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THE IMPACT OF EMPLOYER ATTITUDE TO GREEN COMMUTING PLANS ON REDUCING CAR DRIVING: A MIXED METHOD ANALYSIS

ABSTRACT

Reducing car trips and promoting green commuting modes are generally considered important solutions to reduce the increase of energy consumption and transportation CO_2 emissions. One potential solution for alleviating transportation CO_2 emissions has been to identify a role for the employer through green commuter programs. This paper offers an approach to assess the effects of employer attitudes towards green commuting plans on commuter mode choice and the intermediary role car ownership plays in the mode choice decision process. A mixed method which extends the traditional discrete choice model by incorporating latent variables and mediating variables with a structure equation model was used to better understand the commuter mode choice behaviour. The empirical data were selected from Washington-Baltimore Regional Household Travel Survey in 2007-2008, including all the trips from home to workplace during the morning hours. The model parameters were estimated using the simultaneous estimation approach and the integrated model turns out to be superior to the traditional multinomial logit (MNL) model accounting for the impact of employer attitudes towards green commuting. The direct and indirect effects of socio-demographic attributes and employer attitudes towards green commuting were estimated. Through the structural equation modelling with mediating variable, this approach confirmed the intermediary nature of car ownership in the choice process. The results found in this paper provide helpful information for transportation and planning policymakers to test the transportation and planning policies effects and encourage green commuting reducing transportation CO_2 emissions.

KEY WORDS

latent variable; mediating variable; discrete choice model; structural equation model; travel mode choice; car ownership; green commuting

1. INTRODUCTION

The carbon dioxide (CO_2) level that causes global warming has been increasing rapidly since 1990 and many countries are trying to reduce these CO_2 emissions. Transportation accounts for a third of CO_2 emissions, and therefore many solutions are proposed to reduce the growth of energy consumption and transportation CO_2 emissions. Work commute trips by automobile represent 20-25 percent of all trips made in the United States [1]. One potential solution to greatly alleviate transportation CO_2 emissions has been to identify a role for the employer in reducing car commuting and promoting more green commuting alternatives through green commuting plans. Green commuting plans are implemented by employers to encourage their employees to choose environmentally friendly transportation modes to work. In the UK green commuting plans have been an important transport policy since 1990s [2, 3] and now they gain more attractions in the United States as well. Green commuting plans have been encouraged in Washington and Baltimore Region, and a travel survey was conducted in 2007 and 2008. In this way it has become important to model the effects of employer attitudes towards green commuting plans on commuter travel behaviour, and to find out whether positive attitudes of employers towards green commuting plans can promote green commuting of their employees.

Travel mode choice behaviour has been largely analyzed using discrete choice model. The traditional discrete choice model assumes that an individual's decision-making process is based on utility maximization and that the systematic part of the utility function depends on some observable attributes and covariates. However, these attributes and covariates can only explain part of the utility while a large part remains unexplained. In recent years, research has recognized that psychological factors such as attitudes, lifestyle, and values that reflect individual heterogeneity affect an alternative's utility and further the individual's travel behaviour [4-6]. Therefore, the aforementioned factors that are difficult to operationalize in the model are usually considered as latent variables and should be incorporated in the model. Although the framework of integrated choice and latent variable model has been proposed and extended [7, 8] there are still relatively limited applications in the literature due to the lack of appropriate full information estimation software for the integrated model [4]. A simple sequential estimation approach has been used in previous studies [9, 10]. The expected values for the latent variables are calculated in the first stage, and then they are added into the explanatory variables, traditional discrete choice mode is estimated in the second stage. Although this method is straightforward, it may lead to inconsistent and biased estimates of random utility functions [11].

It has been well known that personal attitudes and perceptions could influence the traveller's behaviour. Johansson et al. found that both attitudes towards flexibility and comfort influenced the individual's mode choice [5]. Kim et al. analyzed the effects of pro-environmental attitudes on mode choice behaviour, and the results showed it directly and significantly influenced the mode choice behaviour [6]. Schwanen and Mokhtarian modelled commuting mode choice accounting for cognitive dissonance (the mismatch between one's current neighbourhood type and one's preference for neighbourhood type) as measured by the attitudinal indicators. The neighbourhood type dissonance was significantly associated with commuting mode choice [12]. Gardner and Abraham tested the impact of environmental concern, personal moral norms concerning mode choice, and attitudes on non-car transportation modes, and indicated that these factors potentially influenced the traveller's mode choice behaviour [13]. These previous studies mostly focused on how personal attitudes and preferences affect mode choice behaviour from the traveller perspective. However, commuter travel mode choice decisions do not merely depend on household, individual, mode specific attributes, but also depend on employer attitudes towards different transportation modes such as green commuting. Therefore, incorporating latent variables representing employer attitudes towards green commuting into mode choice model can lead to a comprehensive understanding of the mode choice behaviour.

Most current applications of integrated choice and latent variable model only consider direct effects of latent variables on travel mode choice, and car ownership is always constructed as an explanatory variable in the model in addition to socio-demographic variables. The causal relationships between latent variables, socio-demographic variables, and car ownership are commonly neglected. Car ownership is a critical mediating link in the connection between the built environment and travel behaviour: the built environment presumably influences car ownership, which in turn affects travel behaviour [14]. Travel decisions for an individual are embedded in choice hierarchy given by Ben-Akiva and Atherton [15]. Car ownership is considered as a medium-term decision, and it is conditional on long-term decisions such as residential location and workplace location. Car ownership, in turn, influences short-term decisions such as travel destination and daily car use. Recent empirical research also indicates that car ownership which is considered as a mediating relationship between the built environment and travel behaviour is more in line with the actual decision process [16-18]. However, in most studies, car ownership is assumed exogenous to travel mode choice decision, thereby inadequately analyzing the role car ownership plays in travel mode choice.

The aim of this paper is to develop a model-integrated choice model and latent variable and mediating variable with a structural equation model that not only is able to analyze the direct effects of employer attitudes towards green commuting on commuter travel mode choice, but is also able to recognize the indirect effects of socio-demographic attributes, and latent variables through mediating variable car ownership on travel mode choice behaviour, contributing to our understanding of the effects of employer attitudes towards green commuting on commuter travel mode choice and the role car ownership plays as a mediating variable in travel mode choice. Furthermore, simultaneous estimation approach, which is a full information estimation method, was used in this paper to overcome the deficits of sequential approach.

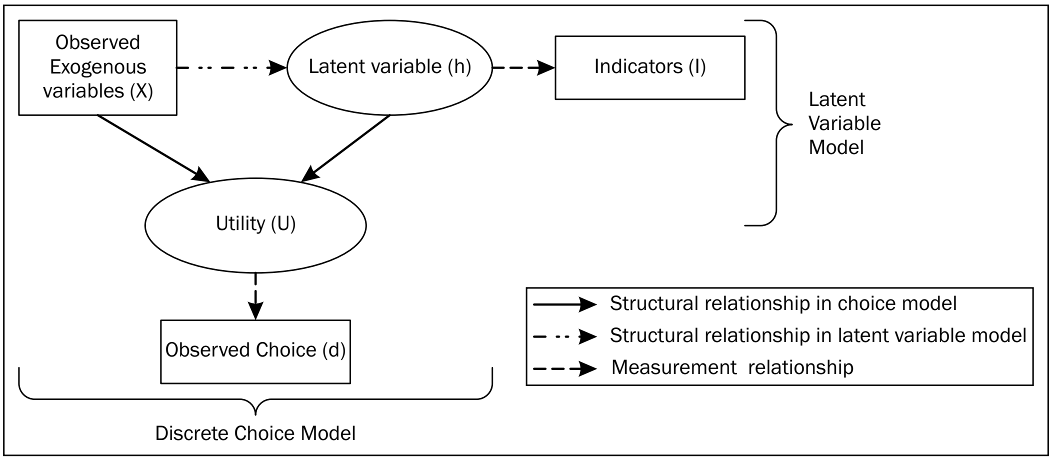

Figure 1 - Framework for the integrated choice and latent variable model

This paper is organized as follows. The next section introduces the general structure of integrated choice and latent variable model and different estimation approaches. Section 3 presents the model and describes the data used in this research. Section 4 gives the model estimation results. The main findings and limitations are presented in the last section.

2. METHODOLOGY

The integrated choice and latent variable model consists of two major components: a structural equation model and a choice model. The framework of the integrated model, adapted from Ben-Akiva et al. [7] is shown in *Figure 1*. The structural equation model describes the relationship between the latent variables and their indicators and causes, while the discrete choice model explains mode choice.

2.1 Structural equation model

The structural equation model consists of two submodels: measurement equation and structural equation. The measurement model which is a confirmatory factor model relates the endogenous and exogenous latent variables to their corresponding indictors. The indicators can be continuous, binary, or categorical variables expressed by responses to attitudinal and perceptual survey questions. The structural model represents the interrelationships among the latent variables and observed exogenous variables.

Consider a structural equation model with endogenous latent variables η, exogenous latent variables ξ, and observed exogenous variables X. The measurement model can be expressed as:

$$I = \Lambda_\eta \eta + \nu \tag{1}$$

$$J = \Lambda_\xi \xi + \sigma \tag{2}$$

where Λ_η and Λ_ξ are matrices of factor loading, and ν and σ are measurement errors.

The structure model can be formulated as:

$$\eta = \mathrm{B}\eta + \Gamma_1 \xi + \Gamma_2 X + \varsigma \tag{3}$$

where B, Γ_1, and Γ_2 contain regression coefficients and ζ are measurement disturbances. The vectors ν, σ, and ς are assumed to be independently, identically distributed (i.i.d) multivariate normal variables.

2.2 Discrete choice model

The random utility component is based on the assumption that a decision maker n, faced with a finite set C_n of alternatives i, chooses the option i which provides the maximum utility U_{ni}. The structural equation of the choice model is given by the random utility function:

$$U_{ni} = V(X, \xi, \eta; \beta) + \varepsilon_{ni} = \beta_x X_{ni} + \beta_\xi \xi_{ni} + \beta_\eta \eta_{ni} + \varepsilon_{ni} \tag{4}$$

where β are parameters to be estimated for observed exogenous variables, latent exogenous variables, and latent endogenous variables. ε are i.i.d. extreme value error terms. Assuming utility maximizing behaviour, the measurement equation for the observed choices is shown as follows:

$$y_{ni} = \begin{cases} 1 & \text{if } U_{ni} \geq U_{nj}, j \neq i \\ 0 & \text{otherwise} \end{cases} \tag{5}$$

2.3 Likelihood function and estimation

Since all information about the latent variables x_n^*(ξ and η) is contained in the observed indicators T_n(I_n and J_n), the joint probability of the choice and latent variables is considered. Assuming that random errors ν, σ, and ε are independent, integrating over the joint distribution of the latent variables leads to the following function:

$$P(y_n \mid X_n, x_n^*; \beta, \Lambda, \mathrm{B}, \Gamma, \delta) =$$

$$= \int_{R_{x_n^*}} P_y\left(y_n | X_n, x_n^*; \boldsymbol{\beta}, \boldsymbol{\varepsilon}\right) f\left(T_n | x_n^*; \Lambda, \boldsymbol{\nu}\right)$$

$$g(x_n^* \mid X_n; \mathrm{B}, \Gamma, \varsigma) dx_n^* \ldots \tag{6}$$

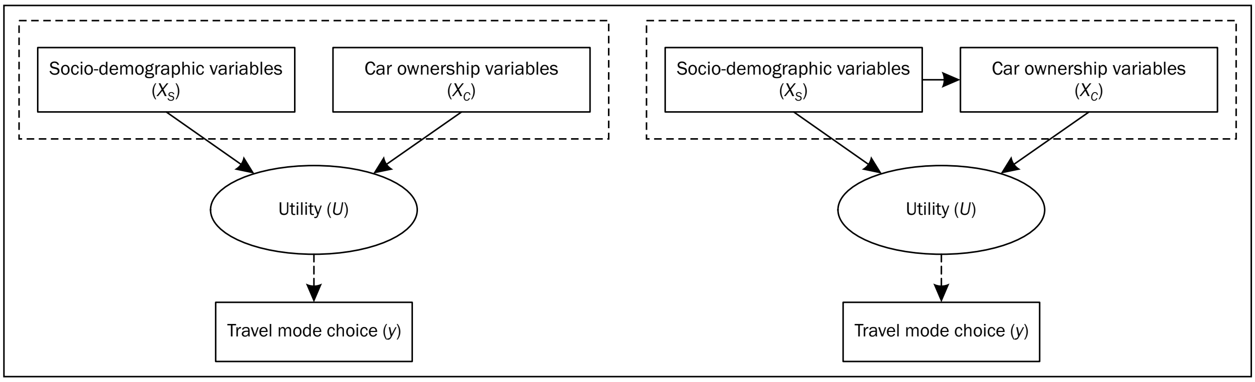

Figure 2 - Potential relationships socio-demographic, car ownership and travel behaviour

where P_y denotes the probability function of the choice model (Equation 4), the density function f for the latent variable indicators relates to the measurement model (Equation 1 and Equation 2), the density function g corresponds to the structural model for the latent variable (Equation 3), δ designates the full set of random errors, $R_{x_n^*}$ denotes that integration is over the range space of the vector of latent variables.

To estimate the integrated choice and latent variable model, two methods are now available: the sequential approach, where the latent variables are constructed before being incorporated into the discrete choice model as further regular variables [4, 5, 19], and the simultaneous approach where both processes are done together [20]. The first approach brings measurement error into the model and therefore results in inconsistent and inefficient estimates [21], and the second approach which is full information estimation method overcomes this limitation. Moreover, simultaneous approach can be used to test more complex relationships between observed exogenous variables, providing the direct and indirect effects of mediating variables on the travel behaviour. However, it has been far less used due to its higher complexity, especially as the number of latent factors increases.

3. MODEL SPECIFICATION AND DATA SOURCE

3.1 Model specification

Traditionally, travel mode choice is modelled both as a function of socio-demographic characteristics of the decision maker such as gender, age, car ownership, household size, employment status, etc., and of attributes of different travel mode choice alternatives such as travel time, travel cost, etc. In recent years, incorporating the unobserved or latent variables such as comfort, reliability, environmental preferences, safety, and convenience into the model of travel mode choice have offered great potential to enhance the understanding of the travel behaviour. Most latent variables are constructed from the decision maker perspective in travel mode choice model. For the commuters, the employer attitudes towards green commuting also play an important role in the individual's decision making process. For example, employer provides subsidies for transit if the employer has a positive attitude towards green commuting. Limited studies, however, incorporate latent variables into the model on how employer attitudes affect actual travel mode choice behaviour.

Car ownership is mainly used as an exogenous variable in most studies, in addition to socio-demographic variables to explain travel behaviour, as shown in the first model structure in *Figure 2*. Travel mode choice behaviour is directly influenced by socio-demographic and car ownership. However, car ownership itself is also influenced by the socio-demographic characteristics, such as workplace location, residential location, household size, and income. This results in an indirect effect of the socio-demographic characteristics on travel behaviour through the mediating variable car ownership. As shown in the second model structure in *Figure 2*, it includes the relationships between the two exogenous variables. Consequently, car ownership is the dependent variable in one set of relationships and at the same time it is an explanatory variable of travel mode choice behaviour.

Regarding the framework of the integrated choice and latent variables, mediating variable in this study is shown in *Figure 3*. Based on factor analysis results, two unobservable factors related to employer attitudes towards green commuting plans were included in the model: public transportation preferences (η_{public}), and car use discouragement (η_{car}). The latent variable model was developed to analyze the structural relationship among the mediating variable car ownership, and the latent variables using relevant indicator variables. The utility of each travel mode was determined by the socio-demographic variables, car ownership variables, mode specific attributes, and latent variables in the discrete choice model. In this study, multinomial logit (MNL) model with three alternatives

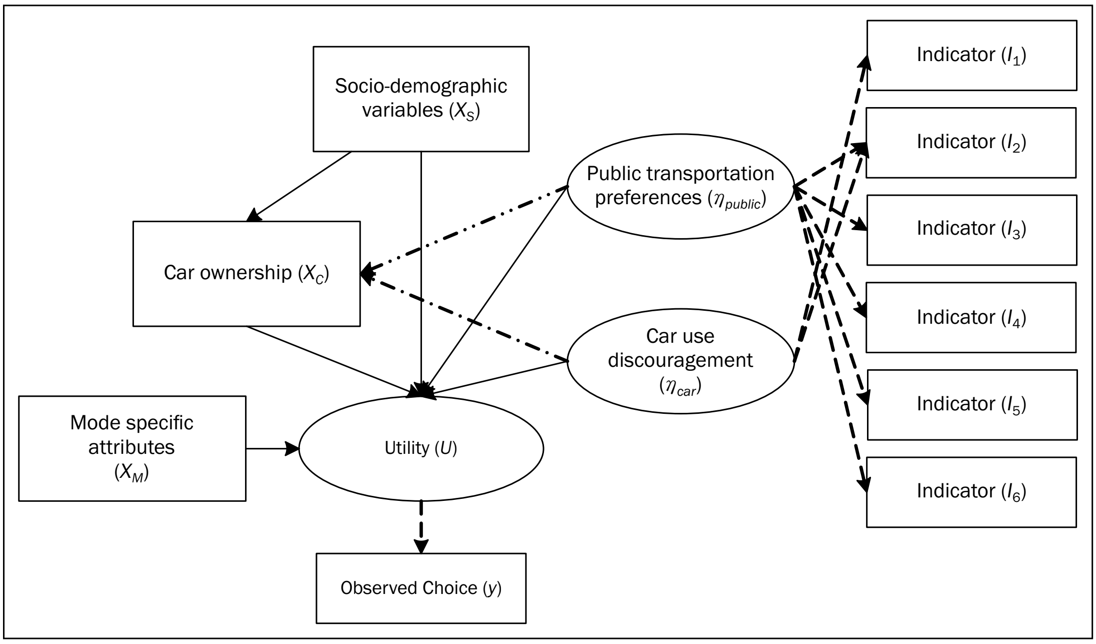

Figure 3 - Framework of the integrated choice model and structural equation model

(car, transit, and non-motorized mode (i.e. walk and cycling)) was employed as the discrete choice model.

In order to test the integrated choice and latent variable, and mediating variable model presented in this paper, and to assess to what extent the latent variable and mediating variable provides additional explanatory power and model fit, a traditional MNL model without latent variable and mediating variable was first estimated, only containing directly observed explanatory variables describing the choice alternatives. In the following, the integrated choice and latent variable, and mediating variable model presented in this study were estimated.

3.2 Data source

The data used in this study are drawn from the Washington and Baltimore Regional Household Travel Survey (HTS), which was conducted by Baltimore Metropolitan Council (BMC) and Transportation Planning Board at the Metropolitan Washington Council of Governments (MWCOG) during 2007-2008. As with most household travel surveys, detailed socio-demographic and trip information for each person were collected. In addition to the HTS, origin-destination travel time and cost matrices by different modes were obtained from Maryland Statewide Transportation Model (MSTM). MSTM is a multi-layer model working at a regional, statewide, and urban level. The model is driven by the economic and land use assumptions and includes both person and freight travel. The passenger and truck from both BMC regional and statewide model components provide traffic flows allocated to a time period (a.m. peak, p.m. peak, and off-peak).

The sample data used for the modelling process are selected from HTS, including all the travel from home to workplace in the morning (6 a.m.-12 p.m.). The sample consists of 8,331 respondents. Almost 20% of the respondents are single person households. The average sample age is 44. The proportion of respondents with students is 41.1%, 2,153 respondents (25.5%) live in suburban and rural areas, and 6,178 respondents (74.2%) live in urban or central business district (CBD) areas. 2,827 respondents (33.9%) work in CBD areas, and 5,504 respondents (66.1%) work in urban, suburban, or rural areas. In the sample 6,572 respondents (78.9%) use car for commuting, whereas 1,430 respondents (17.2%) and 329 respondents (3.9%) use transit, walking and cycling, respectively. Household, individual and travel characteristics of the sample data are described in *Table 1*.

In the travel survey, the respondents had to indicate their transportation benefits from the employers using binary indicator variables, as shown in *Table 2*. The latent variable is observed indirectly by the indicators to identify the employer attitudes towards green commuting plans. Positive attitudes of employer to public transportation can be expected to positively affect the commuter's inclination to make environmentally friendly mode choices such as public transit, walking and cycling. Similarly, another attitude, car use discouragement, could also be expected to positively influence the public transport use, reducing car-based commuting trips. There are six indicators in the latent variable model to represent employer latent attitudes towards green commuting plans: five indicators for public transportation preferences (η_{public}), and two indicators for car use discouragement (η_{car}).

Table 1 - Descriptive statistics of sample data for the trips from home to work (N=8,331)

Variable Name	Variable Description	Mean	St. Dev.
Household characteristics			
Household size	Household size is equal to or more than three persons (1=yes)	0.42	0.493
Household workers	Number of workers in household	1.76	0.689
Household income	Income1: Household income is less than $50,000 (1=yes)	0.20	0.399
	Income2: Household income is between $50,000 and $100,000 (1=yes)	0.38	0.486
	Income3: Household income is equal to or more than $100,000 (1=yes)	0.42	0.493
Household students	Number of students in household	0.68	0.974
Car ownership	Number of household vehicles available	2.01	1.061
Residential location	Household located in suburban or rural area (1=yes)	0.26	0.438
Workplace location	Person working in the central business district (CBD) (1=yes)	0.34	0.474
Individual characteristics			
Age	Age in years	44.33	12.636
Gender	Male (1=yes)	0.49	0.500
Race	White people (1=yes)	0.75	0.435
Jobs	Person having more than one job (1=yes)	0.06	0.243
Travel-related characteristics			
Travel time (min)	Travel time given for the chosen modes	35.82	22.847
Travel distance (mile)	Travel distance given for the chosen modes	11.768	10.783

Meanwhile, the “public transportation preferences” and “car use discouragement” latent variables could also be expected to influence car ownership of the commuters. Several previous studies have identified that there is a potential relationship between the household car ownership and transit subsidies [22-24]. The structural relationship between the two latent variables and mediating variable car ownership was also tested in this study.

In this paper, simultaneous estimation approach was conducted to estimate the integrated model using the software package Mplus to overcome the limitation of sequential approach. Maximum likelihood method is a generally used estimating procedure in structural equation model. A basic assumption of the ML-estimator is the multivariate normal distribution of all continuous endogenous variables in the model [25]. However, this assumption is not always fulfilled and, moreover, the final outcome variable travel mode choice is categorical. In order to deal with this issue, a robust maximum likelihood (MLR) estimator was used instead.

4. MODEL RESULTS

Confirmatory factor analysis was first used to test the reliability and validity of the measurement model with the mean and variance adjusted weighted least square (WLSMV) parameter estimator. Goodness-of-fit index for the measurement model indicates that two unobservable factors related to employer attitudes towards green commuting should be included in the model. The results of the measurement relationships are shown in *Table 3*. All indicator variables in the latent variable model are positive and significant at 95% level, which means that all indicators contribute to the construction of the two latent attitudes.

Table 2 - Latent variable and indicators (N=8,331)

Indicator Name	Indicator Description	Mean	St. Dev.
Parking (I_1)	Whether employer provides non-free parking or not (1=yes)	0.45	0.497
Transit subsidies (I_2)	Whether employer provides subsidies for transit/vanpooling (1=yes)	0.18	0.388
Guaranteed ride (I_3)	Whether employer provides guaranteed ride home available to employee (1=yes)	0.04	0.187
Non-motorized environment (I_4)	Whether employer provides bike/pedestrian facilities or services (1=yes)	0.11	0.317
Commuting information (I_5)	Whether employer provides information on commute options (1=yes)	0.09	0.288
Bicycle facility (I_6)	Whether employer provides secure bicycle facility at work location (1=yes)	0.38	0.485

Table 3 - Estimation results for the measurement relationships in the latent variable model

Indicators	Public transportation preferences (η_{public})		Car use discouragement (η_{car})	
	Parameter	t-stat	Parameter	t-stat
Parking (I_1)	—	—	1.000	—
Transit subsidies (I_2)	1.000	—	1.131	12.499
Guaranteed ride (I_3)	0.704	10.355	—	—
Non-motorized environment (I_4)	1.339	9.053	—	—
Commuting information (I_5)	1.309	10.597	—	—
Bicycle facility (I_6)	0.455	9.947	—	—

Table 4 shows the estimation results of the traditional MNL model without latent variables and integrated model. As expected, travel cost, and travel time have significantly negative signs. Comparing the two model results shows that the integrated model provides greater explanatory power regarding commuter travel mode choice behaviour. The likelihood ratio index improves from 0.317 to 0.366. Similarly, the

Table 4 - Estimation results for the traditional and integrated model

Variables	Traditional MNL model				Integrated choice and latent variable, mediating variable model			
	Transit		Walking and bicycling		Transit		Walking and bicycling	
	Parameter	t-stat	Parameter	t-stat	Parameter	t-stat	Parameter	t-stat
Constant	-0.549	-2.873*	-0.963	-2.530*	-3.492	-7.904*	-2.112	-4.189*
Household characteristics								
Size	0.125	1.203	-0.018	-0.089	-0.109	-0.537	-0.007	-0.028
Workers	0.353	4.799*	0.413	3.274*	0.348	2.465*	0.374	2.417*
Income1	0.351	4.354*	0.088	0.475	1.003	4.676*	0.589	0.405
Income3	0.063	0.585	0.580	3.851*	0.014	0.089	0.385	2.103*
Students	-0.151	-2.917*	0.111	1.300	-0.187	-1.906	0.097	0.931
Car ownership	-1.095	-14.679*	-1.122	-9.106*	-0.983	-7.257*	-0.962	-6.381*
Residential location	-1.217	-10.253*	-0.164	-0.716	-1.929	-7.571*	-0.075	-0.259
Workplace location	2.003	27.508*	1.669	11.269*	2.525	14.013*	1.930	9.070*
Individual characteristics								
Age	-0.012	-4.271*	-0.012	-2.478*	-0.012	-2.163*	-0.007	-1.203
Gender	0.272	3.896*	0.795	6.258*	0.622	4.411*	0.991	6.193*
Race	0.047	0.597	0.828	4.800*	-0.065	-0.421	0.938	4.683*
Jobs	-0.426	-2.933*	-0.260	-0.967	-0.687	-2.351*	-0.388	-1.188
Travel-related characteristics								
Travel cost	-0.245	-13.047*	-0.245	-13.047*	-0.291	-11.754*	-0.291	-11.754*
Travel time	-0.076	-11.260*	-0.076	-11.260*	-0.087	-10.053*	-0.087	-10.053*
Latent variables								
Public transportation preferences (η_{public})	—	—	—	—	0.663	8.253*	0.546	6.404*
Car use discouragement (η_{car})	—	—	—	—	2.131	10.719*	1.160	6.702*
Observations	8,331				8,331			
LL_{κ}	-24,934.325				-21,743.428			
LRI	0.317				0.366			
AIC	49,237.195				45,596.855			
Adjust BIC	49,978.243				45,808.601			

*Note: Car is the reference alternative; LRI is likelihood ratio index $LRI = 1-(LL_{\kappa}/LL_{\kappa 0})$, $LL_{\kappa 0}$ is the log-likelihood value when all the parameters are set equal to zero; AIC is Akaike information criterion; BIC is Bayesian information criterion; * indicates significant values at or above the 95 percent level.*

Akaike information criterion (AIC) and adjusted Bayesian information criterion (BIC) are lower. Furthermore, both latent variables significantly influence the commuter mode choice with expected signs at the 95% level, indicating that employer preferences for public transportation and car use discouragement increase the likelihood of choosing green modes over driving to work, which is consistent with our hypothesis.

The MNL results from the integrated model for the variables of household, individual, and travel-related characteristics suggest that these characteristics have important roles in the commuter mode choice decisions. As expected, low income groups are found to contribute positively to choosing public transit to work. More cars imply greater availability and thereby greater probability of usage for commuting trips. People in households with more students tend to prefer the car mode. People living in suburban areas are significantly more likely to choose driving to work. This seems logical because there are usually limited transit services for suburban residents. It is found that people who work in the CBD are significantly more likely to use green commuting modes. This finding may be due to the fact that there are better transit services and better non-motorized environments in the downtown area. In terms of individual characteristics, males are significantly more likely to use green modes to work, which is not consistent with expectations. This might be so because female members of the family need to run more errands on their way home, like pick up kids, buy groceries, etc. Young adults are significantly more likely to choose public transit to work, which may be due to the fact that they have limited car availability thus contributing to greater propensity of using transit. The variable of race is found to have positive coefficients for walking and bicycling modes, indicating that white people are significantly more likely to choose walking and bicycling to work with respect to others. As expected, people who have more than one job are significantly more likely to choose driving to work.

As shown in *Table 5*, turning to the mediating variable, it is found that two latent variables have significantly negative effects on car ownership at the 95% level. This indicates that positive attitudes of employers towards green commuting plans can also reduce their employees' household car ownership. Household size and number of workers in a household are positively related to car ownership. This may be due to the fact that intra-household decisions related to activities among household members increase the need to own more cars. As can be expected, car ownership is significantly affected by low income negatively, and by high income positively. Households located in suburban areas are significantly more likely to own more cars. Because of limited transit services and long commuting distances, the need to own more cars increases within these households. People who work in CBD area are less likely to own more cars.

In traditional choice model, only the direct effects can be found. However, focusing on direct effects only would lead to inconsistent conclusions in some cases [26, 27]. Based on the extended conditional logit choice model by incorporating mediating variable with a structural equation model, the indirect effects of socio-demographic attributes, and latent variables through mediating variable car ownership were recognized. For example, household size is not significantly associated with travel mode choice if direct effects were only focused on, as shown in *Table 4*. However, travel mode choice behaviour is likely to be influenced by household size but mainly in an indirect way through interaction with car ownership. As shown in *Table 6*, the indirect effect of household size on travel mode choice is significant at the 95% level through mediating variable car ownership. Similar example relates to the influence of income on the travel mode choice. It is believed that high income groups can afford to own more cars, which increases the likelihood of choosing car over transit to work. However, the direct effect of high income on transit is not significant. The estima-

Table 5 - Estimation results for the mediating variable in the latent variable model

Variables	Mediating variable: car ownership	
	Parameter	t-stat
Constant	0.695	22.783*
Size	0.368	18.359*
Workers	0.575	34.480*
Income1	-0.340	-12.262*
Income3	0.279	14.380*
Residential location	0.378	16.589*
Workplace location	-0.144	-7.033*
Public transportation preferences (η_{public})	-0.038	-4.627*
Car use discouragement (η_{car})	-0.097	-9.619*

*Note: * indicates significant values at or above the 95 percent level*

Table 6 - Estimation results for the indirect and total effects of socio-demographic variables and latent variables on travel mode choice behaviour through mediating variable car ownership

Variables	Transit				Walking and bicycling			
	Indirect effect		Total effect		Indirect effect		Total effect	
	Parameter	t-stat	Parameter	t-stat	Parameter	t-stat	Parameter	t-stat
Size	-0.362	-6.834*	-0.471	-2.329*	-0.354	-6.096*	-0.361	-1.529
Workers	-0.565	-7.037*	-0.218	-1.770	-0.553	-6.223*	-0.179	-1.292
Income1	0.335	6.128*	1.338	6.086*	0.327	5.616*	0.916	3.809*
Income3	-0.274	-6.657*	-0.260	-1.603	-0.268	-5.915*	0.116	0.637
Residential location	-0.372	-6.557*	-2.301	-8.693*	-0.364	-5.914*	-0.439	-1.510
Workplace location	0.141	4.736*	2.667	14.387*	0.138	4.579*	2.068	9.691*
Public transportation preferences (η_{public})	0.037	3.843*	0.700	8.416*	0.036	3.684*	0.582	6.691*
Car use discouragement (η_{car})	0.096	6.422*	2.168	10.856*	0.094	5.549*	1.196	6.913*

*Note: * indicates significant values at or above the 95 percent level.*

tion results show that this is mainly indirectly, caused by the interaction between car ownership and income. This finding indicates that the travel mode choice behaviour is not mainly directly caused by high income but rather their higher car ownership level. The indirect effect of residential location on walking and bicycling is significant at the 95% level. Its negative sign implies that living in suburban areas (characterized by low density, limited diversity, and car-orientated design) will lead to fewer non-motorized trips [28, 29]. Furthermore, the indirect effects of the two latent variables on car choice are also significantly negative, which may be highly helpful for a policy analysis standpoint.

The total effect is the sum of the direct and indirect effects of a socio-demographic variable and latent variable, as shown in *Table 6*. Depending on the sign, the indirect effect of one variable on mode choice may strengthen or offset its direct effect. Comparing the direct, indirect, and total effects in *Table 4* and *Table 6*, it is found that the total effects of household size, low income, residential location, workplace location, and the two latent variables have larger magnitudes than the direct effects due to the synergism of the indirect effects. While the total effects of household workers and high income are the net outcome of the direct and indirect effects, it is logical that household workers and high income have negative total effects on transit mode choice. The magnitude of the negative indirect effect of household workers is larger than its positive direct effect, leading to a negative sign on total effect. Similar example relates to the effect of high income on transit mode choice.

5. CONCLUSION

Car-based commuting travel in the morning peak period is the most severe time of day. Due to the serious traffic congestion, transportation CO_2 emissions are increasing. In large metropolitan areas, such as Washington-Baltimore region, the major freeways are highly occupied and congested by commuters. Car use is partly reduced with the public transit service availability, but it is still not enough. The effects of employer attitudes towards green commuting on commuter mode choice were tested and the role the car ownership plays in the mode choice was found by incorporating latent variable and mediating variable into discrete mode choice model. The data used in this paper were selected from the Washington-Baltimore Household Travel Survey in 2007-2008, including all the travelling from home to workplace in the morning hours. The model parameters were estimated using simultaneous estimation approach. The integrated model has turned out to be superior to the traditional MNL model. The direct and indirect effects of employer attitudes towards green commuting have strong influences on travel mode choice behaviour, as shown by the empirical results.

Although travel cost is significant for the mode choice, transportation and planning policies should not only focus on influencing car use directly by measure of increasing car travel cost from the traveller's perspective such as traffic congestion, road pricing and gasoline taxes, but also it should focus on measures from the employer's perspective, for example, through car parking management, public transport initiatives, and pedestrian and bicycling incentives. Our empirical analysis indicated that household size and income influence travel mode choice mainly in indirect ways through mediating variable car ownership. The direct effects of household size and high income on the mode choice are not significant. However, the indirect effects are significant at the level above 95%. Similar results can be found in the research of built environment and travel behaviour reported by Acker and Witlox [16]. This indicates that ignoring car ownership as a mediating variable is likely to result in a misspecification of the effects of socio-demographic attributes on travel mode choice behaviour. The effects of some socio-demographic attributes on mode choice might be underestimated: the total effects of household size, low income, residential and workplace location, and employer attitudes towards green commuting exceed their direct effects on the mode choice. This approach confirms the intermediary nature of car ownership and indicates that considering car ownership as a mediating variable in the integrated mode could correctly test the transportation and planning policies that intend to discourage car use to reduce the transportation CO_2 emissions.

Further studies can be identified, which not only includes the applications of the framework based on the mixed method of structural equation model and discrete choice model, but also includes the use of advanced model structures such as mixed integrated model to account for the heterogeneity across individuals in the travel behaviour decision.

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摘要

雇主对绿色出行项目的态度对降低小汽车出行的影响：基于联合建模方法的研究

降低小汽车出行，促进绿色出行被认为是降低交通能源消耗和碳排放的重要措施。其中，通过一系列的雇主绿色出行项目具有潜在的降低交通碳排放的可能。基于此，本文研究了雇主对绿色出行项目的态度对通勤者出行方式选择行为的影响，同时，考虑了家庭拥有小汽车数在出行方式选择行为过程中的中介效应。为了更好地了解通勤者的决策行为，本文将潜在变量和中介变量加入到传统的离散选择模型中。并应用美国华盛顿-巴尔的摩区域家庭出行调查数据进行了实证研究，分析了上午期间从家出行到工作地的全部出行。模型估计采用同时估计法，估计结果表明本文应用的联合模型比不考虑雇主绿色出行态度的MNL模型结构更加合理。家庭社会经济属性和雇主态度对通勤者出行方式选择行为的直接效应和间接效应均被估计。通过中介变量的结构方程模型验证了家庭拥有小汽车数在出行方式选择行为过程中的中介属性。本文研究为检验交通和规划政策对鼓励绿色出行降低交通碳排放的影响提供了方法支撑，有助于交通和城市规划的科学政策的制定。

关键词

潜变量，中介变量，离散选择模型，结构方程模型，交通出行方式选择，家庭拥有小汽车数，绿色出行

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