteristics such as daily journey time was investigated through the development of three RPL models. Table 5 provides the coefficient estimates for the MNL and RPL models with and without heterogeneity. Reported pseudo R squared for all models were in the range of 0.2–0.4 against all models, which revealed that the models were a good fit [56]. The signs associated with all parameters were found to be expected. Negative coefficient estimates associated with purchase cost indicate that the overall utility associated with an E2W alternative reduces with an increase in purchase cost. The attributes relating to charging duration and acceleration were also associated with a negative sign, indicating that an increase in charging duration or time to accelerate would act as a deterrent to an expected result. On the other hand, OC savings, range, and top speed were observed with significant positive estimates, indicating their positive role toward overall utility. Investigating evidence of heterogeneity with respect to age, monthly family income, and journey time using two-wheelers indicates that users belonging to different age groups perceive top speed and range significantly differently. Users belonging to a higher age-group perceive top speed or range to be more/less important than their younger commuters. Similarly, users who travel longer were found to associate more importance to reduced OC savings and increased top speed. Heterogeneity could not be observed with respect to charging duration and acceleration across different user sub-groups. These findings would help the manufacturers and planners develop E2W friendly infrastructure in the Indian context.

The interpretation of coefficient estimates is not straightforward except for significance. Therefore, the marginal rates of substitution between the non-cost parameters and purchase cost, or ratio of coefficients of non-cost attributes and purchase cost, were estimated as the WTP associated with each attribute. In the RPL models, all parameters except purchase cost were considered random. Fixing the cost parameter would ensure a straightforward calculation of the WTP associated with parameters. WTP could be estimated by simply dividing the coefficient of that attribute by the coefficient of cost. In addition, the distribution of the WTP became the distribution of the attribute's coefficient [56]. WTP is

interpreted as the perceived benefit associated with a unit change for continuous attributes. For example, WTP results indicate that future users of E2W would be willing to pay ₹8852 (US\$120.2) (Table 6) extra for a 1-h reduction in charging duration, indicating the importance associated with charging duration by the future customers. Table 6 summarizes WTP estimates derived from the MNL and RPL models with complete datasets without considering heterogeneity and different socio-economic sub-groups. The following section presents a brief interpretation of the WTP estimates with respect to the overall sample and different sub-groups, respectively.

Table 5. Coefficient estimates for the multinomial logit (MNL) and random parameter logit (RPL) models.

Attributes	Model 1	Model 2	Model 3A	Model 3B	Model 3C
	MNL Model Estimates	RPL Model Estimates	RPL Model Estimates	RPL Model Estimates	RPL Model Estimates
	Overall Sample	Overall Sample	Age Heterogeneity, Years	Monthly Income Heterogeneity, ₹/Month	Average Daily Journey Time Heterogeneity, Hours/Day
Random Parameters in Utility Functions					
	Coefficient Estimate (Absolute t-Ratio)				
OC savings (%)	0.013 (7.77)	0.013 (7.13)	0.010 (3.03)	0.007 (3.17)	0.017 (7.03)
Range (km)	0.011 (5.58)	0.010 (5.26)	0.007 (2.40)	0.007 (2.99)	0.013 (5.10)
Top speed (km/h)	0.033 (13.75)	0.035 (13.12)	0.027 (6.16)	0.031 (10.01)	0.037 (10.24)
Charging duration (hours)	−0.182 (−3.17)	−0.239 (−3.96)	−0.269 (−2.80)	−0.261 (−3.70)	−0.232 (−3.18)
Acceleration (s)	−0.141 (−8.18)	−0.161 (−8.60)	−0.167 (−5.07)	−0.179 (−7.89)	−0.163 (−7.09)
Non-random parameters in utility functions					
Purchase cost (₹)	−0.024 (−6.13)	−0.027 (−6.26)	−0.026 (−5.99)	−0.027 (−6.16)	−0.028 (−6.38)
Heterogeneity in mean, Parameter: Variable					
OC savings (%)				0.015 (4.51)	−0.009 (−2.72)
Range (km)			0.005 (2.36)	0.009 (2.89)	−0.005 (−1.70)
Top speed (km/h)			0.010 (2.09)	0.009 (2.03)	
Charging duration (hours)					
Acceleration (s)					
Log likelihood function	−1669.54	−1669.39	−1667.03	−1656.94	−1664.88
McFadden Pseudo R-squared	0.20	0.24	0.24	0.25	0.24

Table 6. Summary of willingness-to-pay (WTP) estimates derived from the MNL and RPL models.

Attributes	WTP Estimates (₹)							
	Model 1	Model 2	Model 3A		Model 3B		Model 3C	
	MNL Model	RPL Model	RPL Model with Age Heterogeneity		RPL Model with Monthly Income Heterogeneity		RPL Model Average Daily Journey Time Heterogeneity	
	Overall Sample	Overall Sample	≤35 Years	>35 Years	≤50,000 ₹/Month	>50,000 ₹/Month	<1 h/Day	>1 h/Day
OC Savings (%)	542	481	385	385	259	815	607	286
Range (km)	458	370	269	462	259	593	464	286
Top speed (km/h)	1375	1296	1038	1423	1148	1481	1321	1321
Charging Duration (hours)	7583	8852	10,346	10,346	9667	9667	8286	8286
Acceleration (s)	5875	5963	6423	6423	6630	6630	5821	5821

5.3. Interpretation of Willingness-to-Pay Estimates

Table 6 presents a summary of the marginal WTP associated with different attributes specific to E2W. For better understanding, WTP estimates are interpreted separately for each attribute.

5.3.1. Operating Cost Savings

Operating Cost (OC) savings is an attribute that accounts for the percentage savings associated with E2W operation cost per km. OC for E2W is calculated with respect to the Manual on Economic Evaluation of Highway Projects in India-IRC SP-30 [57]. The OC estimation includes fuel/electricity cost, insurance premium, maintenance costs, battery replacement costs, tire replacement, etc., for the standard E2W model at the current Indian market scenario. Subsequently, it is assumed that with improvement in E2W operational characteristics, there will be a reduction in OC. Hence, the levels presented in the paper represent better quality E2Ws with OC savings of 10%, 30%, and 50% compared to the base/standard E2W model, respectively. From Table 6, it can be observed that the WTP estimate ranges from ₹259 (US\$3.5) to ₹815 (US\$11). Therefore, users are willing to pay a minimum of ₹259 (US\$3.5) to a maximum of ₹815 (US\$11) extra for every 1% OC savings/km of operation. From the heterogeneity analysis, age was not found to be statistically significantly influencing parameter estimate. As a result, the WTP estimates for improvement in OC savings were found to be similar for both lower age (≤ 35 years) and higher age (> 35 years) group commuters. However, the increase in commuters' monthly family income has a positive influence on OC savings. Commuters belonging to the low-income group ($\leq 50,000$ ₹/month) are willing to pay ₹259 (US\$3.5), and those belonging to the high-income group ($> 50,000$ ₹/month) are willing to pay ₹815 (US\$11.2) for every 1% increase in OC savings offered by the E2Ws. This finding indicates that individuals with high income are willing to pay significantly higher for reduced operating costs. It can be inferred that further improvements in the OC savings might motivate the prospective users with higher income to purchase an E2W. Similarly, the heterogeneity of preferences among the commuters with different average daily journey time reveals that individuals with shorter journey times (≤ 1 h/day) are willing to pay ₹607 (US\$8.3). Individuals who travel for a longer duration (> 1 h/day) are willing to pay ₹286 (US\$3.9) for every 1% increase in the OC savings. The relatively lower willingness to pay associated with OC by the commuters traveling for a longer time could be attributed to the lack of adequate charging stations along the corridors in India. A similar observation was made in previous studies as well [58]. It can be inferred that further reductions in OC would attract the commuters with a higher monthly income and those who generally travel for a shorter duration in the Indian context.

5.3.2. Range

The range is defined as the maximum distance that a fully charged E2W can travel. Range levels of 120, 150, and 180 km have been considered in the stated choice experiment. WTP estimates reveal that overall users irrespective of any socio-economic sub-group are willing to pay ₹370 (US\$5) for every 1 km increase in the range of an E2W. The heterogeneity analysis has revealed a difference in WTP values between the lower age (≤ 35 years) and higher age (> 35 years) group commuters. The lower age group commuters' are willing to pay a sum of ₹269 (US\$3.7), whereas the higher age group commuters' WTP is ₹462 (US\$6.4) for every 1 km increase in the range of the E2W. The higher age group individuals majorly use two-wheelers for revenue-generating trips and preferred the improvement in range than their younger counterparts. Individuals in their 30s and 40s tend to travel relatively more than the remaining age category [11]. Hence, the higher age group commuters have perceived higher benefits associated with the further improvements in the range of E2W. Research by Lin and Tan [59] has reported that the WTP probability is associated with improved range increases by 4.53% for the higher age individuals. Monthly family income was also found to be significantly influencing the WTP estimates across user groups. The WTP estimate for the lower-income ($\leq 50,000$ ₹/month) group was estimated to be ₹259 (US\$3.6), and that of the higher income ($> 50,000$ ₹/month) group was ₹593 (US\$8.2) for every 1 km increase in the range of the E2W. It indicates that the higher-income group commuter value ranges more than that of the lower-income groups. So, it can be inferred that improvement in range could motivate the individuals with higher income to use

E2W. Similarly, the WTP value for commuters with the lower journey time (≤ 1 h/day) is estimated to be ₹464 (US\$6.4), and that of the commuters with higher journey time (>1 h/day) is estimated to be ₹286 (US\$3.9) for every 1 km increase in the range of the E2W. This finding of higher WTP estimates of the lower journey time group could be due to the commuters' range anxiety. Due to a lack of adequate public charging facilities, the commuters with lower journey time have emphasized a further increase in the range of the E2Ws. The commuters' range anxiety can be reduced when there are adequate charging stations along the route [60]. Therefore, the improvement in range would eventually attract the commuters belonging to the higher age category, those with a higher monthly income, and those who would travel for shorter duration.

5.3.3. Top Speed

The top speed is defined as the highest speed that the E2W can achieve. Top speed values of 40, 60, and 80 km/h have been considered in the stated choice experiment. Table 6 shows that the WTP estimates for every 1 km/h increase in the top speed of the E2W range from a minimum value of ₹1038 (US\$14.1) to a maximum value of ₹1,481 (US\$20.4). This is an indication of the significance of the speed on the choice behavior of the future users. The derived agility and reliability achieved while traveling on the congested road is the major motivation behind the higher WTP associated with better top speed. The commuters usually prefer traveling at higher speeds to reduce the total travel time [14]. From heterogeneity analysis, it is found that the lower age (≤ 35 years) group commuters' WTP estimate is ₹1038 (US\$14.1). In contrast, that of the higher age (>35 years) group is estimated to be ₹1423 (US\$19.6) for every 1 km/h increase in the top speed of the E2W. It indicates the stronger preferences of higher age commuters toward reduced journey time while traveling by E2W. Monthly family income was also found to significantly influence user preference toward improvement in top speed. The WTP estimates for further improvements in a top speed of E2W was reported to be ₹1481 (US\$20.4) for the high-income group ($>50,000$ ₹/month) commuters, whereas for the low-income group ($\leq 50,000$ ₹/month), the WTP is estimated to be ₹1,148 (US\$15.8) for every 1 km/h improvement in the top speed of the E2W. Similarly, the commuters with lower travel duration (≤ 1 h/day) and higher travel duration (>1 h/day) are reported to have perceived further improvement in speed of the E2W at a similar level of significance. Hence, the WTP values for both the commuter groups with different travel duration were the same. Therefore, the top speed improvement would make the E2W an appealing alternative to the commuters belonging to the higher age and higher income category in the Indian context.

5.3.4. Charging Duration

The charging duration refers to the total time duration required for charging the battery of the E2Ws. The charging duration values of 3, 4, and 5 h were considered for the stated choice experiment. It can be observed from Table 6 that the commuters' WTP estimates for improvement in charging capacity are varying from a minimum value of ₹7583 (US\$102.4) to a maximum value of ₹10,346 (US\$140.5) for a 1-h reduction in the charging duration. However, no heterogeneity in preferences could be observed among the commuters belonging to different socio-economic backgrounds. High WTP estimates associated with this attribute indicate that charging duration is one of the most important attributes influencing future users' decision to purchase an E2W or not. It can be hypothesized that irrespective of the socio-economic background, most commuters would be highly motivated to use the future generation E2Ws with an improved charging technology that would reduce the total time duration for charging the E2Ws. This finding demonstrates the importance of reducing the charging duration to make E2Ws a more appealing alternative than the conventional two-wheelers.

5.3.5. Acceleration

The acceleration of the E2Ws is defined as the total time (seconds) required to accelerate from 0 to 60 km/h. In this paper, the acceleration time levels of 4, 7, and 10 s have been considered. Similar to the charging duration, there was no heterogeneity in preferences that could be observed. However, with respect to WTP estimates, acceleration was found to be the second most important attribute, with WTP estimates ranging from a minimum of ₹5821 (US\$80.4) to a maximum of ₹6630 (US\$91.6) for every 1-s reduction in the acceleration time of the E2W. The improvement in the acceleration is considered a key-value addition to electric vehicles' performance [61]. It was reported that an increase in range or speed or having faster acceleration could positively influence the choice probability of the electric vehicles [5]. Therefore, it can be assured that the increase in acceleration capacity of the E2Ws would eventually make E2Ws a more competitive and attractive alternative to the Indian commuters.

A sensitivity analysis is carried out in the following section to better understand the relative influence of the E2W specific attributes on future users' choice decisions.

6. Sensitivity Analysis

In this section, the percentage change in the probability of choosing an alternative compared to the base alternative is used as an indicator to evaluate the impact of various attributes toward improvements of E2W operational characteristics. For the stated purpose, a base E2W alternative is defined by the following levels of each attribute: Purchase cost: ₹80,000; OC Savings: 10%; Range: 120 km; Top-speed: 40 km/h; Charging Duration: 5 h; Acceleration: 10 s.

Subsequently, a total of 12 E2W alternatives (Table 7) were assumed for comparison with the base alternative. For developing the alternatives, the level of each attribute of the base scenario was improved at a time, keeping other attribute levels fixed. In each case, the alternative scenario was compared to the base scenario to estimate the change in choice probability. For sensitivity analysis, the parameter coefficients derived from the RPL model (without heterogeneity) were used. Equations (8) and (9) represent the utility of the base and the i^{th} E2W alternative. Equation (11) represents the formula for estimating the percentage change in probability of choosing an alternative compared to the base alternative.

$$U_{\text{base}} = -0.027 * \text{Purchase cost}_{\text{base}} + 0.013 * \text{OC savings}_{\text{base}} + 0.010 * \text{Top speed}_{\text{base}} - 0.239 * \text{Charging duration}_{\text{base}} - 0.161 * \text{Acceleration}_{\text{base}} \quad (8)$$

$$U_{\text{alt}_i} = -0.027 * \text{Purchase cost}_{\text{alt}_i} + 0.013 * \text{OC savings}_{\text{alt}_i} + 0.010 * \text{Top speed}_{\text{alt}_i} - 0.239 * \text{Charging duration}_{\text{alt}_i} - 0.161 * \text{Acceleration}_{\text{alt}_i} \quad (9)$$

$$\text{Probability of Choosing Alternative}_i, P(i_n) = \frac{e^{U_{\text{alt}_i}}}{e^{U_{\text{base}}} + e^{U_{\text{alt}_i}}} \quad (10)$$

$$\text{Change in probability of choosing an alternative (\%)} = \{P(i_n) - (1 - P(i_n))\} * 100 \quad (11)$$

Subsequently, a sensitivity analysis is conducted, and the corresponding percentage shifts from the base level to the respective alternatives are presented in Table 7.

The choice probabilities have been estimated in relevance to the base mode and 12 different E2W alternatives presented in Table 7. It is found from the sensitivity analysis that the change of purchase price from ₹80,000 (US\$1087) to ₹90,000 (US\$1222.8) would have a -14% shift, indicating that the choice probabilities of selecting the base mode is 14% higher than the alternate mode. A subsequent increase in the purchase price to ₹100,000 (US\$1358.7) would further reduce the choice probability of the alternate mode by 26%. Similarly, an improvement in OC savings of the alternate mode to 30% from 10% would increase its choice probability by 14%. The subsequent improvement of OC to 50% would eventually increase the choice probability of the alternate mode by 26%. The sensitivity analysis done by increasing the range from 120 to 150 km would increase the

choice probability of choosing the alternate mode by 16%. The subsequent enhancement of range capacity to 180 km increases the choice probability by 30%. Furthermore, the improvement in speed from 40 to 60 km/h would increase the choice probability by 30%. However, a similar increase of speed to 80 km/h increases the choice probability by 60%, which is highest among all the alternate modes considered in this research. Further analysis shows the reduction in charging duration from 5 to 4 h would increase the probability of choices by 12%, and a further reduction to 3 h would subsequently increase the choice probability by 24%. Finally, a change in the alternate mode's acceleration value from 10 to 7 s would increase the choice probability by 24%. A subsequent change in acceleration to 4 s would increase the choice probability by 44%. The sensitivity analysis has provided some valuable insights and policy-level implications with respect to E2W operational characteristics.

Table 7. Summary of the sensitivity analysis.

Attributes	Coefficients	Attribute Levels												
		Base Level	Alt_1	Alt_2	Alt_3	Alt_4	Alt_5	Alt_6	Alt_7	Alt_8	Alt_9	Alt_10	Alt_11	Alt_12
Purchase cost (₹1000)	−0.027	80	90	100	80	80	80	80	80	80	80	80	80	80
OC savings (%)	0.013	10	10	10	30	50	10	10	10	10	10	10	10	10
Range (km)	0.010	120	120	120	120	120	150	180	120	120	120	120	120	120
Top speed (km/h)	0.035	40	40	40	40	40	40	40	60	80	40	40	40	40
Charging duration (hours)	−0.239	5	5	5	5	5	5	5	5	5	4	3	5	5
Acceleration (seconds)	−0.161	10	10	10	10	10	10	10	10	10	10	10	7	4
Utility of the alternatives (U)		−2.2	−2.47	−2.73	−1.93	−1.67	−1.89	−1.58	−1.51	−0.81	−1.96	−1.72	−1.72	−1.23
Percentage change in probability of choice from base mode to alternative mode														
Base Level to Alt_1		−14%												
Base Level to Alt_2		−26%												
Base Level to Alt_3		14%												
Base Level to Alt_4		26%												
Base Level to Alt_5		16%												
Base Level to Alt_6		30%												
Base Level to Alt_7		34%												
Base Level to Alt_8		60%												
Base Level to Alt_9		12%												
Base Level to Alt_10		24%												
Base mode to Alt_11		24%												
Base mode to Alt_12		44%												

Firstly, top speed can be identified as the most important attribute influencing future users' choice decisions with respect to both WTP estimates and sensitivity analysis. Results reveal the largest shift in probability with respect to better speed (44%) along with a significant estimate of WTP (₹1038 to ₹1423) (US\$14.1 to US\$19.3). Therefore, with the improvement in E2W's top speed, it can be hypothesized that a significant proportion of prospective users may be positively influenced to use the E2W designed to operate at a higher speed level. This finding is in agreement with previous studies [14]. Chiu and Tzeng [14] compared the relative impact of different E2W attributes on commuter perception and found top speed to have a major influence on commuters' mode choice decisions. Therefore, manufacturers and policymakers are recommended to emphasize improving the speed of E2W to make E2W a more appealing alternative for prospective users. If the top speed of the E2W can be relative to the design standards of motorized two-wheelers (120 km/h), then the E2W mode could even be considered as a competitive mode to the motorized two-wheelers. Therefore, improvement in the top speed of the E2W could significantly influence the overall mode of the E2W in the Indian context.

Secondly, the time taken to accelerate from the stop condition to 60 km/h has been observed as the second most influential attribute in terms of WTP estimates and a shift in probability from sensitivity analysis. Prospective users are willing to pay the second-

highest price for improvements to the acceleration of E2Ws. From the sensitivity analysis, it has been observed that the improvement in the acceleration capacity of E2Ws is greatly influencing the choice probability of the prospective users to shift to the upgraded E2Ws. Some previous studies have concluded that improving the performance of E2Ws in terms of acceleration increases the likelihood of E2Ws being chosen as a regular mode for personal mobility [5,30]. This is because the agility and acceleration of E2Ws attract more commuters due to their ability to move faster on congested streets [14]. In contrast to this result, Guerra [11] found that Indonesian commuters expressed conflicting opinions about the acceleration components of E2Ws. Since E2Ws are a new technology in Indonesia and most commuters did not have the experience of driving E2Ws, they believed that the acceleration of E2W might be less competitive than that of motorized two-wheelers. However, in this research, for conducting the stated choice experiment, values of 4, 7, and 10 s were considered, which reflected almost the existing performance level of the motorized two-wheelers in the Indian context. Therefore, in this research, it is observed that the prospective users have expressed willingness to pay a significant amount for further improvements in the acceleration of E2Ws. Therefore, to increase the overall share of E2Ws in the Indian context, it is necessary to upgrade the acceleration capacities of the future E2Ws in the Indian context. For attributes such as range and charging duration, it is observed that improvements in these characteristics have relatively less impact on the future users' choice probabilities compared to speed and acceleration. Such findings could be key tools for assessing the E2W market and formulation of key promotion strategies for the organizations involved in the manufacturing and sale of E2Ws in the Indian context. One of the major policy measures that could be suggested to the government is the recommendation on subsidy on the purchase of E2W. Results indicate 14% and 26% reductions in the probability of future users choosing an E2W with the increased purchase price. This observation clearly indicates that subsidy purchasing E2W can play a major role in increasing E2W ownership in a typical Indian context. The Government of India (GoI) currently has a subsidy plan for the purchase of electric vehicles. The research findings clearly recommend developing an appropriate subsidy policy specifically planned for E2W for increased ownership.

7. Conclusions and Contributions

This paper presents an approach for evaluating E2W alternatives for proposed improvements in E2W attributes by capturing the prospective users' perception through a Stated Preference (SP) survey. Based on the analysis and results, this research makes several unique conclusions and contributions to the existing body of research.

- Firstly, the demonstrated methodological approach presents a unique method for producing quantitative estimates of perceived benefits associated with E2W specific attributes. Valuation provides useful insights on the different operational characteristics of E2W and would act as a guideline for planners in the typical Indian context. Although results are case study specific in nature, this paper makes a major contribution with respect to the proposed methodology, which applies to other city settings as well. This methodology develops the basis for a tool to estimate economic benefits related to E2W operational characteristics. This methodology would provide insights to both manufacturers and prospective users for informed decision-making specific to E2W. The majority of the past studies in the context of E2W in general, and E2W attribute valuation, in particular, has been taken up in developed countries such as China [62], USA [14,63], and Norway [64] or countries where E2W is already a popular or established mode of transport such as Taiwan [28,65] and Indonesia [11]; however, due to the significant difference in the transport and socio-economic characteristics of commuters, results derived from such studies cannot be directly applicable to a country such as India, where E2W is at its nascent stage. Hence, this methodology and related findings would be a distinct contribution to the body of E2W commuting specific research literature in general, in the context of India in particular.

- Secondly, the WTP estimates and shift in choice probability for an individual associated with various E2W operational characteristics are substantial for prospective users belonging to different socio-economic strata. This indicates that there is substantial scope for improvement in E2W-specific attributes in the typical Indian context. The WTP estimates are crucial inputs for assessing future users' perceived benefits that may help the manufacturers and government decision-makers. This research indicates improving the speed, acceleration level of the current E2W models, and suggestions for devising an appropriate government subsidy plan for increased patronage.
- Third, this paper has explored the unobserved heterogeneity across user perception to assess the influence of age, income, and journey duration on factors influencing E2W choice decisions. Such investigations are relatively new in E2W research and, therefore, they substantially strengthen the present academic body of the literature. Such findings help manufacturers and policymakers, as they help toward market segmentation in the Indian context.
- Fourth, the research results, specifically the utility equation coefficients and WTP estimates associated with the set of attributes, clearly reveal the role of econometric model specification on WTP estimation. The less restricted and relatively parameter-rich models (RPL models with heterogeneity) were statistically superior and explored more behavioral information than the simpler MNL models. This research also presents a successful application of constrained triangular distribution for the estimation of RPL models. The model specification and estimation results are found to be in accordance with the existing research literature [18,19].
- Fifth, this research's major contribution is combining the approach of WTP estimation and the sensitivity analysis to arrive at the important attributes from the stated choice experiment. WTP values provide monetary estimates for the improvement of different attributes. WTP units are different for different attributes such as OC (₹ per % OC savings/km), top speed (₹ per km/h increase in top speed), and acceleration (₹ per the second decrease in acceleration time), which makes the interpretation of most important attribute relatively difficult. Sensitivity analysis in terms of percentage shift in probability due to an improvement of a particular level of a specific attribute would provide all estimates in percentage, thereby making the interpretation simpler for the policymaker. Combining both these indicators, top speed, followed by acceleration, was the most important attribute influencing an individual's perception on E2W-specific attributes in the typical Indian context.

The authors wish to state the limitations and future scope of this research before closing. First, although this paper provides a broader insight into the actual perceptions of E2W prospective users in the Indian context, it can be stated that there are some limitations concerning data collection. During the data collection, the respondents were allowed to decide whether they wanted to participate in the survey. As a result, it could have led to self-selection bias toward the data collected. The respondents might have relatively positive opinions about the usage of E2W. Therefore, as a future extension of this research, the analysis should be carried out for a more generalized result by considering the users with modes other than two-wheelers. Secondly, in this paper, the authors investigated the impact of socio-economic and travel-related characteristics on prospective users' perceptions toward E2W. However, the authors did not investigate the influence of driving experience, knowledge, and familiarity with E2W on users' perception. As a further extension of the existing research, the authors would like to include the investigation of the aforementioned attributes as well. Such analysis might help the manufacturers to better frame the effective promotional strategies in the Indian context. Thirdly, this paper has analyzed prospective users' perceptions toward E2W through MNL and RPL models. The authors would like to mention that the coefficient of the attributes obtained from this research might vary across the commuters, and the results are not tested for transferability. Hence, the results obtained for Hyderabad city may not be representative of other urban areas. Therefore, the authors would like to extend this existing research to different cities across India to

provide a generalized input to the manufacturers and the policymakers. Furthermore, the methodology and the survey instrument are generic, which could even be used in cities of other developed and developing countries planning for introducing E2W as an alternative mode of transport.

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