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TOTAL TRAVEL TIME ANALYSIS FOR STUDENTS IN A METROPOLITAN AREA: A STUDY FROM INDIA

Krishnapriya Molath Gopi[1], Soosan George Tanenlimalil[2], Bybin Paul[3]
[1,3] *Department of Civil Engineering, Mar Athanasius College of Engineering, Kerala, India*
[2] *Department of Civil Engineering, Saintgits College of Engineering, Kerala, India*

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Abstract: Efficient transportation system management is possible only through managing travel needs of commuters, using travel demand models. The extend by which a commuter need to travel for accomplishing his/her daily needs is here represented by the total travel time. Total travel time is one of the activity-travel behaviour which is least considered by transportation researchers. Travel demand studies often focus the workers, but give little attention to the students. In a developing country like India, students also contribute a major share in morning and evening peak hour traffic. This study presents the analysis of total travel time for the student community incorporating the socio-demographic features using activity based modelling approach. Preliminary analysis gives details on daily activity-travel pattern, mode choice preferences and other particulars of students in the study area. Statistical models are developed and simulation of choice probabilites is also done for understanding the factors affecting total travel time behaviour, for students in a usual working day.

Keywords: activity based modelling, total travel time, disaggregate model, students, developing country.

1. Introduction

Activity based approach in travel demand modelling is the latest and accurate travel demand modelling approach which works on the basic assumption that travel is a derived demand, which is derived from the need of individuals to perform an activity. The fundamental theories behind activity based approach were developed during 1970s (Hägerstrand, 1970; Chapin, 1974; Cullen and Godson, 1975). An individual have to perform different activities like work, education, shopping, recreation etc. to fulfill his/her day-to-day needs. There will be in-home and out-home activities, among which the individuals need to travel for performing out-home activities. The extent to which each commuter needs to travel can be effectively represented by the travel time for that particular activity. According to activity the total population can be divided in to segments like workers, students etc. Most of the travel studies focus on workers, but students are usually neglected. In a developing country like India, the share of student category is also very big next to workers and therefore it is necessary to analyse different travel behaviour elements related to students, for deriving better solutions for transportation problems.

[1] Corresponding author: krishnapriyamg@mace.ac.in

An appropriate representation of all sub population will definitely improve the regional travel demand models. Among these sub population workers are given importance in most of the transportation researches and the presence of students are mostly absent. Only a few researches have taken the students into consideration and its exploratory analysis itself gives out that the students behave differently compared to the general population (Khattak *et al.,* 2011). Mode choice behaviour of students is modelled in Germany and Canada, using multinomial logit modelling (MNL) method (Müller *et al.,* 2008; Whalen *et al.,* 2013; Mitra and Buliung, 2014).

Accessibility indicators and travel time can be used as the variables that represent ones friction to travel for participating different activities (Frank *et al.,* 2008). Travel time for different modes is also compared in order to find the relationships with environmental accessibility (Salonen and Toivonen, 2013). Total travel time can also be considered as an urban mobility performance measure to address different transportation congestion problems (Lomax and Schrank, 2010). Different travel demand modelling studies conducted in India for all segments of population is also an important element of discussion. The exploratory and statistical analysis of activity-travel behaviour of non-workers in Bangalore city were studied. Analysis of activity participation behaviour, trip chaining, mode choice behaviour, etc. was done using MNL modelling method (Manoj and Verma, 2015). Mode choice analysis of workers in Tiruvanthapuram City, Kerala, was also done using MNL modelling method. Its results shows lower age group prefers two-wheeler and higher age group prefer car compared to bus. Female commuters prefer public vehicle and male commuters prefer private vehicles more. Other parameters like income, vehicle ownership, distance, time/distance and cost/distance also have significant effect on the mode choice decision (Ashalatha *et al.,* 2013). Mode choice decision of workers in Chennai city is also modelled. Study include alternate behavioural framework such as random utility minimisaiton, random regret minimisation etc. in addition to most widely used random utility maximisation rule for mode choice decision. Policy results are also evaluated for comparing the performance of all these rules used for selecting the mode choice (Parthan and Srinivasan, 2013). Activity travel pattern analysis for workers in Calicut City, Kerala is also performed using mutinomial logit modelling method (Sreela and Anjaneyulu, 2018).

However, the attempts to develop models to represent the travel behaviour of students are comparatively less, especially for developing countries. Major studies contribute into mode choice or school choice behaviour of students. Total travel time is also an important variable to be considered in choice modelling, as it is measure of extend of travel as well as a choice set over which total travel time reducing measures can be explored. In the present study the total travel time behaviour of students is analysed using disaggregate modelling method. The objectives of the study is to model the total travel time behaviour of students to identify the variables that have significant effect on it and also to perform simulation of choice probabilities on potential variables, whose variation can influence the total travel time behaviour of students.

2. Data Analysis and Modelling Framework

Total travel time (TT) of an individual is here calculated as the total travel time taken for a single tour for the primary activity. For students education is their primary activity and illustration of total travel time (TT) calculated for an education tour is shown in Fig. 1. The travel time taken by a student to travel from home to school/college and back from school/college to home is considered as the total travel time. Students who are not permanently residing at their home are not considered for modelling. In the case of public/school bus the total travel time includes time for accessing bus stop, waiting time and time to reach school/college from bus stop. Based on the total travel time, the tours are classified into three, they are short tours (TT1) in which TT ≤ 30 minutes, medium tours (TT2) in which TT between 31 -60 minutes and long tours (TT3) in which TT ≥ 61 minutes; as per referring similar studies (van Exel and Rietveld, 2010) and opinion from transportation experts.

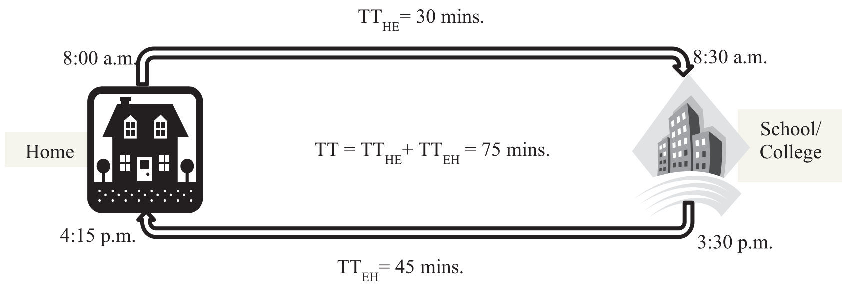

Fig. 1.
Total Travel Time for a Tour for Education

2.1. Study Area and Data Collection

Kochi Municipal Corporation, Kerala is the study area selected for the present study. Kochi is the commercial, industrial and financial capital of Kerala and the most densely populated corporation in the state, with a population density of 6340 persons/ km^2. As per 2011 Census, population of Kochi is 602,046 with 296,949 males and 305,097 females. Literacy rate of KMC is 97.36%, which is very high compared to any other major cities in India. Kochi Municipal Corporation spreads over an area of 94.88km^2 and it is well connected by road, rail, air and water modes. Total road length for Kochi city is 614km and the existing road density is 6.47km/ sq. km. The narrow roads and improper planning of city area have made it one of the cities with worst traffic conditions within India. Kochi is the potential target of central and state government authorities to implement sustainable development strategies to mitigate the existing traffic problems. Kochi city is selected as 5th among the 20 major cities in the first round selection under Smart City Mission by Ministry of Urban development, Government of India. It is also considered under Kerala Sustainable Urban Development Project (KUDP) by Kerala Government.

Primary and secondary data is used for modelling the total travel time behaviour of students. Direct household interview method is adopted for primary data collection and total 2989 household details are there in the final database for analysis. An official consent letter was issued for data collection by Kochi Mayor, which have successfully increased the response rate of survey to 96.67% (Gopi *et al.,* 2018). Secondary data is collected from reports of government bodies as well as from former researches within the study area.

2.2. Multinomial Logit (MNL) Models

Multinomial logit model has been widely used for choice modelling, which gives the choice probabilities of each alternative as a function of the systematic portion of the utility of all the alternatives (Koppelman and Bhat, 2006). The basic form of MNL model for probability of choosing alternative j is shown in Equation (1).

$$\Pr(\text{Choice j}) = \frac{\exp(\beta_j x_{ji})}{\sum_{m=1}^{J} \exp(\beta_m x_{mi})},\ j = 0,\ldots,J, \qquad (1)$$

Where '*i*' indicates the observation or individual and '*j*' and '*m*' indicates the choices. '*β*' represents the coefficient of the variable '*x*' considered. The decision of choosing an alternative is based on utility maximisation rule. It can be stated as alternative, '*i*', is chosen among a set of alternatives, if and only if the utility of alternative, '*i*', is greater than or equal to the utility of all alternatives, '*j*', in the choice set, *C*. This can be expressed mathematically as shown in Equation (2):

$$\text{If } U(X_i, S_t) \geq U(X_j, S_t)\ \forall\, j \Rightarrow i > j \forall j\ \in C \qquad (2)$$

where *U*( ) is the mathematical utility function, X*i, X j* are vectors of attributes describing alternatives i and j, respectively, *S t* is a vector of characteristics describing individual *t* that influence his /her preferences among alternatives, *i* > *j* means the alternative to the left is preferred to the alternative to the right, and ∀*j* means all the cases, *j*, in the choice set. That is, if the utility of alternative *i* is greater than or equal to the utility of all alternatives, *j*; alternative *i* will be preferred and chosen from the set of alternatives, C. In this study MNL modelling is used for total travel time analysis.

2.3. Model Estimation

An estimation method which scores different estimation results in terms of how well they identify the chosen alternative is accomplished by using maximum likelihood estimation method. The procedure for maximum likelihood estimation involves two important steps: 1) developing a joint probability density function of the observed sample, called the likelihood function, and 2) estimating parameter values which maximize the likelihood function (Hensher *et al.,* 2005). The likelihood function for a sample of '*T*' individuals, each with '*J*' alternatives is defined using the mathematical Equation (3):

$$L(\beta) = \prod_{\forall t \in T} \prod_{\forall j \in J} (P_{jt}(\beta))^{\delta_{jt}} \qquad (3)$$

Where δ_{jt} =1 is chosen indicator (=1 if *j* is chosen by individual *t* and 0 otherwise) and P_{jt} is the probability that individual *t* chooses alternative *j*. Logarithm of the likelihood function is considered for simplifying the calculations as shown in Equation 4.

$$\text{Log likelihood} = LL(\beta) = \text{Log}\,(L(\beta)) \qquad (4)$$

The values of parameters that maximize likelihood function are obtained by finding the first derivative of likelihood function and equating it to zero. The models are calibrated using two third of the total data and one third is used for validation.

2.4. Measures of Goodness of Fit

After calibration of the model it is tested for accuracy using goodness of fit measures. Goodness of fit measures is calculated for each parameter as well as for overall model. Wald statistics or P-value (significance value) is calculated for finding the significance of each parameter. The coefficient estimated is considered to be significant at 90% of confidence level or more when the absolute value of corresponding Wald statistics is 1.64 or more. Similar to higher value of likelihood function gives the better model, so as likelihood ratio index (rho-squared value) and adjusted rho-squared value. It is similar to R-squared value similar to regression analysis. The value should come in the range of 0-1. Rho-square value and adjusted rho square value with respect to constant model is calculated as shown in Equation (5) and Equation (6).

$$\text{Rho} - \text{square value with repsect to constants} = \rho_c^2 = 1 - \frac{\text{LL}(\hat{\beta})}{\text{LL}(c)} \tag{5}$$

$$\text{Adjusted rho} - \text{square value w.r.t constants} = \bar{\rho}_c^2 = 1 - \frac{\text{LL}(\hat{\beta}) - \text{K}}{\text{LL}(c) - \text{K}_{ms}} \tag{6}$$

Where $\text{LL}(\hat{\beta})$ is log likelihood value of the model calibrated, $\text{LL}(c)$ is log likelihood value of constant only model calibrated, K is number of degrees of freedom (parameters) and K_{ms} is number of degrees of freedom in constant only model. The likelihood ratio test can be used in the same way as F-test in the regression models. It is approximately equal to the chi-square value of the model. It is calculated as shown in Equation (7):

$$\text{Likelihood ratio} = -2[\text{LL}(c) - \text{LL}(\hat{\beta})] \tag{7}$$

Percentage correctly predicted is also used to find the goodness of fit of the calibrated model. In the present study modelling is done using the software package NLOGIT 6, by coding the utility equation for each alternative (Greene, 2016).

2.5. Post Estimation Analysis

After developing the final model post estimation analysis are done in order to find the potential policy variables. In this study the post estimation techniques like calculation of elasticity and simulation of choice probability is done. Simulation of choice probability gives the variation of probability of choosing an alternative for a particular variation in the value of an attribute. Whereas, elasticity are calculated for the behavioural interpretation of an attribute over the alternative, which is not possible to explain using the sign of estimated parameter. *Elasticity* is a unit less measure that can describe the relationship between the percentage changes in probability of quantity demanded with respect to percentage change in some independent variable (Hensher *et al.,* 2005). The direct elasticities for MNL model can be mathematically explained as the elasticity of probability of alternative i for decision maker t, with respect to a change in the k^{th} attribute of the i^{th} alternative i.e. X_{ikt}, as observed by decision maker t which can be calculated as shown in Equation (8).

$$E_{X_{ikt}}^{P_{it}} = \frac{\partial P_{it}}{\partial X_{ikt}} * \frac{X_{ikt}}{P_{it}} \tag{8}$$

3. Data Structure

Total 2527 home based education samples are available for total travel time modelling. In which 1685 samples are used for model calibration and 842 samples are used for model validation. Personal, household, activity-travel and residential location variables are used for model calibration. Percentage distribution of tours with respect to total travel time and distribution of age for the students is given in Fig. 2 and Fig. 3. The other categorical variables considered for modelling and its details are given in Table 1.

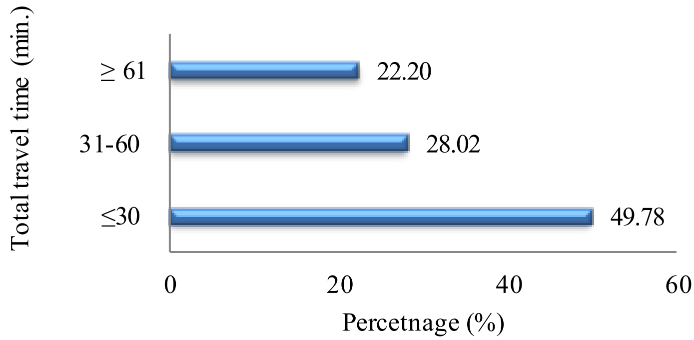

Fig. 2.
Percentage Distribution of Tours by Total Travel Time

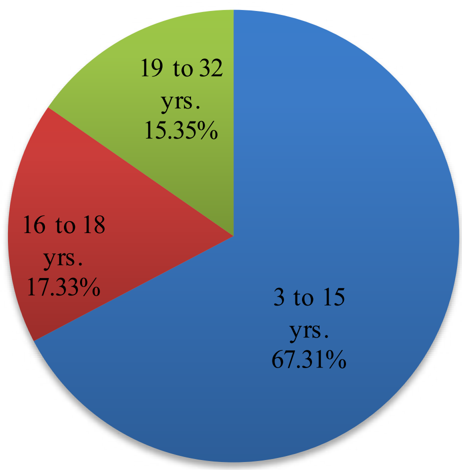

Fig. 3.
Percentage Distribution of Students by Age

Table 1
Categorical Variables and Coding in Total Travel Time Model

Variables	Coding	N	Marginal Percentage (%)
Gender			
Male	GENM	1273	50.38
Female	GENF	1254	49.62
Driving License ownership	**DLN**		
Yes	1	229	9.06
No	0	2298	90.94
Education level			
School level	ED1	1699	67.23
Higher secondary and more	ED2	828	32.77
Activity pattern			
HEH (Simple)	AP1	2499	98.89
HEH + (Complex)	AP2	28	1.11
Mode used			
Walk/ Bicycle	WCY	661	26.16
Public vehicle	PB	1656	65.53
Private Vehicle	PR	210	8.31
Population Density (persons/hector)			
<25	PPD1	212	8.39
25 to 50	PPD2	1356	53.66
50 to 100	PPD3	743	29.40
> 100	PPD4	216	8.55
N	2527		

In the total sample 50.38% are male and 49.62 % are female. Only 9.06% of them have driving license ownership and almost 98% of them have simple activity pattern for education. Mode used and population density of the place of residence is also considered for modelling. The other variables are considered as explanatory variables and the coding, minimum value, maximum value, average and standard deviation of each variable is given in Table 2.

Table 2
Explanatory Variables and Coding in Total Travel Time Model

Variables	Coding	Mean	Minimum value	Maximum value	Standard deviation
Travel distance (km)	TD	9.58	0.10	60	8.58
Distance to nearest bus stop (km)	DBS	0.547	0.02	2.00	0.33

4. Results and Discussion

Medium tour (TT2) is considered as the base alternative in total travel time model. Significant parameter estimates, goodness of fit measures and validation results of total travel time model for students is given in Table 3. The value of Wald statistics and 95%

confidence interval limits for the estimated parameters is also given in the table. Travel distance is one of the most influencing factors and as travel distance increases students have more probability to perform long tours and as travel distance decreases students have more probability to perform short tours. Choice of travel mode for education also has influence on total travel time. Students who prefer private mode, walk or bicycle usually perform short tours and students who choose public bus or school bus always took long time to travel for education. Travel time by public bus and school/college bus is comparatively very high even in cases where the travel distance is less.

Table 3

Parameters Estimated for Total Travel Time Model for Students

Variables	Coefficient	Wald Statistics	95 % confidence interval limits	
Total travel time ≤ 30 minutes (short tours)				
Constant	3.482	6.489	2.430	4.533
TD	-0.583***	-15.604	-0.656	-0.509
PR	1.553***	3.963	0.785	2.321
WCY	1.475***	5.633	0.962	1.988
GENM	-0.328*	-1.832	-0.680	0.023
PPD1	0.565*	1.654	-0.105	1.234
PPD4	-0.519*	-1.748	-1.101	0.063
DBS	-0.712**	-2.499	-1.271	-0.154
Total travel time ≥ 61 minutes (long tours)				
Constant	-4.135	-5.092	-5.726	-2.543
TD	0.234***	12.708	0.198	0.271
GENM	-0.342*	-1.890	-0.696	0.013
DBS	0.439*	1.654	-0.081	0.959
Goodness of fit measures				
Log likelihood for constant only model				-1752.861
Log likelihood at convergence				-824.1151
Likelihood ratio /Chi square value (P-value)				1857.491(0.000)
Rho-squared value				0.5298
Adjusted rho-squared value				0.5263
Percentage correctly predicted				79.407
N				1685
Validation: Percentage correctly predicted				73.63
***, **, * ==> Significance at 1%, 5%, 10% level				

Gender of the students is also influencing the total travel time choice for education. Male students more prefer medium tours for education compared to short and long tours. Students coming from low population density region prefer short tours, whereas students from high population density region significantly least prefer short tours. Accessibility to nearest bus stop from place of residence is another factor that influence the total travel time. As accessibility to nearest bus stop decreases students have more tendencies to perform long tours and least tendency to perform short tours. Chi-square value of the final model has P-value 0.000, from which it is evident that the calibrated model is significantly different from the constant only model. Rho-squared and adjusted rho-squared value are reasonably good value and the percentage correctly predicted is also high i.e., 79.407%. Model is also validated using 1/3rd of the total data and percentage correctly predicted value obtained is 73.63%, whose variation is within 10% with that of calibrated data. So the model can be considered as a reasonably good model for total travel time analysis of students.

Point elasticities and cross elasticities are calculated for the exploratory variables and given in Table 4. The calculated elasticities shows that an increase in travel distance by unit percentage can decrease the probability of choosing short tour by 4.65% and increase the probability of choosing long tour by 1.79%. Distance to nearest bus stop has point elasticities for short tour and long tour are -0.336 and 0.198 respectively.

Table 4

Elasticities of Explanatory Variables in Total Travel Time Model for Students

Alternatives	Travel distance (TD)	Distance to nearest bus stop (DBS)
Point elasticities		
Short tour	-4.6500	-0.3361
Medium tour	-	-
Long tour	1.7900	0.1982

Choice probabilities are also simulated over travel distance and accessibility to nearest bus stop and the same is given in Fig. 4 and Fig. 5. Choice probability of short tours has a steep negative slope up to 12km travel distance and its value attains zero after that. Choice probability for medium tour increases has an increasing tendency up to 12km and then it decreases. Long tour has an exponential increase in its choice probability with travel distance after 7km. After 17km long tours have the highest probability to choose by the students. When the accessibility from nearest bus stop from place of residence is decreased short tour has a steep negative slope and both medium and long tour have positive slope. When the accessibility to nearest bus stop decreases beyond 2.6km, then the probability of choosing the long tours attains the highest value.

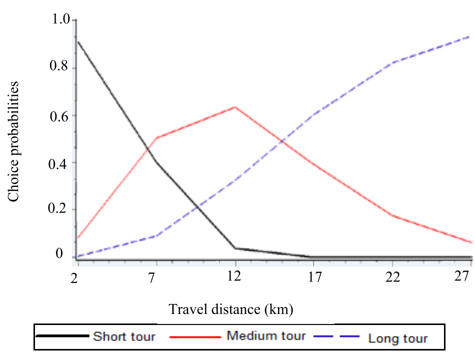

Fig. 4.

Simulation of Choice Probabilities of Total Travel Time Over Travel Distance

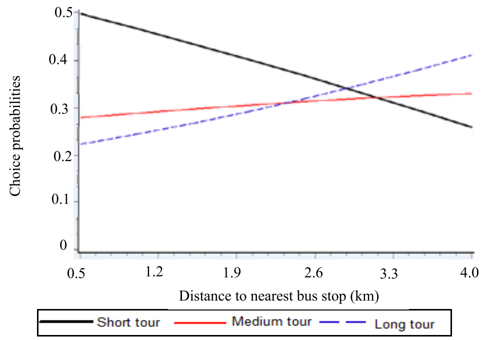

Fig. 5.
Simulation of choice probabilities of total travel time over Distance to nearest bus stop

5. Conclusions

In an ideal urban system the need to travel, in order to fulfill different personal and household needs for the dwellers, should be the minimum. Total travel time of a commuter reflects the extend up to which an individual need to travel for a particular activity, which is a least explored characteristics in transportation studies. Students always form a significant segment of the total population which is neglected in most of the transportation studies. Here total travel time model for students is calibrated to find out the influencing variables. Parameter estimates of total travel time model for students indicates the significant variables that influence total travel time of students for education are travel distance, gender, mode choice, population density of place of residence and also its accessibility to nearest bus stop. The goodness of fit measures and validation of the model indicates that the model is reasonably good for total travel time behaviour prediction. From point elasticities it is found that travel distance is relatively elastic over total travel time. Simulation of choice probabilities shows the variation in choice probabilities with respect to both travel distance and accessibility to public transport. Short tours have maximum probability for travel distance up to 7km, medium tours are more preferred from 7 to 15 km and after that long tours have maximum probability.

This paper provides valuable insights on total travel time behaviour of students in metropolitan region of a developing country. The findings from the present study are very relevant for attaining the goals of Smart City Mission for Kochi city, as one of its main focus is the improvement of transportation system in the city area by reducing in travel time, for an overall reduction in road congestion and improvement of air quality parameters (Smart city challenge Stage 2, Smart city proposal, 2016). Similar total travel time models can be developed for other segments of population like workers, non-workers etc., to get the total picture about the whole population and post estimation analysis of the calibrated model can be done to identify the policy variables which have the potential to reduce the total travel time for different activities.

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