Influence of Built Environment on Transport Model Choice

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Despite growing research interests in transport behavior limited policy-driven efforts have been made towards understanding mobility behaviors of people in developing countries like India, such behaviors are best studied in the choices people make while travelling or commuting especially in terms of modal choices The mediating effects of travel-distance car-ownership, and an additional human-vehicle-environment interaction variable is considered in our work The relationships among these variables are described using a framework of discrete choice model and structural-equation-model. Using a survey-based methodology, direct and indirect effects of built environment and socio-demographics on travel mode choice is revealed.

Keywords: Mode Choice, Built Environment, Car Ownership, Travel Distance, Human-Vehicle-Environment Interaction

1. Introduction

An important goal among transportation researchers has been to study how people travel in terms of space and time (Chen et al. 2016). The mobility behaviors of people are best studied in the choices they make while commuting, be it for transport modes, destination, routes etc. (Boyce et al. 1983). Analyzing the mode choice behavior of the people in urban settings is one of the key elements in public transport planning and management (Hunecke et al. 2010). The research community in this field have devoted their work in gaining deeper insights into the important aspects and factors influencing urban mobility. The expected goals of such efforts are to facilitate mobility of transport users, promote public transport systems, reduce congestion in roads, enhance traffic safety, and contribute towards establishing a sustainable transport system (Ye & Titheridge 2017). Increasing dependency on cars as primary modes of travel has been identified by many to substantially contribute to the aforementioned traffic-related problems. Moreover, relevant literature in this field of study increasingly links car ownership with the built environment, while implying the reduction of the former as an effective solution in the long run for sustainable urban mobility (Ding et al. 2017; Ye & Titheridge 2017; Wang et al. 2018).

While ample studies have been conducted in developed countries, similar investigations in developing counties such as India are scarce and studying travel behavior in small to medium-sized (i.e. Tier II/III) cities are even fewer. Moreover, the research done on travel behavior across Indian cities has been most mostly restricted to understanding transport patterns in bigger cities (Maunder et al. 1997; Srinivasan& Rogers 2005; Chandaet al. 2016). The influence of certain environmental characteristics as intermediary disposition on travel mode choice has not been thoroughly explored. The mediating and/or moderating effects of travel distance (or time), car ownership, travel costs, convenience, comfort, reliability, pollution and road infrastructure are considered in the present work, and said relationships among them are described using a framework of discrete choice model (DCM) and structural equation model (SEM). The work builds upon the integrated SEM-DCM model by Ding et al. (2017), where the variables mentioned after travel distance and car ownership are added to exhaustively account for the context of travelling or commuting in smaller Indian cities. These new variables are grouped within a single construct that represents human-vehicle-environment interaction (HVEI), the concept behind which is adopted from traffic engineering (Day 1995; Lenard& Hill 2004; You et al. 2019).A survey-based methodology is adopted to generate a suitable dataset to reveal the direct and indirect effects of aforementioned built environment on travel mode choice.

2. Methodology

Structural equation modeling (SEM) – a widely used “general statistical technique” for modeling in behavioral studies (Hox & Bechger 1998) – is an appropriate tool for the present study. Using SEM, the proposed model towards a covariance structure between the observed variables that are visualized in terms of graphical “path diagrams”. The SEM part of the integrated model framework is composed of endogenous variables – car ownership, travel distance (or travel time) and an additional HVEI variable addressed earlier in the paper. The HVEI is a compound variable defined in terms of travel costs, convenience, comfort, reliability, pollution and road infrastructure. The final endogenous variable is travel mode choice, which is linked by the other endogenous variables in mediating roles with socio-demographic and built environment variables; the latter variables signify the dependence of travel decision-making on residential self-selection, which are assumed to come from two primary sources (Ding et al. 2017): “personal characteristics” and “attitudes”. A relationship is also assumed between the socio-demographic variables and built environment, implying the former to be seemingly exogenous within the model framework. The direct effect of car ownership, travel distance, and HVEI on mode choices can be captured using the model structure, while also capturing the indirect effects of built environment through the mediation of the other three endogenous variables. Figure 1 presents an extension of Ding et al. (2017)’s model initially proposed for the present study.

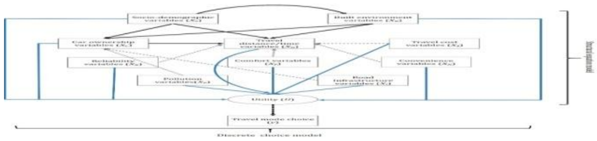

Figure 1 *Proposed Initial Integrated Model Framework of SEM and DCM*

A complex web of direct and indirect relationships can be visualized between the endogenous and exogenous variables in figure 1, which are described using the SEM component as (Oud and Folmer, 2008; Ding et al. 2017)

$$\eta = B\eta + \Gamma\xi + \zeta \tag{1}$$

Where, η is the matrix of endogenous variables (L x 1), ξ is the matrix of exogenous variables (K x 1), *B* is the matrix of coefficients of the endogenous variables (L x L), Γ is the matrix of coefficients of the exogenous variables, and ζ is the matrix of residuals of the endogenous variables.

The DCM component of the proposed model structure is appropriately defined using Multinomial (MNL) logit model, which is based on random utility theory (RUT) (Ben-Akiva & Lerman 1985). The assumption under RUT is that each traveler *n*, when faced with a finite set of alternatives (C_n), chooses the alternative *i* that yields the highest payoff in terms of utilityU_{ni}. The random utility function of the said model is described expressed in terms of the explanatory variables forming the deterministic and stochastic parts as follows (Ding et al. 2017):

$$U_{ni} = V(\xi, \eta; \beta) + \varepsilon_{ni} = \beta_\xi \xi_{ni} + \beta_\eta \eta_{ni} + \varepsilon_{ni} \tag{2}$$

Where, β represents the parameters that are estimated for the endogenous variables and *observed* exogenous variables, and ε_{ni} represents the *unobserved* portion of the utility; under the MNL framework ε_{ni} terms are assumed to be independently identically distributed (*i.i.d.*) extreme value for all *i*. The measurement equation for the observed choices are presented as:

$$y_{ni} = \begin{cases} 1 \; if \; U_{ni} \; \geq U_{nj} i \neq i \\ 0 \qquad otherwise \end{cases} \tag{3}$$

Where, y_{ni} indicates the choice of individual *n* choosing alternative *i* or otherwise.
The joint probability (*P*) of observing given choice and the endogenous variables depends on the distribution of ε_{nj}, given as

$$P(y_n|\eta, \xi;\ \beta_\eta, \beta_\xi, \Gamma, \delta) = \int_{R_\eta} P_y\ (y_n|\eta, \xi;\ \beta_\eta, \beta_\xi, \varepsilon)\ f(\eta|\xi;\ \Gamma, \zeta)\ d\eta \tag{4}$$

Where, P_y is the probability function for the choice model. *f* is the density function corresponding to the structural model for endogenous variables, $R_\eta$is the range space of the vector for endogenous variables, and $\boldsymbol{\delta}$is the full set of random errors.

Ding et al. (2017) estimated their integrated model using a simultaneous approach involving the maximum likelihood method, with a key assumption that the continuous endogenous variables follow a multivariate normal distribution. The present study is carried out along a similar framework for the integrated SEM and DCM model represented in figure 1. The complex pattern of relationships in this model is, however, rendered too muddled in this formed. For this reason, the new variables are grouped under a single construct that represents HVEI, and rearranged to a more ordered form as shown in Figure 2 below.

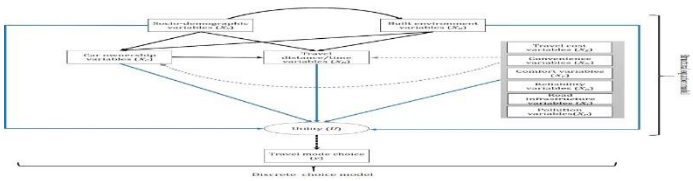

Figure 2 *Proposed Revised Integrated Model Framework of SEM and DCM*

The revised model framework is still complex enough to be solved using the MNL framework, which is why this study limits the scope of research within the SEM component as applied to an empirical study driven by the following research question: *What are the influences of travel distance, car ownership, and human-vehicle-environment interaction on the relationship between built environment and a transport user's mode choice?* A pilot study was conducted to generate a preliminary dataset for testing the SEM component of the proposed model framework.

3. Data Specification

A structured survey questionnaire used for the survey is designed on the basis of a list of constructs and corresponding attributes (questions) presented in Table 1. A total of thirty-two measurable variables are proposed for the eight constructs – further boiled down to three constructs for the proposed model in figure 2. The target population are people in India who have access to both private and public mode of transportation i.e. anyone presently capable of making the choice of travelling among available transport modes – car, bus, train, and others (such as walking, bikes, motorbikes, auto rickshaws, carts etc.). The objective of the study is to understand travel mode choices of transport users in smaller (Tier II/III) Indian cities; for this reason the author used convenient sampling for a pilot study to collect data from 43 participants from the state of Assam, India (where all urban settings can be classified under Tier II/III). The responder demographic was 27.90% female, and 69.77% male (with one gender unspecified entry), with majority (86%) being from the age group of 18-34. 67% of all respondents were regular employee, so they commute on a regular basis (yet no question has been posed on commuting, but only in terms of mode choices while traveling to other places in general).

Table 1 *Variables and Constructs*

Construct		Attribute	Citation
Travel distance/time		1. In-vehicle time is not excessive (TD1) 2. I use my trip time productively (TD2) 3. The trip time is a useful transition between home and work (TD3) 4. Travel time is generally wasted time (TD4)	*(Ding et al. 2017); (Chanda et al. 2016)*
Car ownership		1. Need a car to do many of the things I like to do (CO1) 2. Traveling by car is safer overall than taking transit (CO2) 3. Getting to work without a car is a hassle (CO3) 4. Fuel efficiency is an important factor for me in choosing a vehicle (CO4) 5. I like driving (CO5) 6. I would like to own at least one more car (CO6) 7. We could manage pretty well with one fewer car than we have (or with no car)	*(Ye &Titheridge, 2017)*
Human-vehicle-environment interaction	**Travel costs**	1. Expenditure incurred for travelling is fair (TC1) 2. My household spends too much money on owning and driving our cars (TC2)	*(Chanda et al. 2016); (Ye &Titheridge, 2017)*
	Convenience	1. Out-vehicle time is short (CV1) 2. Convenient in transferring to other transport modes (CV2) 3. Information of boarding point on route is clear (CV3)	*(Chen & Li, 2017)*
	Comfort	1. Feeling comfortable on seats (CF1) 2. It is not too crowded inside the vehicle (CF2) 3. It is clean inside the vehicle (CF3) 4. Interference among passengers are very little (CF4) 5. Clear and correct destination information (CF5)	*(Chen & Li, 2017); (Chanda et al. 2016)*
	Reliability	1. Estimated arrival time of mode is accurate and in time (RE1) 2. Actual waiting time is very close to the estimation (RE2) 3. Vehicle reaches destination at right time (RE3) 4. Vehicle personnel are polite and willing to serve passengers (RE4)	*(Chen & Li, 2017); (Chanda et al. 2016)*
	Pollution	1. Air quality is a major problem in this region (PO1) 2. I try to limit my driving to help improve air quality (PO2) 3. Vehicles should be taxed on the basis of the amount of pollution they produce (PO3) 4. Vehicle is not very noisy (PO4)	*(Ye &Titheridge, 2017); (Chanda et al. 2016)*
	Road infrastructure	1. The region needs to build more highways to reduce traffic congestion (RI1) 2. I am willing to pay a toll or tax to pay for new highways (RI2) 3. Quality of road discourages me from driving myself (RI3)	*(Ye &Titheridge, 2017)*

Demographic data was also collected on education, occupation type, income levels, number of cars owned in the household, frequency and purpose of trips made in a month. Figure 3 and figure 4 plots the type of vehicle owned, and income groups from the survey results.

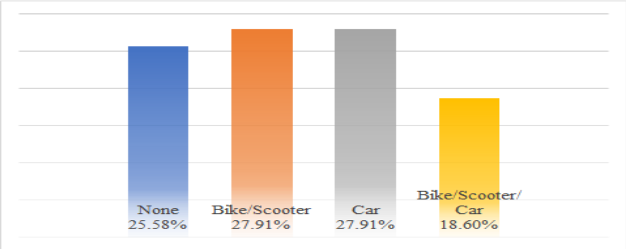

Figure 3 *Vehicle Ownership Characteristics*

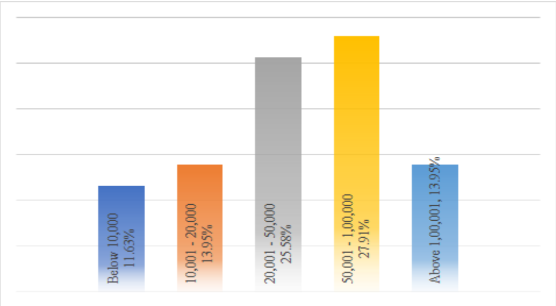

Figure 4*Monthly Income (in INR)*

Based on the findings from the pilot survey, a sample of the ratings provided by the respondents for the different attributes in the model frame work is shown in Table 2.

Table 2 *Attribute Ratings by Pilot Survey Responders*

	Strongly disagree	Disagree	Neutral	Agree	Strongly agree
Travel time (TD1)	4.65%	25.58%	37.21%	30.23%	2.33%
Car ownership (CO4)	2.33%	9.30%	30.23%	51.16%	6.98%
Travel costs (TC1)	4.65%	13.95%	53.49%	23.58%	2.33%
Convenience (CV2)	4.65%	16.28%	48.84%	27.91%	2.33%
Comfort (CF1)	0.00%	11.63%	48.84%	37.21%	2.33%
Reliability (RE1)	2.33%	16.28%	30.23%	44.19%	6.98%
Pollution (PO2)	11.63%	16.28%	41.86%	30.23%	0.00%
Road Infrastructure (RI3)	2.33%	6.98%	39.53%	37.21%	13.95%

Figure 4 indicates that most of the respondents (53.49%) are from a mid-income level in the Rs. 20,000 – 1,00,000 range, but since more than a quarter of the respondents are students, the middle-income share should be higher if sample size is increased with more employed respondents. Only 25.58% of the respondents in the pilot study sample don't own a vehicle, and an equal share of respondents (27.91%) own either a 2-wheeler or 4-wheeler vehicle, with 18.60% reporting to own both. The isolated correlation between vehicle ownership and income have been found to be quite low from simple regression, but this is not of concern in the present model framework, neither is a proper finding from such a small pilot sample. Besides the socio-economic factors, further work needs to be done on built environment measurements that has not been developed within the framework so far. Built environment factors identified are: population density, employment density, land use mixture, connectivity, distance to transit, and accessibility. The HVEI variables overlap with these factors at several places, which implies a stronger correlation between the two constructs, albeit further complicating the model.

To estimate the impact of each individual factors on the final endogenous variable i.e. travel mode choice, the model will be solved using the MNL framework. The work is at its conceptual stage, with the pilot study conducted for an initial validation of the proposed variables and constructs. To reveal the direct and indirect effects of built environment on the travel mode choice, further data analysis for the SEM and DCM components will be carried out using SPSS Amos, R, Strata, or a combination of them. A survey will be conducted on a much larger sample of respondents (possibly from a different location than of the pilot study). To reduce biases in the survey data, the popularly suggested sampling method – Simple Random sampling method can be used. To reduce *under coverage*, snowball sampling can be incorporated. Data collection is to be done using the survey technique by means of a structured questionnaire. To reduce bias on the data, web-based surveys with social networking services may be used. Below 30% on average, considering a big part of it will be an external survey.

4. Conclusions

The underlying purpose behind this study is to understand travel behavior of people through short-term and long-term choices of transport users, driver awareness, facility planning etc., which can be implemented for policy making to address various traffic management problems including congestion, accidents, health and safety, and pollution. The present study proposes an integrated structural equation model (SEM) and discrete choice modeling (DCM) framework of a model to understand the direct and indirect effects of built environment on travel mode choice of tr5ansport users. The proposed model is an extension of Ding et al. (2017)'s modeling framework where travel distance and car ownership play mediate the influence of built environment on the final endogenous variable. Additional endogenous variables are added viz. travel cost, convenience, comfort, reliability, pollution, and road infrastructure, all clubbed together in form of a human-vehicle-environment interaction (HVEI) construct. The study is at a conceptual phase, and a small pilot survey is conducted from forty-three respondents using convenience sampling. At this stage of the study, a number of limitations can be addressed, starting from the sampling method of the survey. *Over coverage* and *under coverage* can be reduced by snowball sampling, and the bias can be reduced by adopting simple random sampling for the subsequent survey that is to be conducted on a larger scale. The proposed MNL framework is applicable under accessible econometric environments enabled by software such as SPSS Amos, Strata, and R. The built environment factors are to be developed, and the factors and variables under the HVEI construct are to be refined based on further data analysis of the pilot survey data, and then from subsequent survey data. The proposed model framework will be instrumental in unique and useful findings on transport demands specific to small and medium Indian cities otherwise usually not available in abundance. Further outcomes can also be used to nudge transport users towards more favorable travel behavior.

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