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Heterogeneity based Mode Choice Behaviour for Introduction of Sustainable Intermediate Public Transport (IPT) Modes

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Abstract

Intermediate public transport (IPT) supplements the public transport system by providing first and last-mile connectivity to commuters. A feeder service based on sustainable intermediate public transportation can be made attractive by improving its mobility, accessibility, convenience, and comfort for its users. Sustainable IPT modes have a lower impact on the environment and can cater to the current and future needs of transportation. In this study, commuters' choice responses were collected using a stated preference survey instrument, and the database was analyzed using a Random Parameter Logit (RPL) model. Face-to-face interviews were conducted with respondents who were approached at random. A different combination of values from the levels of attributes was used to create choice scenarios for each IPT mode. Different types of IPT modes were identified in the study act as feeder services, which was used to find their utility functions using a random parameter logit model. The random parameter logit model with heterogeneity was used to evaluate the impacts of different socioeconomic and trip features on mean estimations. The utility function was used to find willingness to pay (WTP) for different attributes of an IPT mode to assess the relative value of these attributes. It was observed that WTP values also varied between different levels, which were based on their "monthly income level", "trip purpose", and "fare". "High income level" commuters have a higher WTP for travel time, frequency, and comfort improvements. On the other hand, the "work trip" and "high travel fare" levels of commuters have higher WTP for travel time, frequency, and safety improvements. According to the findings of the study, sustainable IPT modes with high quality of service are recommended because of commuters' willingness to pay for improved safety and comfort. The results so obtained can also be used for a better understanding of the travel behaviour analysis of various IPT modes.

Keywords: Mode Choice Model; Random Parameter Logit Model (RPL); Feeder Service; Willingness to Pay; Stated Preference.

1. Introduction

Urban India is experiencing a huge increase in travel demand due to rapid urbanization and the increased use of private vehicles. The urbanization of developing countries has put a considerable strain on existing urban transportation infrastructure, including public transportation (PT) systems. These systems involve a variety of transit options such as buses, rail, and MRT systems. These systems run along fixed routes with set points to a pre-arranged timetable. In the current situation, the public transportation system is unable to cope with the increasing transport demand both in qualitative and quantitative terms, especially in developing countries. In the absence of well-organized public transportation infrastructure, intermediate public transportation (IPT) options such as auto rickshaws, e-rickshaws, and mini buses fill the gap between supply and demand for mass transportation. It can be referred to as

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modes used on hire for flexible passenger transportation which may or may not follow a fixed route [1, 2]. These modes are different from public transport systems due to their ability to pick up or drop off passengers on demand and provide door-to-door services [3]. IPTs are faster on narrow streets. It requires relatively less space to drive than public transport modes. This system connects commuters to and from major public transportation terminals such as bus stands, metro stations, and railway stations by making them easily accessible from all parts of the city. The IPT mode helps to discourage the use of personal vehicles. As a result, it reduces pollution, improves safety and decreases congestion on roads. Sustainability is the provision of safe, effective, and efficient access and mobility into the future while considering the economic, social, and environmental needs of society. The sustainable IPT modes have a low environmental impact and meet current and future transportation needs [4].

Commuters choose sustainable IPT modes as a feeder service due to the ease of mobility services. An effective and efficient method of integrating feeder services is to enhance the connectivity of public transport terminals. A feeder service helps the integration of several modes of transportation [5]. IPT could serve as a feeder mode by filling the gaps in transport services between mass transit systems and private vehicles [6]. A feeder system in an urban area requires the PT and IPT systems to integrate their operations such that they supplement each other and provide a wider network of services.

Mode choice models are used to determine the variables that influence their choice and the probability of choosing amongst the available options. The decisions to choose between various alternatives for choosing services depend on the attributes of the different options available. The combination of revealed preferences (RP) and stated preferences (SP) data is used to evaluate these models. Commuter mode choice behaviors and preferences are significant not only for their travel choices but also for the future development of IPT modes as part of urban transportation policy. The calculation of models is based on the monetary cost of savings in travel time. The concept of the value of time is evaluated by willingness to pay (WTP). It is essential to know the value of the user's willingness to pay for various feeder services that are part of sustainable IPT options. The WTP values are calculated with reference to different attributes of sustainable IPT modes using the random parameter logit (RPL) model. Individual socioeconomic aspects such as gender, age, monthly income, occupation and trip features (e.g. trip length, trip purpose, trip distance and fare) have an impact on WTP values, which is referred to as heterogeneity.

2. Literature Review

Intermediate public transport (IPT) supplements the public transport system by providing first and last-mile connectivity to commuters. Auto rickshaws, taxis, mini buses, cycle rickshaws, and more recently, e-rickshaws are popular sustainable IPT forms of transportation in urban areas [7]. Urban populations have increased rapidly in developing countries like India. Existing public transport has not been sufficient to cater to the new levels of travel demand. For the most part, IPT appears to have developed in response to the need to fill gaps in traditional urban transportation [8]. Ansari and Sinha [9] conducted a study on IPT to compare the service quality of IPT modes such as e-rickshaws and auto-rickshaws. Kumar and Sinha [10] studied the improvement of service quality of IPT modes, which can require an increase in cost. Ponodath et al. [11] studied the relevance of IPTs in India's transportation sector, including their role and connectivity, as well as the benefits, challenges, and current status.

Feeder service provides ease of access for the commuters in urban cities. These services are intended to pick up passengers in a specific area and carry them to a transfer location. In developing countries, access to public transportation has been limited by inefficient land use planning and reduced service coverage. There are also a limited number of feeder systems available in urban areas. IPTs have excellently performed the feeder function’s capabilities from their origin to public transportation terminals in areas not covered by public transportation modes. Bachok and Zin [12] studied the travel behaviour of rail passengers. In their study, there were described various factors to encourage passengers to use feeder services in lieu of driving their personal vehicles to and from stations. Das et al. [13] described the development of feeder service with respect to walking distance and waiting time. The generalised cost was calculated for various aspects of feeder service. Balya and Kumar [14] analyzed the integration of feeder service to public transport which can be improved the existing public transport system. The comprehensive study by Zhu et al. [15] described potential traffic demands of feeder service between road and rail transit. Chandra et al. [16] have suggested feeder services for connectivity between origin and destination by feeder route and transit services. The study was carried out the number of stops or users increase to maximize the accessibility of feeder service. Das and Maitra [17] highlighted the improvement of the feeder service's qualitative attributes. Tabassum et al. [18] observed the feeder network design of a mass transit system for access and egress trips. Verma and Dhingra [19] proposed the model integrated operation between urban rail and feeder bus with minimized user and operating cost.

The process of determining which mode is opted by the user in a given set of conditions is known as mode choice analysis [20]. Several studies [21, 22] have been conducted to better understand the differences in choice preferences of public transport attributes in relation to individual specific parameters (e.g., gender, income and age) as well as trip-related aspects (e.g., trip purpose and trip length). In the transportation planning process, the mode of travel for any trip is critical. Logit models are ideal for analyzing a mode choice model. Econometric models including multinomial logit (MNL), generalised multinomial logit (GMNL), nested logit (NL) and random parameter logit (RPL) have been widely employed in travel behaviour research [23]. Multinomial logit models are commonly used to evaluate SP data due to their ease of estimate. There are various limitations in the MNL models. First, alternatives, choice sets and responses of choice experiments are independent of error terms. Second, all coefficients of attributes are considered to be equal for all respondents in choice scenarios. While the RPL model solves the shortcomings of MNL models, researchers have shown that RPL models create higher values of coefficient estimations [24]. A random parameter logit (RPL) model has been widely used in modelling of mode choice due to its form of ease of estimation, mathematical structures and ability to alternatives of add/remove choice mode in urban areas. Shahikhaneh et al. [25] used mode choice model to determine the key parameters that influence the motorcyclists' mode choice using a logit model. Meena et al. [26] studied mode choice behaviour specifically for shopping malls and identified the factors that influence a trip maker's mode choice behaviour in the developing country. Givoni and Rietveld [27] have carried out the profile of access and egress modes on trips to and from railway stations. The results observed that the majority of passengers prefer to walk, ride their bikes or take public transportation to and from the railway station. Azimi et al. [28] investigated the influential factors that affect transit users' choices of access and egress modes using MNL model. Hensher and Rose [29] described mode choice models for commuting and non-commuting travel scenarios in the form of emerging public transport infrastructure. An analysis of the elements that impact the mode choice behaviours of users were based on the new public transport system by Weng et al. [30]. Zhou et al. [31] have carried out to analyze quantitative and qualitative attributes of the taxi operation system in Indian cities. Dell'Olio et al. [32] presented to determine the fundamental attributes when users travel transfer from one mode of transport to another using a mixed logit model.

The maximum amount of money that a customer is willing to pay for an extra unit of an item or service is known as willingness to pay [10]. It's a tool for determining the relative relevance of various attributes in the mode choice process. A study by Sadhukhan et al. [21] showed that commuters' willingness to pay in exchange for better transfer services near metro stations. The decomposition impacts of different socio-economic and trip features on evaluation of mean were solved by RPL models with heterogeneity. Greene et al. [33] estimated WTP values for savings of travel time which centered on the random parameter distribution around the distribution mean. Phanikumar and Maitra [34] described willingness to pay for feeder service in urban areas using three types of different RPL models. For each operational status of feeder service, the projected WTP values are important for determining the overall disutility of travel perceived by trip planners. Schwarzlose et al. [35] investigated the WTP values for qualities of public transportation that would improve living standards for the elderly. Satishkumar et al. [36] described the willingness to pay commuters for various types of attributes of feeder systems in India using random parameter logit models. The attributes of waiting time and discomfort of travel were given high value by users. Das et al. [37] described different model specifications to calculate the WTP values of commuters for feeder system to a public transport terminal in areas. The importance of model definition was demonstrated by the differentiation of WTP values derived from various types of models. Majumdar et al. [38] have carried out to willingness to pay of bicycle route choice. The findings show that the perceived degree of risk (a measure of safety) was the most important factor determining bicycle route choice. Dandapat and Maitra [22] investigated trip makers preferred heterogeneity toward several features of public transport service using mixed logit models. The WTP for time savings among trip planners was shown to be higher for business trips. Maitra et al. [39] analyzed willingness to pay for feeder systems using different econometric models in developing countries. The effect of model specification was shown to be most prominent on WTP when access walking distance is reduced.

The purpose of this study is to introduce new modes of sustainable intermediate public transport (IPT). The mode choice behaviour of commuters is establishing utility functions for the proposed sustainable IPT feeder service modes and to compute their utilities. The stated preference (SP) data is used to establish the utility model in the type of ranking, rating and choice. The WTP values are estimated from SP data [40]. The findings will help enhance the quality of feeder service of IPT modes and attract more commuters. The existing public transportation system in developing nations is not well-established and managed to allow for seamless coordination of services with mass transit. Lack of connectivity among public transportation options lengthens transfer times and journey times, lowering customer satisfaction. The study area is constrained by public transportation routes and the high density of public transportation as indicated in Figures 1 and 2 respectively. A distinct mode of transportation's mode share is shown in Table 1. The mode choice of user's behaviour of these IPT modes focuses on factors such as service reliability, punctuality, frequency and waiting time. An IPT user draws the use of feeder service based on several features such as travel time, travel cost, comfort and safety.

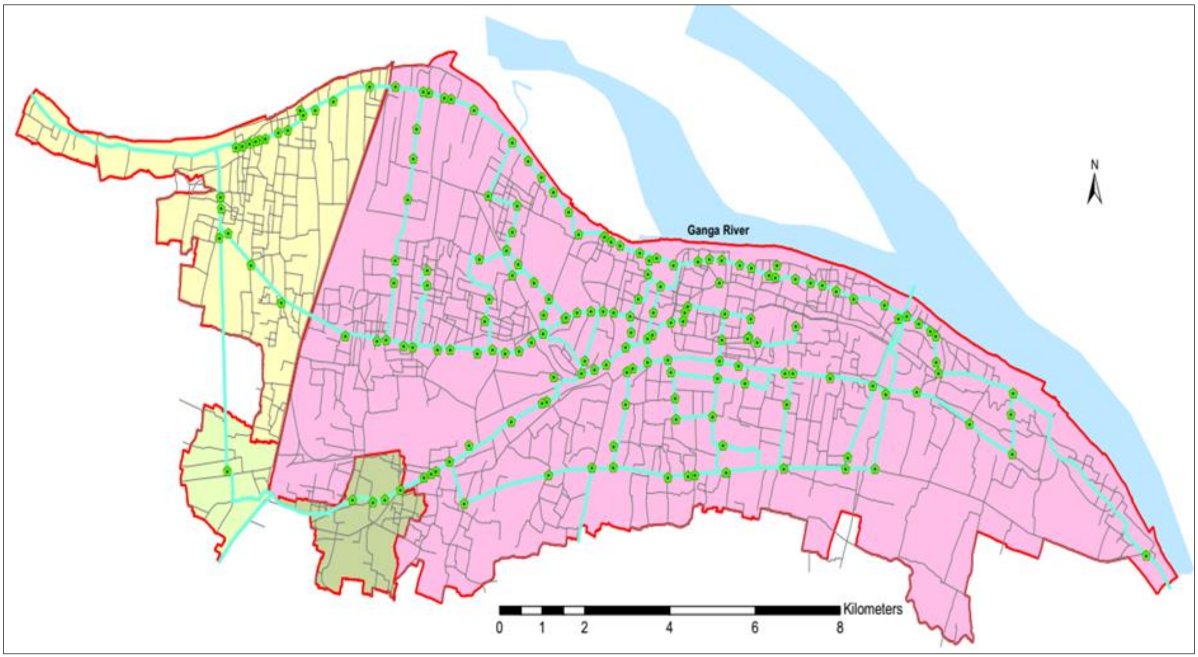

Figure 1. Route Map of Public Transport System

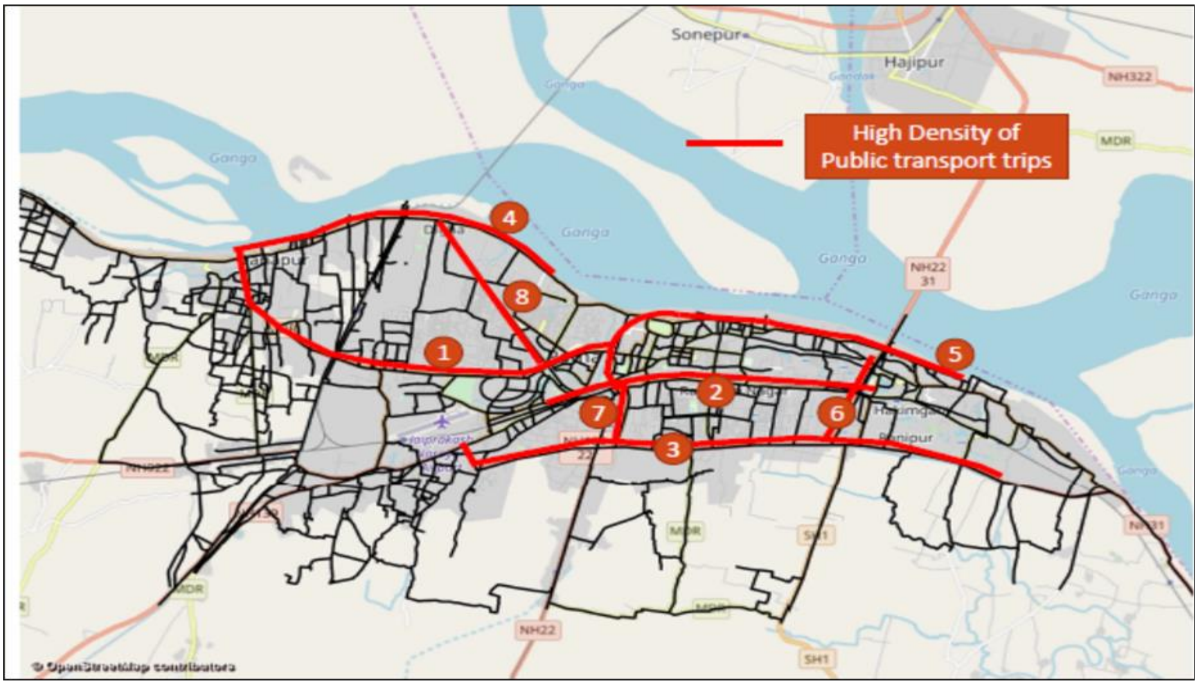

Figure 2. Route Map of High density of Public transport trips

Table 1. Mode Share [41]

Mode of Journey	Percentage (Except walking)
Two-wheeler	36.03%
Private Car	8.26%
Taxi or Ola	1.01%
Rickshaw	2.03%
Bicycle	7.67%
IPT modes	36.61%
Transit (Bus)	8.39%

According to the above literature, only a few researches have been done in the past using feeder service of sustainable IPT modes based on heterogeneity. In previous research, The WTP based on heterogeneity for public transport has been estimated by Dandapat and Maitra (2020). A WTP study for IPT modes has so far been very limited. Further, the use of a heterogeneity based RPL model for the evaluation of WTP is not available in the contemporary literature. The improvement of service qualities of the feeder service of IPT modes in densely populated major cities in India might be a better solution in view of the extent of urban infrastructure and transportation demand. The objective of this study is to build utility functions for suggested feeder service of sustainable IPT modes and to determine the WTP value for different characteristics of a travel mode using RPL models with heterogeneity. In this study, the RPL model with heterogeneity has been used to evaluate the decomposition impacts of different socioeconomic and trip features on mean estimations.

Patna is the capital of India's eastern state of Bihar. Patna, a historic city, has developed a prominent presence in regional trade and business. The map of Patna has been shown in Figure 3. According to the 2018 census, it has a population of 2.62 million people on the southern bank of the Ganges [42]. About 60% of the land is used for residential purposes with the remaining 7.61 percent dedicated to transportation infrastructure. All motorized types of public transportation modes for around 12% of total motorized traffic in the city were running in cities [43]. Every day, a great number of trips of various types, such as work travels, educational trips and recreational trips are created. IPT's high ridership is owing to its unreliable bus service, poor operation and congested road network. Integration of IPT with PT is necessary, especially in places like Patna where there are currently 12 working PT routes and 7 IPT routes. The IPT routes all intersect with the PT routes. The routes of IPT modes in the study area have been shown in Figure 4.

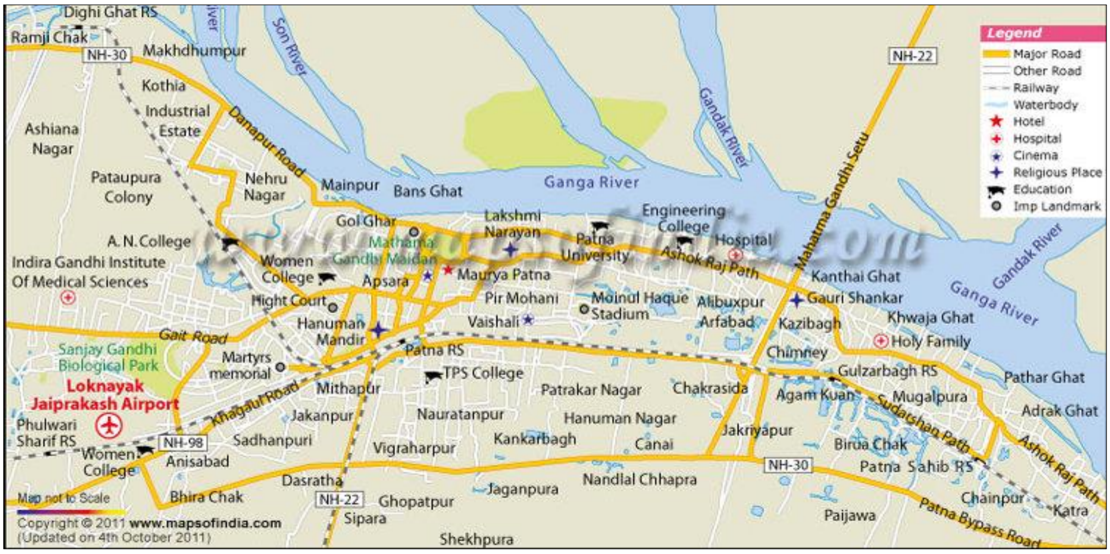

Figure 3. Patna Road Map [44]

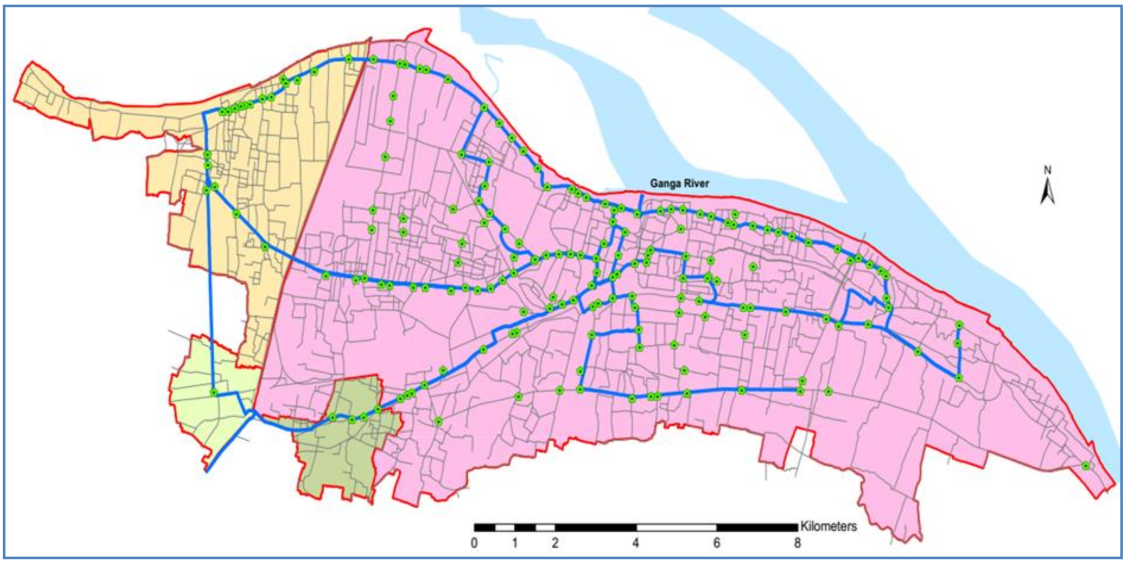

Figure 4. Route Map of IPT Modes

2.1. Theoretical Framework of RPL Model

The random parameter logit model is a well-known modelling approach and this theoretical background is used in a variety of sources [21-23]. The creation of random parameter logit (RPL) models resulted from an upgrade to address the constraints of the MNL model. When a respondent 'n' has to choose amongst 'J' alternatives, the RPL model specifies the utility equation of respondent 'n' for alternative 'j' as follows:

$$U_{nj} = \beta_n X_{nj} + \varepsilon_{nj} \tag{1}$$

where, X_{nj} is the responding variable that links the respondent and alternative. β_n is the vector of coefficients for present variables. ε_{nj} is an independent and identically distributed random term (IID) extreme value type-I distribution and variables for the respondent 'n' describe 'individuals' samples. The random parameters produce a distribution around the mean which allows preference heterogeneity in the sampled size of the population to be revealed. The alternative 'i' for individual 'n' of the utility function in RPL should be:

$$U_{nj} = \beta_n X_{nj} + \varepsilon_{nj} = (\beta + \Delta z_n + \sum^{1/2} v_n) X_{nj} + \varepsilon_{nj} = (\beta + \Delta z_n + \eta_n) X_{nj} + \varepsilon_{nj} \tag{2}$$

or,

$$\beta_{nk} = (\beta_k + \delta_k z_n + \eta_{nk})$$

where, β_{nk} is the random coefficient for the k^{th} attribute presented by individual 'n', $\beta_k + \delta_k z_n$ is Heterogeneity in the random parameters means distribution, η_{nk} is the random vector of random parameter with its stochastic feature, v_n is A simple vector of known variances uncorrelated random variables. The real scale factors are arrayed that offer the unknown standard deviation of the random parameters on the diagonal of the diagonal matrix $\sum^{1/2}$.

For example, if the utility function for exploring respondents tests heterogeneity around the mean parameter estimate of travel time (TT), frequency (f), comfort (c) and safety (s) with reference to the income of respondents is given by:

$$U_i = ASC_i + (\beta_{TT} + \delta_{TT} * Income) * TT + (\beta_f + \delta_f * Income) * f + (\beta_c + \delta_c * Income) * c + (\beta_s + \delta_s * Income) * s \tag{3}$$

ASC is an alternative or mode specific constant that may be removed from the calculation if it is shown to be insignificant. β_{nk} has a universal distribution (uniform, triangular, normal lognormal etc.) in the RPL model and ε_{nj} has an IID extreme value type 1 distribution. The probability (P_n) constrained on z_n for choice 'j' in choice circumstance't' is multinomial logit for a given value of β_n because the remaining term is random, ε_{int} is IID extreme value

$$Pn(\beta_{njt}) = \frac{e^{(\beta_n X_{njt})}}{\sum_{k \epsilon A_t} e^{(\beta_n X_{knt})}} \tag{4}$$

where, the choice set is $A_t = \{A_1,...,A_n\}$ and the whole set of attributes is $X_{tn}=[x_{1tn}, x_{2tn}, ...,x_{jtn}]$. Let the insignificant joint density of $[\beta_{n1}, \beta_{n2},...,\beta_{nk}]$ be $f(\beta_n|\Omega, z_n)$ while the components Ω are the fundamental variables of the distribution of β_n. $(\beta,\delta,\sum)$ and z_n is an observable variable particular to the important factors (socio demographical and socio economical features) that impact the selection of β_n. The product of the conditional probabilities is the conditional probability of seeing the order of a series of choices, represented *k (n,t)* from the choice subsets:

$$S_n(\beta_n) = \prod P\,(k(n,t)t|\beta_n) \tag{5}$$

The number of hypothetical options each respondent chooses in the survey is the sequence of choices in the choice experiment. The integral of the conditional probability in Equation 5 overall values of β is then used to define the unconditional probability for order of series of choices of alternative *i* for individual *n*

$$P_n(i|\Omega, z_n) = \int S_n(i|\beta) f(\beta_n|\Omega, z_n) d\beta_n \tag{6}$$

The exact maximum likelihood estimation is not possible since the integral in Eq. (6) may not be computed analytically. Simulation is used to approximate the probability. The simulated log-likelihood function is then maximised using Halton draws.

2.2. Calculation of WTP Values

The highest amount an individual is ready to give up in exchange for gaining a good or avoiding a bad is defined as the willingness to pay [45]. The utility function can be stated as follows, assuming a linear additive relation between attributes and utility:

$$U\,(X,p) = \sum_n \alpha_n\, x_n + \alpha_n p \tag{7}$$

where X is the vector of n attributes X is $(x_1, x_2,\ldots,x_n)$ and p is the travel cost of the alternative, α_n is the utility of each attributes, α_p is the utility of travel cost. Differentiating the utility Equation 7:

$$dU = \sum_n \frac{\partial U}{\partial x_n} dx_n + \frac{\partial U}{\partial p} dp \tag{8}$$

All attributes excluding x_1 ($dx_i = 0$, $i \neq 1$), along with all non-measured attributes that respondents perceive are considered to be unaffected ($dU = 0$). As a result, the WTP, which is a monetary value for a one-unit change in x_1, is as follows:

$$\frac{dp}{dx_1} = -\frac{(\partial U/\partial x_1)}{(\partial U/\partial p)} \tag{9}$$

3. Research Methodology

The mode choice model was created by combining the results of an RP and SP survey. For travel demand modelling, RP data was commonly employed. On the other hand, SP data was thought to be useful for attribute valuation. SP data was chosen over RP data for this study [46]. The discrete choice experiment (DCE) was a method for determining the relative insignificant disutility of attribute variation as well as probable correlations. In SP survey, the experimental design is the observation of the impact upon one variable, a response variable and given the positive manipulation of the levels of one or more variables which are based on the standard literature [47]. The questionnaire format was created using the commuters' recommendations, preferences, responses, and feedback from the pilot survey. Figure 5 shows a flow chart that represents a schematic overview of the works done.

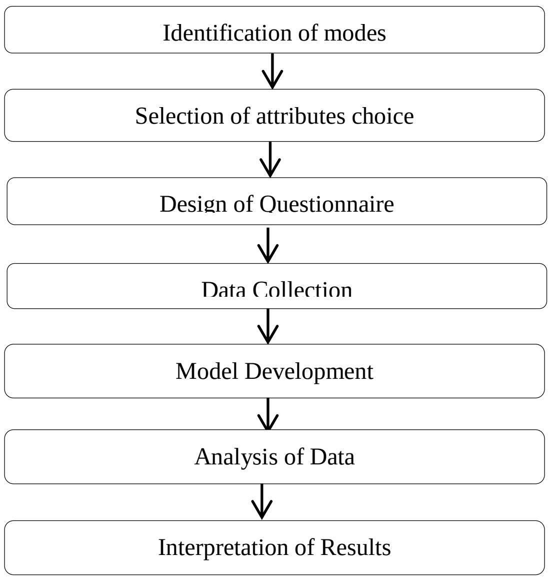

Figure 5. Research Methodology

3.1. Identification of Modes

The initial step was to identify the feeder service modes in the vicinity of the city. The feeder service was studied in several forms which are dependent on numerous criteria such as travel pricing, trip time, social acceptance, environmental conditions, and so on. It was determined to include e-rickshaw, auto-rickshaw and a suggested high-quality sustainable electric minibus in the study as alternatives basis on the results of the pilot study. The different IPT modes such as auto-rickshaw and e-rickshaw respectively have shown in Figures 6 and 7 respectively.

3.2. Selection of Attributes

The second step was started by deciding on the attributes related to the trips on the selected choice of modes. These were discovered through a survey of the literature, reconnaissance and discussions with specialists and commuters. Based on that research, the attributes for the stated choice experiment in this study were chosen. The various attributes chosen for study were travelling time and cost per unit distance, comfort, safety and waiting time in the model based on research by Hensher et al. [23]. Table 2 provides a brief summary of selected attributes of feeder service of IPT modes.

Table 2. Description of Selected Attributes

Attributes	Description
Travel Time per km	It refers to the average travel time taken by the vehicle per kilometre.
Travel Cost per km	It refers to the average fare of the vehicle per kilometre.
Safety	It refers to the degree of safety by the commuters.
Comfort	It means the comfort level of seating.
Frequency	It refers to the time gap between the successive availability of vehicle.

Figure 6. Auto Rickshaw

Figure 7. E-Rickshaw

3.3. Design of Questionnaire

3.3.1. Defining Different Levels of the Attributes

The purpose of survey instruments was to collect the respondents' information from characteristics of the trip, socioeconomic factors and stated objectives in the set of choice preferences. The questionnaire was divided into three parts. The socioeconomic characteristics like age, gender, related information, income, occupation etc. were collected from commuters in the first part of the questionnaire. The second part gathered data about the respondent's trip features, such as travel cost, trip distance, trip purpose and frequency. In the third part, the four different and unique scenarios in the stated choice survey were provided to the respondents. In each scenario, the respondents were given to choose between three different IPT modes and five attributes connected with travels on those modes. Levels of attribute were chosen on the basis of the current situation, possible practical options and review of the literature. Six attributes with four levels were considered for the design of choice set by Chintakayala and Maitra [24]. On the other hand, four attributes with four levels were considered for the design of choice set by Phanikumar and Maitra [34]. The pilot survey yielded the mean values of the attributes in review and three levels were established. The highest degrees of safety, comfort and frequency level was used as the reference levels and each attribute was varied at three levels. The various attributes along with their levels have been presented in Table 3.

Table 3. Attributes related to their Levels

Attribute	Levels	Level description
Travel Time (per km)	I	4 min
	II	3 min
	III	2 min
Travel Cost (per km)	I	Present Fare + Rs.3
	II	Present Fare + Rs.2
	III	Present Fare + Rs.1
Safety	I	Low
	II	Medium
	III	High
Comfort	I	V.O>No. of Seats (Low)
	II	V.O=No. of Seats (Medium)
	III	V.O<No. of Seats (High)
Frequency	I	Every 6 minutes
	II	Every 4 minutes
	III	Every 2 minutes

3.3.2. Generation of Choice Sets

According to Hensher et al. [23], all alternatives of modes in sets of choice scenarios were 'finite', 'mutually exclusive' and 'exhaustive'. The design of full factorial was used to solve a huge number of different choice scenarios which is not practicable to regulate in the view of the present investigation which has five attributes and the lowest amount of three levels for every attribute. On the other hand, a full factorial design significantly minimizes the complexity of the design by taking into account the primary effects and interaction at higher order based on Hensher et al. [23]. A D-optimal design was obtained by combining five factors with three levels each. The scenarios obtained from the D-optimal design were divided into different categories to ensure stability in alternative sequences. Using the JMP software, D-optimal design was created to produce a number of 48 different choice sets after selecting attributes and their levels in the present study. The four sets of questionnaires carried four choice sets each in the result. Every set of choices included three alternatives with a different range of a set of factors at various levels. Alternative 1 represented the e-rickshaw while alternative 2 and alternative 3 represented auto-rickshaw and electric minibus respectively. A single survey was required of each respondent. In other terms, each respondent for a survey was instructed to choose one of the three options in every set of choices.

3.4. Data Collection and Database

In the stated choice survey, a face to face interview was completed to obtain a representative set of data. A total of 425 respondents were interviewed. The answers of 21 respondents were disqualified owing due to an incorrect survey or improper choices. 404 datasets were considered appropriate for the current investigation. As a consequence, a number of 1616 corrected data (from 404 respondents) were applied to analyze the database and calculate willingness to pay using RPL models. The data was compiled in an excel file and encoded in NLOGIT 4.0 for analysis. The quantitative variables such as trip time and cost per km were used in numerical values. The qualitative variables were used by coding. The collected data were entered into an excel file in a CSV spreadsheet. A CSV spreadsheet (also known as a 'comma-separated' format) contains a line of forms of words at the top and rows of input data with comma-separated. The input data was then entered into NLOGIT 4.0 application [48]. Using this software, the results were obtained based on random parameter logit (RPL) using maximum likelihood estimation.

4. Results and Discussion

4.1. Socioeconomic and Travel Characteristics

The socioeconomic characteristics of users as reflected by their gender, age, monthly household income and occupation are thought to be important aspects in mode choice. In age and gender distribution, the male population among the age groups 21 to 30 used IPT modes at the mass level. The lowered and middle income level group is the largest user of IPT modes because these groups belong to students and workers. Table 4 lists the various socioeconomic variables that were used in this analysis. The travel characteristics of the respondents were required to fulfil by their trip rate, trip purpose, trip distance and trip fare. Many users are travel for education purposes at the rate of 4 to 5 times a week. The IPT modes are majorly used by work trip and educational trip makers. The travel characteristics have been shown in Figures 8 to 11 respectively.

Table 4. Socio-economic features of respondents

Category	Description	Number of observations	Percentage (%)
Gender	Male	1169	72.34
	Female	447	27.66
Age Group (In years)	<18	134	8.29
	18 - 30	632	39.11
	31 - 45	446	27.60
	46 - 60	278	17.20
	> 60	126	7.80
Monthly Household Income (in INR)	<10,000	689	42.64
	10,000 - 20,000	411	25.43
	20,000 - 35,000	283	17.51
	35,000 - 50,000	148	9.16
	>50,000	85	5.26
Occupation	Daily Wage Earner	81	5.01
	Salaried	343	21.23
	Self Employed	255	15.78
	Student	708	43.81
	Unemployed	192	11.88

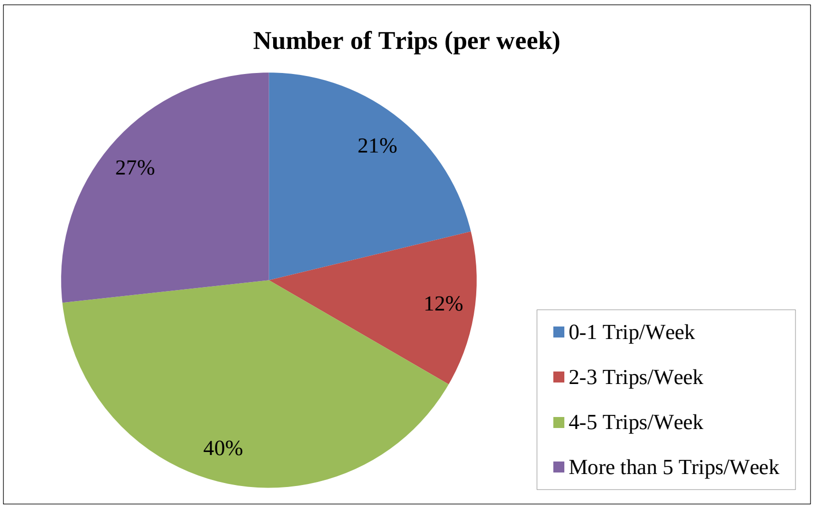

Figure 8. Number of Trips

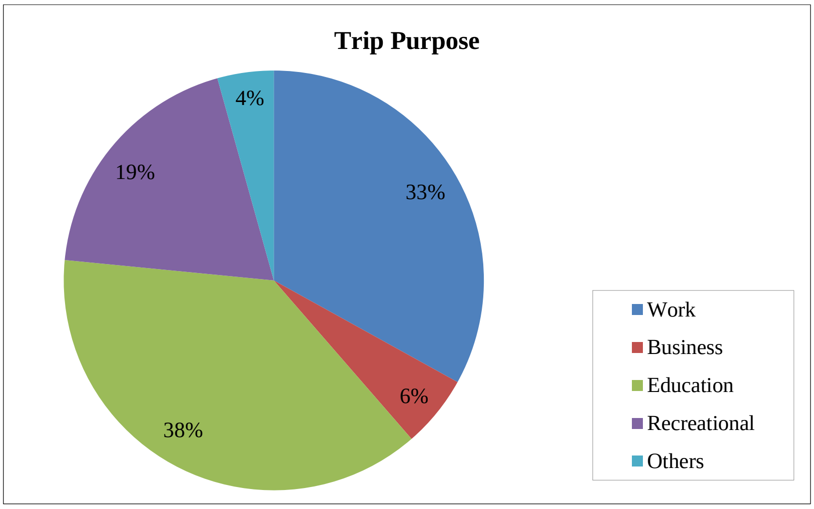

Figure 9. Trip Purpose

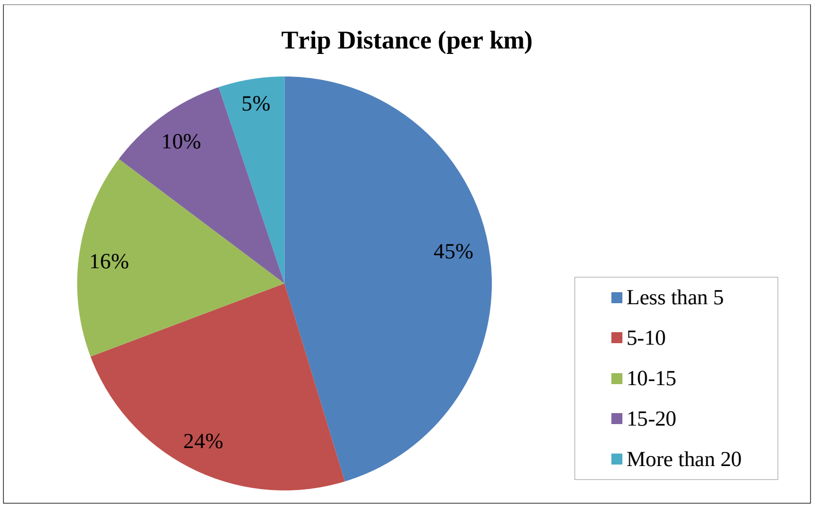

Figure 10. Trip Distance

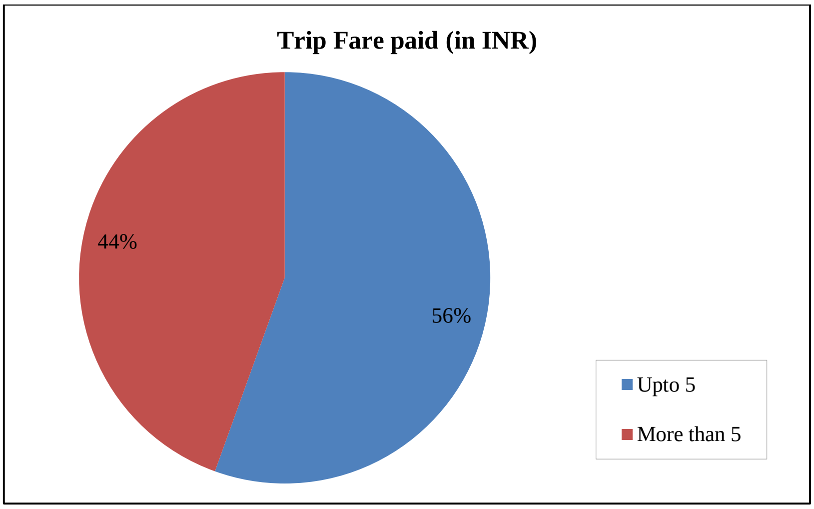

Figure 11. Trip Fare paid

4.2. Model Development

The data collected from the SC survey has been evaluated by creating the RPL model with correlated choice using NLOGIT 4.0 econometric software. All attributes related to their levels were specified to give a constrained triangular distribution using 50 Halton draws. Table 5 shows the coefficient estimates from RPL model with correlated choice and obtained WTP values. It can be seen that the signs of all the attribute coefficients are as expected. All alternative-specific constants are thus statistical significance with a 95 percent confidence level. The negative indications of quantitative characteristics like travel time and fare suggest that as the quantity of these features increases, so does the disutility. All attributes in RPL models were considered to be random and to have a constrained triangular distribution except for the travel cost [34, 37]. In the present work, travel fare is considered as nonrandom parameters in the development of RPL models. The existence of various attributes or levels is observed disutility in comparison to their respective base level when qualitative attributes have a negative sign. The value of R2 at 0.2482 is also determined to be satisfactory for stochastic research, indicating that the model can be deemed to be a good fit [23].

All of the coefficients for different attributes and levels are negative. This signifies that certain attribute levels are viewed as having a lower utility than the base level. For frequency levels 1 and 2, comfort levels 1 and 2 and safety levels 1 and 2, the coefficient is negative. This indicates that, in comparison to the base level, the users regard these features as of low utility. From Table 5, it is found that travel time is observed as disutility by the IPT mode of users. A frequency of a mode determines how long it takes to wait. Level 1 of frequency denotes a lower frequency and thus a longer wait time whereas level 2 of frequency denotes a larger frequency and a shorter wait time. With regard to the base level, level 1 of the frequency coefficient is -0.6079, while level 2 of the frequency coefficient is -0.2601. This implies that as the mode's frequency rises, so does its utility. In other words, as the amount of time spent waiting increases, the efficiency of a mode of transportation decreases. According to the coefficients of several factors, the coefficient value of level 1 of frequency is more than trip fare and time. With regard to the comfort, level 1 of comfort coefficient is -0.8467, whereas level 2 of comfort coefficient is -0.7253. This means that as a travel mode becomes more comfortable, its utility improves. A higher level of comfort is linked to a higher level of utility. Safety is given top consideration by commuters. According to the data, the magnitudes of coefficients for safety levels 1 and 2 are the largest. Safety level 1 has a coefficient of -2.4738, whereas safety level 2 has a coefficient of -1.2766. As a result, the utility of a means of transportation increases as the level of safety increases and higher use of intermediate public transportation will result from improved safety.

Table 5. Estimates from RPL Model and obtained WTP values

Attributes	Coefficient (T – Statistics)	WTP values
Random parameters in utility functions		
Travel Time	-0.5376 (-5.28)	1.59
Frequency 1	-0.6079 (-1.93)	1.80
Frequency 2	-0.2601 (-1.25)	0.77
Comfort 1	-0.8467 (-3.82)	2.51
Comfort 2	-0.7253 (-4.39)	2.15
Safety 1	-2.4738 (-2.96)	7.35
Safety 2	-1.2766 (-6.62)	3.79
Non-random parameters in utility functions		
Fare	-0.3365 (-4.78)	
Mode Specific Constant (E-Rickshaw)	-0.5806 (-3.76)	
Mode Specific Constant (Auto Rickshaw)	-0.8658 (-6.61)	
No. of Observations	1616	
Log Likelihood function	-1334.78	
Adjusted R^2	0.2482	

The mode-specific constants represent the mean influence of mode-specific unobserved influences after accounting for the influence of alternative attributes and some socioeconomic variables [29]. The electric minibus has been designated as the base travel mode and the alternative-specific constant has been set to zero. The mode-specific constant for an e-rickshaw is -0.5806. The auto rickshaw mode-specific constant is discovered to be -0.8658. Both are negative signs when all other variables are held constant. It suggests that commuters prefer the benefits of taking an electric minibus to the other two forms of transportation since they are more convenient. Since then, the mode-specific constant of the auto rickshaw has been lower than that of the electric rickshaw. As a result, commuters regard the benefits of an e-rickshaw ride over those of an auto rickshaw ride.

The marginal WTP values are based on RPL model coefficient estimates. All WTP parameters are measured in Indian rupees (INR) for each trip except travel time and cost, which are recorded in INR per kilometre. The value of trip time (VOTT) refers to the readiness to pay for trip time. According to Table 5, the VOTT has INR 1.59 per km. The WTP for level 1 of frequency is INR 1.80 whereas the WTP for level 2 of frequency is INR 0.77. This suggests users are willing to pay INR 1.80 each travel to upgrade from level 1 to level 3 of frequency, but just INR 0.77 per journey to upgrade from level 2 to level 3 of frequency. This reflects the commuter's unwillingness to wait for longer amounts of time. Comfort 1 and comfort 2 have WTP values of INR 2.51 and INR 2.15 respectively. Commuters in less comfortable vehicles are ready to pay INR 2.51 still to upgrade to high level of comfort vehicles while commuters in medium-comfort vehicles will only willing to pay INR 2.15 more. Commuters prioritize safety the most and are willing to pay a greater amount to commute in a safer way. Safety 1 and safety 2 have WTP values of INR 7.35 and INR 3.79 respectively. Users are willing to pay two times as much to move from level 1 (low level of safety) to level 3 (high level of safety) of safety than from level 2 (medium level of safety) to level 3 (high level of safety) of safety. Several researchers have observed higher WTP values from RPL models [34, 37]. Phanikumar and Maitra [34] studied that trip makers have a higher WTP in order to be more comfortable. In the present work, the results are found that the most significant attribute of an IPT mode is safety followed by frequency.

RPL models with heterogeneity are used to study the effects of all socioeconomic and travel factors. Several studies have stated on the effect of socioeconomic/trip variables such as age, income, travel distance etc. on WTP values [36] [37]. For three attributes, namely monthly income, trip purpose, and fare the effects of heterogeneity on the estimates of mean with random parameters were shown to be statistically important. It should be noted that some parameter estimations related to heterogeneity were determined to be insignificant at the 10% significance level. As a result, the models were re-estimated with the insignificant parameters (concerning heterogeneity) kept constant. The following subsections go through these RPL models with heterogeneity.

4.2.1. Income Heterogeneity

Respondents with a monthly income of greater than INR 35,000 were classified as being in the 'high income level' while those with a monthly household income of less than INR 35,000 were divided as being in the 'low income level'. These two income groups were used to represent by a dummy coded variable with (1, 0) in the RPLINH model specification. The RPLINH model's coefficient estimates and resulting WTP values for commuters in the 'low income level' and 'high income level' are described. The coefficient estimates of the RPLINH model are all statistically significant as shown in Table 6. The adjusted R2 (0.2495) shows a satisfactory match for the model. The influence of monthly household income on mean estimates of travel time, comfort 1, level 1 and level 2 of frequency is discovered to be decomposition.

Table 6. Estimates from RPLINH Model and observed WTP values

Attributes	Coefficient (T – Statistics)	WTP values	
		Low Income	High Income
Random parameters in utility functions			
Travel Time	-0.5121 (-3.99)	1.51	1.67
Frequency 1	-0.4251 (-1.19)	1.25	2.55
Frequency 2	-0.1087 (-0.42)	0.32	1.29
Comfort 1	-0.8325 (-3.12)	2.45	2.57
Comfort 2	-0.7425 (-3.75)	2.19	2.19
Safety 1	-2.9051 (-3.11)	8.57	8.57
Safety 2	-1.3882 (-6.26)	4.90	4.90
Non-random parameters in utility functions			
Fare	-0.3390 (-4.83)		
Mode Specific Constant (E-Rickshaw)	-0.5849 (-3.80)		
Mode Specific Constant (Auto Rickshaw)	-0.8644 (-6.62)		
Income heterogeneity			
Travel Time	-0.0551 (-0.31)		
Frequency 1	-0.4421 (-0.95)		
Frequency 2	-0.3296 (-0.93)		
Comfort 1	-0.0433 (-0.12)		
No. of Observations	1616		
Log Likelihood function	-1332.47		
Adjusted R^2	0.2495		

The WTP of commuters in the 'high income level' for travel time is greater than that of commuters in the 'low income level'. In the RPL model, there is no heterogeneity in mean estimates of comfort 2 and safety (level 1 and 2) and there is no variation in WTP values across commuters of different income categories as shown in Table 6. WTP values for commuters due to improvement from frequency 1 to frequency 3 in the 'high income level' and 'low income level' changes from INR 2.55 per trip to INR 1.25 per trip. It should also be noted that the WTP of 'low income level' users for the upgrade from frequency 2 to frequency 3 is just INR 0.32 per trip that is extremely low when compared to the WTP of 'high income level' users for the same upgrade of INR 1.29 each trip. Commuters from higher income households have higher WTP values [37]. Sadhukhan et al. [21] observed that commuters with a 'high income level' place a larger value on safety than 'low income level' commuters. Dell'Olio et al. [32] estimated that income levels influenced the evaluation of the fare. The WTP of 'high income level' users is much greater (INR 2.57 per trip) than 'low income level' users (INR 2.45 per trip) for a change from comfort 1 to comfort 3 in present study.

4.2.2. Trip Purpose Heterogeneity

Commuters making work trips were classified as 'work trips' while other trips were classified as 'non-work journeys'. This was done to catch the heterogeneity influence of trip purpose on mean estimates to create a database. In the RPL model, all coefficients of trip purpose estimates are statistically important as shown in Table 7. The adjusted R2 (0.2515) indicates a satisfactory match for the model. Preference heterogeneity is discovered in the trip purpose heterogeneity (RPLTPH) model on mean estimations of several parameters for commuter's trip purpose. The decomposition impact of trip purpose on mean assumptions of travel time, frequency 2, safety 1 and safety 2 has been discovered. The coefficient estimates show that 'work trip' commuters have higher subjective disutility towards travel time, frequency 2, safety 1 and safety 2 than 'non-work trip' commuters.

Table 7. Estimates from RPLTPH Model and observed WTP values

Attributes	**Coefficient (T – Statistics)**	**WTP values**	
		Work Trip	**Non-Work Trip**
Random parameters in utility functions			
Travel Time	-0.3454 (-2.66)	2.12	1.03
Frequency 1	-0.8549 (-2.27)	2.56	2.56
Frequency 2	-0.1741 (-0.63)	0.99	0.52
Comfort 1	-0.9348 (-3.32)	2.80	2.80
Comfort 2	-0.8207 (-4.06)	2.46	2.46
Safety 1	-2.9428 (-3.09)	11.61	8.82
Safety 2	-1.2549 (-5.53)	3.79	3.76
Non-random parameters in utility functions			
Fare	-0.3335 (-4.81)		
Mode Specific Constant (E-Rickshaw)	-0.5899 (-3.87)		
Mode Specific Constant (Auto Rickshaw)	-0.8825 (-6.72)		
Trip Purpose heterogeneity			
Travel Time	-0.3633 (-2.02)		
Frequency 2	-0.1574 (-0.45)		
Safety 1	-0.9302 (1.25)		
Safety 2	-0.0113 (0.04)		
No. of Observations	1616		
Log Likelihood function	-1328.89		
Adjusted R^2	0.2515		

Table 7 shows that ‘work trip' commuters have a higher WTP for travel time (INR 2.12 per minute each trip) than ‘non-work trip' users (INR 1.03 per minute per trip). This refers to commuters on 'work trips' being more concerned about the value of time. Table 7 shows that WTP values do not differ statistically significantly for ‘work trip' and ‘non-work trip' users when using frequency 3 instead of frequency 1. For the transition from frequency 2 to frequency 3, ‘work trip' commuters have roughly 1.90 times higher WTP (INR 0.99 alternatively of INR 0.52 each trip) than ‘non-work trip' users. For a move from safety 1 to safety 3, the WTP of ‘work trip' users is much greater (INR 11.61 per trip) than that of ‘non-work trip' users (INR 8.82 per trip). Sadhukhan et al. [21] observed that commuters who perform 'work trips' are regular travellers. In present study, WTP of ‘work trip’ commuters is considerably higher than ‘non-work trip’ commuters.

4.2.3. Fare Heterogeneity

The database was differentiated between two levels of fare, namely "high fare level" and "low fare level" of users, which explore the heterogeneous impact of fare (paid by users related to their trips). According to the survey data, commuters who paid more than INR 5.00 for their fare were classified as being in the "high fare level", while those who paid less than INR 5.00 were classified as being in the "low fare level". In the RPL model, a variable dummy coded with (1, 0) was used to represent these two groups (based on the fare paid). In Table 8, the RPL model's estimated coefficients and resulting WTP values are presented.

As shown in Table 8, all coefficients of fare estimation in the RPL model are statistically significant. The modified R2 value of 0.2505 shows a satisfactory fit for the model. Only the contexts of travel time, frequency 2, and safety 1 show fare (paid by users) heterogeneity (RPLFH) impacts on the mean estimate of transfer facility features. The WTP of commuters in the "high fare level" for travel times is INR 0.01 greater than that of commuters in the "low fare level". The WTP of commuters in the "high fare level" for the moves from frequency 2 to frequency 3 and from safety 1 to safety 2 is 2.38 and 1.37 times greater than that of commuters in the "low fare level", indicating that "high fare level" commuters are more concerned. The impacts of fare heterogeneity on mean estimates are found in the domains of access time and environmental attributes by Sadhukhan et al. [21]. In the current study, commuters with a "high fare level" experience greater disutility in terms of travel time and safety than "low fare level" commuters.

Table 8. Estimates from RPLFH Model and observed WTP values

Attributes	Coefficient (T – Statistics)	WTP values	
		Low travel fare	High travel fare
Random parameters in utility functions			
Travel Time	-0.5308 (-4.15)	1.55	1.56
Frequency 1	-0.7715 (-1.86)	2.26	2.26
Frequency 2	-0.1705 (-0.61)	0.50	1.19
Comfort 1	-1.0259 (-3.51)	3.01	3.01
Comfort 2	-0.9103 (-4.31)	2.67	2.67
Safety 1	-2.2125 (-2.91)	6.49	8.91
Safety 2	-1.2809 (-5.92)	3.76	3.76
Non-random parameters in utility functions			
Fare	-0.3407 (-4.73)		
Mode Specific Constant (E-Rickshaw)	-0.6008 (-3.79)		
Mode Specific Constant (Auto Rickshaw)	-0.8677 (-6.58)		
Fare heterogeneity			
Travel Time	-0.0041 (-0.02)		
Frequency 2	-0.2351 (-0.64)		
Safety 1	-0.8262 (1.07)		
No. of Observations	1616		
Log Likelihood function	-1330.63		
Adjusted R^2	0.2505		

5. Conclusion

The purpose of the study is to evaluate the decomposition impacts of different socioeconomic and trip characteristics based on mode choice behaviour for the introduction of sustainable IPT modes. Commuter’s choice of travel mode is heavily influenced by the characteristics of competing modes. Because of commuters' different preferences for these attributes, all of the attributes cannot be considered equally important. According to the study, travel time, travel cost, safety, comfort, and frequency are all important factors impacting mode choice. The utility of service is greatly affected by qualitative factors such as frequency, comfort level, and safety, especially in urban regions. All of the attributes of feeder service are considered along with the corresponding WTP values. The highest WTP is found for improving safety, followed by frequency and comfort.

RPL models were created to account for heterogeneity in essential socioeconomic, demographic, and trip factors. RPL produces marginal utility distributions and WTP distributions by dividing attribute coefficient distributions by alternative cost coefficient distributions. WTP values vary across different types of commuters based on the income of the monthly household, trip purpose, and fare. Commuters in the "high income level" have a higher WTP for increased frequency and a lower level of comfort. On the other hand, "work trip" commuters have been found to have a higher WTP for safety and frequency (every 4 minutes). Commuters are attracted to IPT modes due to the improvement of safety and comfort features on work trips. Commuters with a "high income" and a "work trip" group were observed to show a large variation in WTP with a slight change in travel time. In terms of the fare paid by commuters, heterogeneity can be established in the mean estimate in addition to the WTP for travel time, frequency (every 4 minutes), and low level of safety. The current study's heterogeneity analysis contributes to the formulation of policies for the enhancement of feeder service for IPT modes, taking into account the preferences of commuters with various socioeconomic and trip characteristics. Among all the options, the sustainable electric minibus has the highest mode specific constant. This suggests that commuters have a slight preference for sustainable electric minibuses and are much more likely to prefer this mode when all other factors such as travel time, cost, and safety are equal. According to the study's findings, sustainable IPT modes with a high quality of service are recommended, taking into account commuters' willingness to pay much more for improved safety and comfort. The introduction of the sustainable electric minibus is recommended among all IPT modes because of the greater alternative to specific constants linked with it.

6. Declarations

6.1. Author Contributions

Conceptualization, S.K., and S.S.; methodology, S.K.; writing—original draft preparation, S.K.; writing—review and editing, S.S.; supervision, S.S. All authors have read and agreed to the published version of the manuscript.

6.2. Data Availability Statement

The data presented in this study are available in the article.

6.3. Funding

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6.4. Conflicts of Interest

The authors declare no conflict of interest.

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