Improving Travel Quality of Low-Income Commuters in China: Demand-side Perspective

Long Cheng
Ph.D., Postdoctoral Fellow
Jiangsu Key Laboratory of Urban ITS, Southeast University
Si Pai Lou #2, Nanjing, China, 210096
Department of Civil and Environmental Engineering, The Hong Kong Polytechnic University
Yuk Choi Road, Hung Hom, Kowloon, Hong Kong, China
Tel: +86-15850600193; Fax: +86-25-83795643; Email: chenglong010203@gmail.com

Xuewu Chen, Corresponding Author
Ph.D., Professor
Jiangsu Key Laboratory of Urban ITS, Southeast University
Si Pai Lou #2, Nanjing, China, 210096
Tel: +86-25-83795643; Fax: +86-25-83795643; Email: chenxuewu@seu.edu.cn

William H. K. Lam
Ph.D., Professor
Department of Civil and Environmental Engineering, The Hong Kong Polytechnic University
Yuk Choi Road, Hung Hom, Kowloon, Hong Kong, China
Tel: +852-27666045; Fax: +852-23346389; Email: william.lam@polyu.edu.hk

Shuo Yang
Ph.D. candidate
Jiangsu Key Laboratory of Urban ITS, Southeast University
Si Pai Lou #2, Nanjing, China, 210096
Tel: +86-15295507726; Email: youngs700@hotmail.com

Pengfei Wang
Ph.D. candidate
Jiangsu Key Laboratory of Urban ITS, Southeast University
Si Pai Lou #2, Nanjing, China, 210096
Tel: +86-15850662732; Email: 740175745@qq.com

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ABSTRACT

Low-income residents can depend on fewer travel options and have restricted mobility. The paper analyzed low-income commuters' mode choice behavior by using data from an activity-based travel survey in Fushun, China. An integrated choice and latent variable model was presented. The model utilized the following latent attitudes: comfort, convenience, reliability, flexibility, safety and environmental preferences. The inclusion of attitudes enables us to capture unobserved heterogeneity of the choice process with a better understanding of travel demands. Post-estimation of the integrated model was then applied to assess the responsiveness of preferences for various transportation modes to changes in policy relevant variables. This was done by calculating the elasticity and marginal effects of choice probabilities with respect to the relevant attributes of travel preferences. The analysis indicates that individuals with high comfort preferences care more about walking environment and they need solutions to enhance their walking experience. However, travelers preferring reliability are more likely to travel by public transit, and measures to inform commuters of real-time bus operation information are proposed. Commuters who emphasize environmental preference are more apt to cycle, and therefore "pro-bike" strategies are recommended. Results of these analysis indicate that different actions should be taken for serving different preferences. Findings should provide useful information to policy-makers and transportation planners to improve low-income commuters' travel quality.

INTRODUCTION

Low-income residents show distinct travel characteristics from others. Most of their trips involve subsistence activities (*1*), namely work or work related purposes. Since low-income people rarely participate in maintenance and discretionary activities, their quality of life suffers. Transportation is a critical element for everyone to accomplish tasks in daily life, the need for low-income residents to stay active and engaged in society is an important social issue for increasingly important travel equity.

In designing an environmentally impartial and socially desirable travel system in line with the poor's preferences, transportation planners must increase their understanding the preferences that influence individual's choice of transportation. In previous research, qualitative aspects such as travelers' preferences were seldom incorporated into the mode choice modeling. Although individual's socio-economic attributes cover some qualitative characteristics, there are other unobserved factors (latent variables) that are important in mode choice behavior such as affective factors, personal attitudes or perceptions. These latent variables enriched models provide better insights for the decision making process (*2,3*).

By presenting an integrated discrete choice and latent variable model, the primary objective of this study is to analyze how latent preferences of low-income commuters affect mode choice and to analyze potential policies which will be necessary to fulfill their demands. These latent variables are unobservable but can be deduced from psychometric indicators which are collected in the survey. These indicators are a series of statements/questions to which respondents give their level of agreement. With the help of these indicators, latent variables can be measured and structural equations can be built in order to integrate the latent variables into mode choice context.

LITERATURE REVIEW

Mode choice has been mainly studied and modeled as a rational process based on the random utility theory. Studies conducted in the field of psychology and social sciences have demonstrated that more abstract psychological constructs, such as attitudes, values, perceptions, affects and desires, are integral to travel mode choice (*4*-*7*). Recent investigations have indicated that attitudes may be better predictors of modal choice than the traditionally used objective measures such as time and costs. With a sample of Swedish commuters, studies (*2*) find that attitudes towards flexibility and comfort, as well as being pro-environmentally inclined, influence individual's mode choice. From the modeling results, the latent variables enriched choice model outperforms the traditional model. It follows that there are other ways, apart from economic incentives, to attract individuals to the desirable public modes of transport from the society's perspective. Attitudinal multinomial logit models were presented (*8*) to indicate that flexibility and autonomy significantly affect mode choice for the journey to non-work activities. Paulssen et al. (*9*) developed an integrated choice and latent variable model that allowed for hierarchical relationships between latent variables and flexible substitution of patterns across modal alternatives. A comparison between observable level-of-service attributes and latent attitudinal variables was made. The result concludes that the latter has greater influences on mode choices. Heinen et al. (*10*) examined how commuters' attitudes towards cycling influence choice decisions. Findings show that the attitudinal factors provide additional explanation for why people cycle to work.

Structural equation models are frequently utilized in exploring the relationship between latent variables and travel behavior. Golob (*11*) developed joint models of attitude and behavior to explain how mode choice and attitudes differed across the population regarding tolled high-occupancy vehicle lanes. The role of psychological factors on mode choice was investigated by structural equation modeling using the data collected in a Chilean university (*12*). The authors included psychological factors through a latent variable approach. They found that it will help to improve the fitness level of revealed preference models.

Policy changes can have major impacts on modal share of urban transportation. Pucher (*13*) has shown how different policies in western European countries result in a lower level of private car usage. These policies include substantially large taxes on gasoline and subsidies to mass transit. Other studies (*14,15*) conclude that bus punctuality and frequency of departures, which reduce overall travel time, have higher effectiveness than fares when attempting to attract potential mode switchers. Using the travel survey data in Nanjing, Cheng et al. (*16*) noted that increased accessibility including mixed land use developments and multi-purpose activity centers should be promoted to facilitate low-income residents' daily travel.

With the scope of this brief literature review, it can be seen that travel behavior can be better explained by including latent variables. However, mobility of low-income commuters, whose travel preferences are distinct from others, does not receive enough attention. Previous policies have focused on changing objective attributes such as travel time and cost to affect travel behavior. They tended to ignore improvement measures originated from internal preferences. In this paper, the primary intention is to further add to the rich body of knowledge about the effects of attitudes on mode choice and also show what actions will be necessary to increase the travel quality of low-income commuters in China, in an obvious attempt to fulfill individual's psychological preferences.

DATA

Data Source

The data used in this paper was collected from a very detailed activity-based travel survey of Fushun on October 29th, 2014. Fushun, a prefecture-level city with an urban area of 1,416 km^2 and a population of 1.4 million, is located in the northeastern part of China. The city features unsmooth terrain and severe weather in winter. A total of 9,954 questionnaires were assigned randomly to residents in traffic analysis zones in accordance to their population. Taking a whole household as a unit, a face-to-face interview was conducted to record all activities involving travel details for all individuals above six years old in the household. Finally, 8,585 samples were obtained after data screening. The International Poverty Line Standard proposed by Organization for Economic Cooperation and Development is utilized to classify the sample into a low-income subset and a non-low-income subset. The standard defines the poverty rate as a level of income at 50% of the regional median disposable income per capita (*16*). As a result, 1,973 low-income and 3,590 non-low-income commuters are included in the following analysis.

Apart from socio-demographics and travel information, data on attitudinal and behavioral questions were collected to construct latent attitude variables including environmental preferences and preferences for safety, comfort, convenience, reliability, and flexibility. The attitudinal questions addressed issues related to modal comfort, convenience, reliability and flexibility, which were answered on a five-point Likert scale from not important at all to very important. The behavioral questions addressed transportation related safety and environmental preference behaviors, like the use of safety belts and individual's environmental awareness. These were also answered on a five-point Likert scale from never to always. Questions on latent variables are shown in TABLE 1.

Descriptive Statistics

The socio-economic characteristics of commuters are shown in TABLE 2. For low-income commuters, 17.6% of their households consist of more than 3 people. That is a much higher percentage compared to that for non-low-income commuters, with only 6.7%. As for car ownership, low-income commuters have 0.25 cars per household, which is lower than that of non-low-income commuters. As expected, the proportion of low-income sample with driving license is substantially low, with just 22.0%. Regarding education level, 85.2% of low-income respondents receive education under college.

TABLE 2 also presents summary statistics of their activity characteristics. In this paper, trip chain or tour refers to a sequence of trips that begins at home, involves visiting one or more other places, and finally ends at home. On average, low-income commuters make 1.07 trip chains per day, with the majority conducting only one tour. Their average subsistence activity (work or school) duration is longer than non-low-income counterparts at 9.10 hours on a typical weekday, which might reflect a strive for a living for low-income residents. In the analysis of the low-income sample, walk accounts for the largest proportion among various modes. Additionally, the most frequently used motorized mode is public transit (PT) with a frequency of 0.91 trips. Bicycle and moped have the lowest share with a rate of only 3.76% and 3.76% respectively (0.09 trips/2.39 total trips). This can be explained by the uneven topography in the city, which is difficult for riding. As expected, the percentage of commuters driving cars to work in low-income sample is quite small.

Descriptive statistical analysis is performed on the low-income sample to help guide model specification. Pearson's chi-square test (χ^2) and one way analysis of variance (ANOVA) are conducted to test significance between mode choice and potential explanatory variables. Results show that all the above socio-economics listed in TABLE 2 significantly affect mode choice. Thus, all these individual specific variables are included in the initial model specification.

METHODOLOGY

Integrated Choice and Latent Variable Model

The integrated choice and latent variable model presented in this paper uses the extended framework for choice behavior provided by Walker and Ben-Akiva (*17*). The framework consists of two components: a discrete choice model and a latent variable model, each having its own set of measurement and structural equations. Unobserved variables are represented by ellipses and observable variables by rectangles. Besides, dashed lines correspond to the measurement equations and solid lines represent structural equations as in FIGURE 1. The latent variable model describes the relationship between latent variables and their indicators and explanatory variables, while the discrete choice model explains individual's mode choice.

Latent variables, represented by X_n^*, are unobserved variables related to attitudes which can be measured with psychometric indicators. Therefore, measurement equations are built in the form of equation (1) to measure latent variables:

$$I_n = f(X_n^*; \alpha) + v_n \tag{1}$$

where I_n is the indicator for individual *n* which is a function of latent variables, a set of parameters α and an error term v_n. The density function of indicators, $f(I_n|X_n^*; \alpha, \theta_v)$, can be obtained using the distribution of v_n with a standard deviation of θ_v.

The structural equations for the latent variables, shown in equation (2), are built in the same way as the classical utility function with explanatory variables X_n. In the equation, λ is a set of parameters and w_n is an error term. Assumptions regarding the distribution of w_n is employed in writing the density function of latent variables, $f(X^*|X_n; \lambda, \theta_w)$, θ_w being the standard deviation of w_n. The simultaneous calibration of these structural and measurement equations enables us to include unobserved constructs in choice models.

$$X_n^* = h(X_n; \lambda) + w_n \tag{2}$$

Having defined the relations related to latent variables, the utility for choosing alternative i can be expressed as a function of individual characteristics X_n and latent variables X_n^* with the following structural equation:

$$U_{in} = V(X_n, X_n^*; \beta) + \varepsilon_{in} \tag{3}$$

where β is a set of parameters and ε_{in} is an error term . In a discrete choice context the probability of individual *n* choosing alternative *i* can be written as follows:

$$P(i|X_n, X_n^*; \beta, \theta_\varepsilon) = Prob(U_{in} \geq U_{jn}, \forall j \in C_n) \tag{4}$$

where θ_ε is the standard deviation of the error term in equation (3) and C_n is the choice set of individual n. Within the integrated model there are two sets of measurement equations which result in a joint probability of observing choice i and indicator I_n expressed in equation (5). Since X_n^* is not observable, in order to write this probability, density functions of latent variables and indicators are incorporated.

$$P(i, I_n|X_n; \beta, \alpha, \lambda, \theta_\varepsilon, \theta_v, \theta_w) =$$

$$\int_{X^*} P(i|X_n, X_n^*; \beta, \theta_\varepsilon) f(I_n|X_n^*; \alpha, \theta_v) f(X_n^*|X_n; \lambda, \theta_w) dX^* \tag{5}$$

Maximum likelihood estimation is used to calibrate the unknown parameters. The log-likelihood function L can be written as in equation (7) with the definition of y_{in} as in (6).

$$y_{in} = \begin{cases} 1 & if \;\; U_{in} \geq U_{jn}; \forall j \in C_n \\ 0 & otherwise \end{cases} \tag{6}$$

$$L = \sum_n \sum_{i \in C_n} y_{in} log P(i, I_n|X_n; \beta, \alpha, \lambda, \theta_\varepsilon, \theta_v, \theta_w) \tag{7}$$

There are many examples of the application of integrated choice and latent variable approach in different choice contexts. For example, Espino et al. (*18*) studied mode choice behavior of suburban trips, and Abou-Zeid et al. (*19*) explored travel behavior with measurement of travel well-being. They both reported an improvement in the quality of estimates and the achievement of more realistic models when including unobserved factors through the latent variable approach.

Sensitivity of Choice Probability

As with any demand study, sensitivity measures of the responsiveness of demand to changes in policy-relevant variables are of great importance. In this study the relevant sensitivity measures are concerned with the responsiveness of the choice probability of a particular alternative to a change in some attribute of latent preferences.

One measure for evaluating the response to changes is to calculate the derivatives of the choice probabilities of each alternative with respect to the variable in question. In this study, we concern the change in probability of an alternative, $P_n(i)$, with respect to the change in attributes of latent variable X^*_{nk}. This measure, the marginal effect, is computing by differentiating $P_n(i)$ with respect to X^*_{nk}:

$$Marg^{P_n(i)}_{X^*_{nk}} = \frac{\partial P_n(i)}{\partial X^*_{nk}} = P_n(i)[1 - P_n(i)]\beta_k \tag{8}$$

where $P_n(i)$ is the choice probability of travel mode i for individual n, X^*_{nk} is k^{th} latent preference, β_k is the calibrated coefficient for that attribute.

Elasticity is another measure that is used to quantify the extent to which the choice probabilities of each alternative will change in response to the changes in the value of an attribute. In general, elasticity is defined as the percentage change in the response variable with respect to one percent change in an explanatory variable. Elasticities are different from marginal effects in that elasticities are normalized by variable units. An elasticity of travel demand, defined for individual, n, and latent attribute, X^*_{nk}, for attribute coefficient, β_k, is:

$$E^{P_n(i)}_{X^*_{nk}} = \frac{\partial P_n(i)}{P_n(i)} / \frac{\partial X^*_{nk}}{X^*_{nk}} = [1 - P_n(i)]X^*_{nk}\beta_k \tag{9}$$

MODEL SPECIFICATION AND CALIBRATION RESULTS

The integrated model has two parts: latent variable model and discrete choice model. The initial analysis is done separately for the two parts which resulted with a good set of explanatory variables for each. Afterwards the integrated model is calibrated in the light of the initial analysis.

Latent Variable Model

In the latent variable model, structural equations and measurement equations for the attitudes are built with the framework shown in FIGURE 2. Taking comfort preference as an example, it can be decomposed into two parts. The first part (left side in FIGURE 2) is similar to regression analysis, which includes an endogenous variable (X^*_{comf}), its exogenous explanatory variable Xs (socio-economics) and an error item w. The other part is like factor analysis, which consists of the latent variable (X^*_{comf}), its indicator variables Is (Quiet, Rest and Nocrowd) and the measurement error v. The error terms, w and v, are assumed to be normally distributed with mean 0 and standard deviation θ_w and θ_v.

The details for the specification can be expressed mathematically as:

$$X^*_{comf} = \sum_{e=1}^{9} \lambda_e X_e + w \tag{10}$$

$$I_k = \alpha_k X^*_{comf} + v_k \tag{11}$$

where X_e is the set of explanatory variables, I_k is the k^{th} psychometric indicator, λ_e is the corresponding regression coefficient, and α_k is the factor loading.

The "regression" and "factor" analysis results for low income commuters are shown in TABLE 3 and TABLE 4 respectively. Only statistical significant coefficients at the individual 5% level are retained. It can be seen that household size does not correlate to latent variables. However, gender, license possession and age significantly relate to these underlying factors. TABLE 4 shows that all factor loadings in the measurement equations are positive and significant, which means all indicators contribute to the contruction of latent preferences. Factor loadings are the correlation coefficients between indicators and latent factors. Analogous to Pearson's r, squared factor loading is the percent of variance in that indicator variable explained by the latent variable. It reveals the explanatory importance of latent variables with respect to indicators. The higher the absolute value is, the more important the indicator is.

In the following two paragraphs, the relationship between the explanatory variables and the preferences (TABLE 3) will be discussed. First, we look at the preference for comfort (X^*_{comf}). There are two notable observations: gender and license possession. Males have weaker preferences for comfort. License possession is positively correlated to preferences for comfort. As for preference for convenience (X^*_{conv}), mopeds ownership, license possession and IC card possession have positive relationships while gender has negative relationships. In terms of reliability (X^*_{rel}), male is found to have weaker preferences. The positive coefficients of license, IC and age indicate their active influences on reliability preferences. As for preference for flexibility (X^*_{flex}), bicycle ownership is positively correlated. The positive value of age variable represents older commuters care more about flexibility.

Safety preference variable and environment preference variable are constructed based on the behavioral indicators. In terms of safety preference (X^*_{safe}), the negative coefficient of moped means that travelers who own mopeds might take unsafe actions, such as violating the speed limit, not using safety belt or running the red light. However, car ownership plays a positive role on safety. It can be explained by the fact that moped travelers who violate traffic rules receive no penalty while car drivers get punishment in China. Men are found to have weaker preferences for safety than women. Individuals with IC cards or older age show higher safety preferences. A little surprising is that preferences for safety weakens with education level. However, this does not imply that safety is not important. Considering indicators used to construct safety preference variable, this merely shows that commuters with higher education level adhere to speed limit, fasten safety belt and obey traffic signal control to a lesser extent than commuters with lower education level. As for environmental preferences (X^*_{env}), bicycle ownership is positively correlated. Nevertheless, driving license possession is inversely related to environmental friendliness. It is found that older commuters are more environmentally inclined.

From the factor loading results in TABLE 4, it is found that "Nocrowd" has the highest importance with respect to comfort and "Rest" has the lowest importance level. This result indicates that low-income commuters care about "Being able to move around while traveling" the most while "Being able to rest or read while traveling" does not matter. "Fast" has the strongest relationship with convenience while "Nohurry" has the lowest loading. The factor loadings display the order of importance of reliability to be "Knowtime", "Ontime" and "Controltime". "Childschool" and "Childplay" have the strongest relationship with flexibility. Factor loadings indicate the most and least important indicators are "Safebelt" and "Redlight" with safety preference. "Public transit is beneficial to protecting the environment (Protect)" is the most important indicator to construct the underlying factor of environmental preference.

Discrete Choice Model

The random utility maximization model is based on the assumption that a decision-maker n, faced with a finite set of mutually exclusive alternatives, chooses the alternative i which provides the greatest utility $U_n(i)$. In our case, choice alternatives are walk, bicycle, moped, public transit (PT) and car. The systematic component of the utility function is postulated as a linear function of individual's observable specific attributes and latent attitudes. Individual specific attributes in the study refer to socio-economics, such as household size and gender. The choice model is built assuming extreme value distribution of the error terms associated with the utility functions of the alternatives. Therefore, a multinomial logit model is obtained with the following probabilities for individual n choosing alternative i:

$$P_n(i) = \frac{\exp(\beta_X X_{ni} + \beta_{X^*} X^*_{ni})}{\sum_{i=1}^{5} \exp(\beta_X X_{ni} + \beta_{X^*} X^*_{ni})} \quad i = walk, bicycle, moped, PT, car \tag{12}$$

where X_{ni} represents the individual socio-economic attributes and X^*_{ni} refers to the latent variables; β_X and β_{X^*} are coefficients to be calibrated.

Integrated Discrete Choice and Latent Variable Model

After having defined all the relations, likelihood function is obtained by replacing equation (12) and structural and measurement equations for latent variables in equation (5). In the model, comfort, convenience, reliability, flexibility, safety and environmental preferences are continuous variables while others are dummy variables. We summarize these results in TABLE 5 with walk as the reference category and only variables at the individual 5% level are included.

Individual's socio-economics have important influneces on mode choices. For example, household size and moped ownership have a statistically significant and positive relationship. This leads credence to the hypothesis that larger households are more likely to ride moped (0.566). Evidently, when certain mode ownership increases, its corresponding choice probability increases. Male commuters are found to have more propensities to use private modes, such as bicycle, moped and car. License possession has a positive correlation with car travel (1.337) but a negative correlation with bicycle usage (-1.007). On the other hand, when commuters possess transit IC card, they are more apt to increase public transit usage (1.027). Age is shown to be positively associated with car ridership. Education level positively relates to motorized vehicles usage, such as car and public transit.

In the study, we focus on the effects of latent variables on mode choice. We find that flexibility does not significantly influence mode choice. Therefore, flexibility enhancement improvement measures including more bus routes or demand response services seem to be unhelpful in fulfilling low-income commuters' preferences. However, preferences for comfort increase the likelihood of choosing walking. This is consistent with the fact that riding bicycles or mopeds on uneven terrain in Fushun City is exhausting. It is found that preferences for convenience promote moped usage (0.312). The reliability variable positively correlates the probability of traveling by public transit. It probably results from the fact that public transit operates on exclusive bus lanes and possesses high reliability. In Fushun, moped weaves with pedestrians or bicycles, which brings about the potential collision risks. Therefore, travelers who have high preferences for safety do not tend to use moped (-0.210). Consistent with our expectations, it is found that environmental preferences positively relate to the likelihood of choosing bicycle (0.289).

The correlations between these latent variables are considered. It is found that three variables are correlated at 10% significance level. They are the comfort preference, the convenience preference and the reliability preference. The comfort preference is correlated with convenience preference with the coefficient of 0.57. The reliability preference is correlated with comfort preference with the coefficient of 0.61.

We further explore the responsiveness of modal choice to changes in the preference variables. The elasticity and marginal effect for each preference are calculated, which is presented in TABLE 6. Preferences for comfort and reliability have influential sensitivity on all low-income commuters' choices, which is consistent with the calibration results of the integrated model in TABLE 5. Travelers with higher comfort preferences are more likely to walk or drive cars. A hypothetical 1 point increase in comfort scores would promote choice probability of walk by 2.62 percent. Meanwhile, 1 percent increase in comfort scores would increase the probability of car use by 0.51 percent. Convenience preferences exert positive marginal effects on moped ride with 0.90 percent rise of choice probability in case of its average scores increasing by 1 point. The elasticity and marginal effect of the reliability preference positively correlates with PT trips. Their choice probability of public transit would increase by 0.61 percent from a 1 percent increase in reliability scores. Moped usage will decrease when commuters appeal for a safe travel experience, which is indicated by the negative results of elasticity and marginal effect (-0.87 and -0.69). As expected, a hypothetical 1 percent increase in average score of environmental awareness brings about 0.22% growth in bicycle choice probability.

POLICY IMPLICATIONS

From the sensitivity analysis of travel preferences, comfort preference is shown to be more closely related to walking and car use. Similar relationships can be found between convenience preference and moped, reliability preference and PT, and environmental preference and bicycle. However, when travelers ask for safety preference, no mode is applicable. These results allow us to formulate policy recommendations to satisfy low-income commuters' travel demands. Considering the affordability of low-income travelers, measures to facilitate car use are not practicable despite the fact that cars are able to meet comfort preferences. Furthermore, mopeds, a kind of private travel mode, have been suggested to be restricted in Chinese big cities for safety issues and intensive urban development. Therefore, we will focus on walk for convenience preference, public transit for reliability preference and bicycle for environmental preference.

Low-income commuters with high convenience preferences desire a high-quality walking environment. Therefore, different types of walking corridors, such as flyover, ground and underground, should be built to make walking facilities integral and continuous. As they are more likely to switch from walking to public transit in daily trips, pedestrian system needs to link with public transit hubs seamlessly. Other measures, such as separation of pedestrians and vehicles in road design, and beautiful walking landscape, are also encouraged in areas of high low-income resident concentration.

The PT mode has the advantages in terms of high reliability. A reliable travel for the bus mode emerges as the most important element in a program aimed at catering to reliability preferences. Consequently, measures such as exclusive bus lanes, faster and more accurate connections and traffic signal priority can lead to an increasing use of PT. On the other hand, subsidized bus fares towards low-income travelers are helpful due to the fact that low-income travelers' affordability is comparatively low. The factor loadings of latent variable model in TABLE 4 suggests that being informed of the arrival time can enhance reliability perception. Thus, reliable services, regarding real-time information provisions such as electronic stop board or Internet-based or cellphone-based service, are of great significance. Due to the reason that most low-income commuters' daily trips are less involved with non-commuting activities (shown in TABLE 2), we prefer to arrange low-frequency bus departures but make them punctual during non-peak hours.

In addition, emphasis has to be put on "pro-bike" measures intended to satisfy commuters who are concerned with enviromental friendliness. First, we appeal for a network of bicycle lanes such that no commuter is exposed to any risks of riding on a road with no shoulders. This strategy can generally be accomplished by enlarging the roadway shoulder and ensuring that a safe and efficient network of bicycle routes in maintained. The second policy option is to pro-actively encourage increased bicycle usage by providing an infrastructure that increases the convenience of bicycle transportation. Public bicycle systems located at low-income community are in priority to facilitate travel and solve the "last-mile" problem of public transit. Bicycle parking facilities at places of low income commuters' employment are also necessary.

CONCLUSIONS

This study presents a latent variable model where we integrate psychometric indicators into the framework using travel data collected in Fushun, China. The integrated model enables us to capture unobserved heterogeneity of choice process with a deep understanding of travelers' internal preferences. In this paper, we have included the latent variables of comfort, convenience, reliability, flexibility, safety and environmental preferences which address the underlying decision making process of low-income commuters when the decision-making process cannot be directly observed. The model gives promising results about the importance of these attitudinal factors in mode choice and motivates us to formulate policy recommendations.

The sensitivity analysis of latent attitudes helps in designing more appropriate strategies to satisfy travel preferences of low-income commuters. For our case, it is clear that different actions are to be taken for serving different preferences. Individuals with high comfort preferences care more about walking environment and they need solutions to enhance their walking experience. However, travelers preferring reliability are more likely to travel by public transit, and measures to inform commuters of real-time bus operation information are proposed. Commuters who emphasize environmental preference are more apt to cycle, and therefore "pro-bike" strategies are recommended.

However, there are some limitations in the present study. For example, in the presented specification, attitudinal indicators are treated as continous variables. However, the scaling for the level of agreement is not necessarily uniform between levels. Therefore, the discrete specification of indicators is an important further step. Furthermore, inclusion of more psychometric indicators is believed to help in the identificaion of latent variables and to increase model forecasting power.

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TABLE 1 Questions on Constructing Latent Variables

Latent variable	Description	Indicator
Comfort preference (Comf)	Traveling in a quiet and calm environment	Quiet
	Being able to rest or read while traveling	Rest
	Being able to move around while traveling	Nocrowd
Convenience preference (Conv)	Not having to transfer while traveling	Notransfer
	Not having to wait for the travel mode while traveling	Nowait
	Being able to arrive at the destination quickly	Fast
	Not being in a hurry while traveling	Nohurry
Reliability preference (Rel)	Having little variation in the daily travel time	Controltime
	Being able to know arrival time of the travel mode	Knowtime
	Being able to arrive at the destination on time	Ontime
Flexibility preference (Flex)	Being able to shop or run errands while traveling	Shopping
	Being able to leave/pick up children at school while traveling	Childschool
	Being able to drive children a ride to play while traveling	Childplay
	Being able to have exercises while traveling	Exercise
	More routes or roads are available while traveling	Moreroute
Safety preference (Safe)	Adhere to the speed limit when driving	Speed
	Fasten safety belt in cars	Safebelt
	Never run the red light	Redlight
Environmental preference (Env)	Private car is one major cause of air pollution in urban areas	Air
	I prefer changing travel mode if it is helpful to the environment	Change
	Public transit is beneficial to protecting the environment	Protect

TABLE 2 Socio-economics and Activity Characteristics

Variable	Coding	Description	Low-income	Non-low-income
Household size	Size	3 people or less	82.4%	93.3%
		More than 3 people	17.6%	6.7%
Bicycle ownership per household	Bicycle	Without bicycles	56.1%	56.1%
		One bicycle	34.9%	34.0%
		Two bicycles or more	9.0%	9.9%
		Average (bicycles per household)	0.56	0.57
Moped ownership per household	Moped	Without mopeds	89.6%	91.8%
		One moped	9.4%	7.2%
		Two mopeds or more	1.0%	1.0%
		Average (mopeds per household)	0.12	0.10
Car ownership per household	Car	Without cars	76.3%	52.6%
		One car	22.2%	41.7%
		Two cars or more	1.5%	5.7%
		Average (cars per household)	0.25	0.54
Gender	Gender	Female	51.4%	51.3%
		Male	48.6%	48.7%
License possession	Lic	No	78.0%	64.2%
		Yes	22.0%	35.8%
Transit IC card possession	IC	No	52.8%	58.4%
		Yes	47.2%	41.6%
Age	Age	< 25	56.0%	43.2%
		25~49 years old	42.6%	55.3%
		≥ 50	1.4%	1.5%
Education level	Edu	Under middle school	41.4%	38.6%
		High school	43.8%	29.7%
		College or above	14.8%	31.7%
The number of trip chain	Chain	1 chain	93.5%	90.5%
		2 chains	5.9%	8.5%
		3+ chains	0.6%	1.0%
		Average (chains per day)	1.07	1.13
Trip duration	Tduaration	Average	1.08 h	1.11 h
Subsistence activity duration	Subduration	Average	9.10 h	8.68 h
Frequency of mode choice	Choice	Walk (trips per day)	0.92	0.88
		Bicycle (trips per day)	0.09	0.07
		Moped (trips per day)	0.09	0.06
		Public transit (trips per day)	0.91	0.72
		Car (trips per day)	0.38	0.88

TABLE 3 Regression Coefficients of Latent Variable Model

Variable	X^*_{comf}	X^*_{conv}	X^*_{rel}	X^*_{flex}	X^*_{safe}	X^*_{env}
Household size	—	—	—	—	—	—
Bicycle ownership	—	—	—	0.05(2.12)	—	0.09(2.57)
Moped ownership	—	0.17(3.90)	—	—	-0.08(-2.27)	—
Car ownership	—	—	—	—	0.22(4.29)	—
gender（male=1）	-0.12(-3.75)	-0.21(-4.66)	-0.13(-3.71)	—	-0.20(-5.44)	—
License possession（yes=1）	0.12(3.81)	0.30(6.56)	0.15(2.75)	—	—	-0.26(-4.95)
IC card possession（yes=1）	—	0.11(2.63)	0.10(3.08)	—	0.13(3.33)	—
Age	—	—	0.25(2.34)	0.22(5.54)	0.78(9.01)	0.70(6.59)
Education level	—	—	—	—	-0.37(-6.92)	—

NOTE: — = coefficients insignificant at individual 5% level. t-statistics are shown in parentheses.

TABLE 4 Factor Loadings of Latent Variable Model

Indicator	X^*_{comf}	X^*_{conv}	X^*_{rel}	X^*_{flex}	X^*_{safe}	X^*_{env}
Quiet	1					
Rest	0.59(23.22)					
Nocrowd	1.68(23.90)					
Notransfer		1				
Nowait		0.99(41.45)				
Fast		1.14(44.85)				
Nohurry		0.80(35.96)				
Controltime			1			
Knowtime			1.32(34.71)			
Ontime			1.20(33.56)			
Shopping				1		
Childschool				1.35(32.60)		
Childplay				1.35(36.27)		
Exercise				1.11(31.94)		
Moreroute				0.92(16.93)		
Speed					1	
Safebelt					1.02(38.68)	
Redlight					0.94(30.13)	
Air						1
Change						1.09(25.20)
Protect						1.12(24.96)

NOTE: t-statistics are shown in parentheses. Blank cells indicate no value for indicator in column.

TABLE 5 Calibration Results of the Integrated Model

	Bicycle		Moped		PT		Car	
Variable	Coeff.	Sig.	Coeff.	Sig.	Coeff.	Sig.	Coeff.	Sig.
Size>3 people	—	—	0.566	0.004	—	—	—	—
1 bicycle	1.782	0.000	—	—	—	—	-0.255	0.024
2+ bicycles	2.366	0.000	1.196	0.000	—	—	0.378	0.031
1 moped	—	—	2.030	0.000	—	—	—	—
2+ mopeds	—	—	2.106	0.000	—	—	—	—
1 car	—	—	-0.924	0.001	-0.245	0.017	1.505	0.000
2+ cars	1.248	0.039	—	—	—	—	2.340	0.000
Gen=male	0.764	0.000	0.401	0.028	—	—	0.385	0.000
Lic=yes	-1.007	0.000	—	—	—	—	1.337	0.000
IC=yes	—	—	—	—	1.027	0.000	—	—
Age=25~49	—	—	—	—	—	—	2.210	0.003
Age≥50	—	—	—	—	—	—	2.281	0.007
Edu=high school	—	—	—	—	0.700	0.000	0.384	0.001
Edu= college or above	—	—	—	—	0.581	0.000	—	—
X^*_{comf}	-0.223	0.046	-0.245	0.022	-0.152	0.002	—	—
X^*_{conv}	—	—	0.312	0.013	—	—	—	—
X^*_{rel}	-0.329	0.008	-0.335	0.004	0.158	0.027	—	—
X^*_{flex}	—	—	—	—	—	—	—	—
X^*_{safe}	—	—	-0.210	0.025	—	—	—	—
X^*_{env}	0.289	0.006	—	—	—	—	—	—
Log likelihood at convergence	-4635.58							
McFadden's ρ^2	0.254							
Adjusted McFadden's ρ^2	0.240							

NOTE: — = coefficients insignificant at individual 5% level.

TABLE 6 Sensitivity Analysis Results of Travel Preference Variables

Latent variable	Sensitivity	Walk	Bicycle	Moped	PT	Car
Comfort preference	Elasticity	—	-0.57	-0.60	-0.49	0.51
	Marginal effect	2.62	—	—	-2.01	—
Convenience preference	Elasticity	—	—	—	—	—
	Marginal effect	—	—	0.90	—	—
Reliability preference	Elasticity	-0.84	-1.55	-1.56	0.61	-1.14
	Marginal effect	—	-0.99	-1.06	3.22	-1.58
Safety preference	Elasticity	—	—	-0.87	—	—
	Marginal effect	—	—	-0.69	—	—
Environmental preference	Elasticity	—	0.22	—	—	—
	Marginal effect	—	0.87	—	—	—

NOTE: — = coefficients insignificant at individual 5% level.

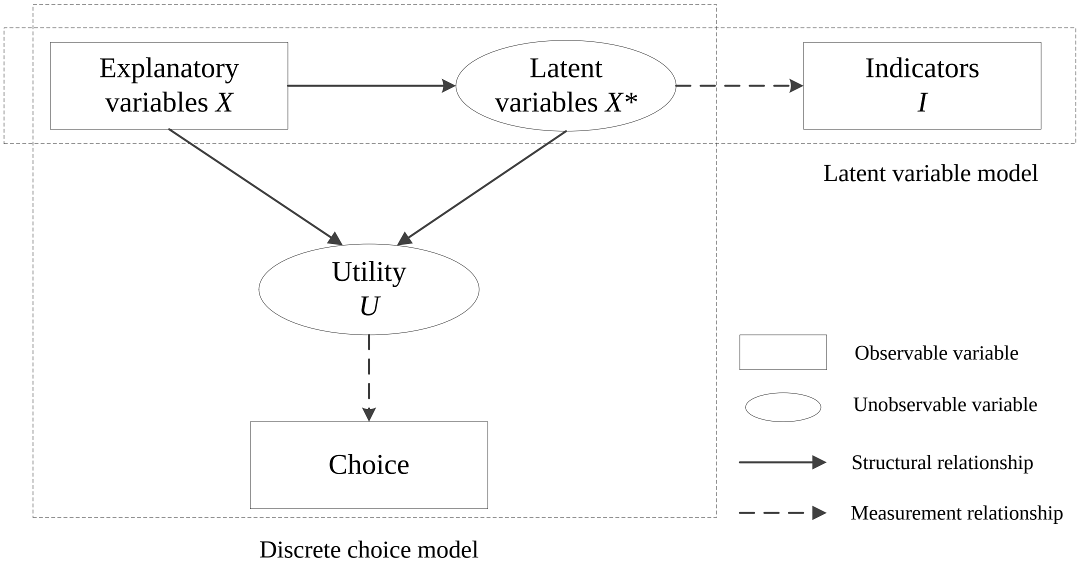

FIGURE 1 Integrated choice and latent variable model.

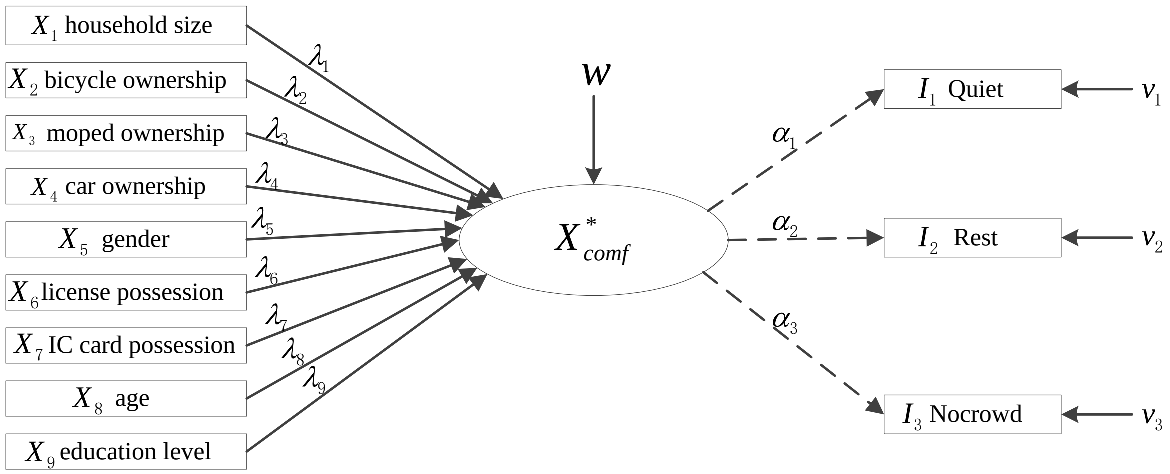

FIGURE 2 Latent variable model framework of comfort preference.