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Psychological Traits to Eco-Friendly Transportation Systems: Latent Class Approach

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Abstract

Differences in psychometric traits can be revealed in the actions of an individual's everyday life, including their transportation mode choice. There are many inexplicable behaviors in mode choice when only individual socio-economic variables and alternative attributes are included. The explanatory power of models can be enhanced if individual heterogeneity is addressed by the incorporation of psychometric traits. We used latent class choice model to this behavior in which latent classes were psychometric traits, and the choice model was mode choice across classes. We simultaneously estimated latent classes and how latent traits impacted mode choice to improve performance. Empirical results indicated that there are people who persist on their own mode and have preferences for environment and specific modes. Characteristics of latent classes were consistent with mode choice behavior.

Keywords: *latent classl, mode choice, psychometric traits, heterogeneity*

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1. Introduction

Eco-friendly transportation systems play an important role to construct a sustainable city. Transit systems, when effectively utilized, not only produce fewer emissions, but they also provide a high level of efficient mobility. Major cities around the world have aggressively adopted transit-oriented policies to provide efficient and sustainable transportation systems to users. Seoul, Korea looks for the similar goals. City of Seoul plans to construct a new 30 km water transit system on the Han River, located in the middle of the city. Although the eco-friendly transportation system is very attractive to policymakers, they are still anxious about its efficacy. Since water transit has never been used for commuters in Seoul, the high level of user uncertainty exists and understanding of user' behavior is very crucial. This study was initiated to assess the potential changes in travel mode choice using a behavior-based realistic model and to incorporate the personal traits in mode choice models .

Modeling mode choice behavior has been studied for several decades in transportation planning practices and research communities to mitigate the level of uncertainty emerging from various factors in combinations. Conventional mode choice models maximize choice utility based on individual socio-economic characteristics and mode attributes (Domarchi et al., 2008; Hartgen, 1974; Johansson et al., 2006). Classical discrete choice model suggest individual choice process as inner process in black box, which is the relationship of observed inputs such as individual attributes and alternative characteristics and observed choice results. Inner process works in black box include cognitive process by representing choice model. (Ben-Akiva et al., 1999). However, it is difficult to explain the observed choice only through socio-economic characteristics and mode attributes. The power of explanation may be enhanced by incorporating psychometric traits and preferences as explanatory variables in a choice model. Generally, choice behavior can be characterized by a decision process which is informed by perceptions and beliefs based on available information and influenced by affect, attitudes, motives, and preferences (Ben-Akiva et al., 1999).

Recently, many researchers have incorporated latent variables into the conventional mode choice model (Ben-Akiva et al., 1999; Johansson et al., 2006; McFadden, 1986; Morikawa, T., 1989; Ortuzar and Willumsen, 2001). Latent variables represent various aspects, such as unobservable variables, psychometric traits and individual heterogeneity. Some transportation experts have tried to establish a mode choice model using latent variables reflecting a traveler's psychometric factors. Psychometric factors have a significant effect on mode choice models (Koppelman and Hauser, 1979; McFadden, 1986; Ben-Akiva, 1992; Morikawa et al., 1996). For example, Christian Domarchi (2008) studied the effect of attitudes, habit, and affective appraisal on mode choice. Results showed that choice can be influenced by factors related to individual attitudes and affective appraisal. Johansson et al. (2006) explored the effects of the latent variables of attitude and personality traits on mode choice behavior. They surveyed attitudinal and behavioral questions to capture the travelers' psychometric latent traits. Using the survey results as indicator variables which represent psychometric latent traits, the MIMIC (multiple indicators, multiple causes) model was used to define five latent variables: environmental preferences, safety, comfort, convenience, and flexibility.

Research for individual heterogeneity have concerned continuously with latent variables study together. Methods which classified people with similar characteristics and attitudes as a class (cluster) showed greater explanatory power. To capture individual heterogeneity, many researchers segmented classes using socio-economic characteristics and attitudes and analyzed the effect on travel behavior and mode choice (Hilderbrand ED., 2003; Manaugh et al., 2010). Sohn and Yun (2009) classified car-dependent people as one group based on certain behavioral survey questions. They studied the psychometric latent traits, such as affective and symbolic motives of mode choice of car-dependent commuters. The latent traits were incorporated into the mode choice model. To identify the latent traits, they adopted indicator variables from nineteen behavioral survey questions which were similar to the survey of Johansson et al. The rest of the estimated model enhanced the explanatory power, except for the car-dependent group (class).

Among the various approaches for including latent variables and class, a LCA (latent class analysis) model is a potential and powerful method. Research about LCA models has proceeded in various areas. This study used LCA models to analyze the effect of psychometric factors on mode choice behavior. LCA models segment classes according to specific preferences and types, which have advantages for the analysis of specific groups and preferences. To effectively target people, it is vital to understand the nature of heterogeneity in preference. The LCA model has been applied in a wide variety of fields, ranging from economics, medical sciences, agriculture, transportation, and marketing (Frenzel B., 2007; Bhatnagar and Ghose, 2004; Beckman and Goulias, 2008; Kemperman and

Timmermans, 2006; Depaire et al., 2008; Boxall and Adamowicz, 2002; Morey et al., 2006; Green and Hensher, 2003; Quagrainie and Engle, 2006; Scarpa and Thiene, 2005; Teichert et al., 2008; Boxall B., 2002).

This study used a LCC (latent class choice) model among the LCA models. Walker and Lee (2007) used a LCC model to represent a living preference, for which the latent classes are lifestyles and the choice model is applied for residential location. They simultaneously estimated lifestyle groups and how lifestyle impacts location decisions to prevent measurement error in sequential methods. However, they did not use preference and attitude data, but rather only individual socio-economic variables, to reflect lifestyles.

Mode choice models developed in this study considered psychometric factors, preference, socio-economic characteristics, and mode attributes together. The incorporation of a LCC model enabled simultaneous mode choice estimation across latent classes using psychometric factors. By segmenting latent classes through psychometric indicators, psychometric factors were reflected in the characteristics of latent classes and could be analyzed as latent variables with socio-economic characteristics and alternative attributes. The abovementioned literature referred to an approach that incorporates psychometric factors which affect mode choice (Domarchi et al., 2008). This method investigates the validity of the choice model that was enhanced by including latent factors and supports to individual heterogeneity. The LCC model used in this research is the first application for mode choice. It also estimated simultaneously the latent classes and resulting mode choice behavior rather than in a two-stage process. To address effects of latent class, we analyzed the model with latent segmentation and the model without latent segmentation.

This paper is organized as follows. The next section reviews studies related to this research work. Section 3 discusses socio-economic characteristics, psychometric indicator data, and stated preference data. Section 4 presents the model and the estimation results. The paper ends with conclusions.

Here introduce the paper, and put a nomenclature if necessary, in a box with the same font size as the rest of the paper. The paragraphs continue from here and are only separated by headings, subheadings, images and formulae. The section headings are arranged by numbers, bold and 10 pt. Here follows further instructions for authors.

2. Methodology

Latent class choice models (LCC) used in this research are appropriate for our hypotheses, which are that different choice behaviors exist across classes and that these choice behaviors are reflected latent traits. These latent traits are not directly identifiable and observable from the data, but to investigate choice behaviors influenced by psychometric traits, we considered mode choice behaviors across latent classes.

Latent class choice models account for heterogeneity in the data by allowing for different latent classes to express different preferences and attitudes in making their choices. Each latent class corresponds to a population segment that differs with respect to the importance given to the attributes of the alternatives when expressing that segment's preferences (Vermunt & Magison, 2005). Latent Class Analysis (LCA) is similar to the clustering method in separating clusters (classes), but LCA based on modeling can be used as a probabilistic analysis tool and includes various scale-type data. LCA is a modeling methodology that estimates probabilistic classes (Magidson & Vermunt, 2002).

LCC used in this study is a kind of LCA and a choice model that simultaneously estimated class segment and choice across classes. In the LCC model, the probability density associated with the response of case i has the form shown in Eq. (1):

$$P(y_i|z_i) = \sum_{x=1}^{K} P(x|z_i^{cov}) \prod_{t=1}^{T_i} P\left(y_{it}\middle|x, z_{it}^{att}, z_{it}^{pred}\right) \tag{1}$$

$P(y_i|z_i)$, where the probability of selecting a particular alternative *i* is equal to the sum over all latent classes *t* and consists of two components. The term $\sum_{x=1}^{K} P(x|z_i^{cov})$ denotes the probability belonging to the specific latent class, given conditional covariates. The term $\prod_{t=1}^{T_i} P\left(y_{it}\middle|x, z_{it}^{att}, z_{it}^{pred}\right)$ denotes the conditional alternative *i* probability given latent class and each attribute.

Using the above equation, the probability of selecting a particular mode *i,* given conditional various characteristics and alternatives, is equal to the sum over all latent classes *x* of psychometric traits multiplied by the probability of belonging to that class. As we can see, from equation (1), LCC is comprised of two components, a class-membership model and a class-specific choice model (Vermunt & Magison, 2005). The front part of the equation is the class-membership model, and the back part is the class-specific choice model.

The class-specific choice model represents the choice behavior of each class and varies across latent classes. A conditional logit model is the probability that case *i* selects alternative *m* at replication *t*, given attribute values and predictor values.

$$P\left(y = m \middle| z_{it}^{att}, z_{it}^{pred}\right) = \frac{\exp\left(\eta_{m|z_{it}}\right)}{\sum_{m=1}^{M} \exp\left(\eta_{m|z_{it}}\right)} \tag{2}$$

$\eta_{m|z_{it}}$ is the systematic component in this utility of alternative *m*.

$$\eta_{m|z_{it}} = \beta_m^{con} + \sum_{p=1}^{P} \beta_p^{att} z_{mp}^{att} + \sum_{q=1}^{Q} \beta_{mq}^{pred} z_q^{pred} \tag{3}$$

To indicate that choice probability depends on class membership *x*, the logistic model is in this form:

$$P\left(y_{it} = m \middle| x, z_{it}^{att}, z_{it}^{pred}\right) = \frac{\exp\left(\eta_{m|x,z}\right)}{\sum_{m=1}^{M} \exp\left(\eta_{m|x,z_{it}}\right)} \tag{4}$$

Also, $\eta_{m|x,z_{it}}$ is the systematic component in this utility of alternative *m* at replication *t*, given that case *i* belongs to latent class *x*.

$$\eta_{m|x,z} = \beta_m^{con} + \sum_{p=1}^{P} \beta_p^{att} z_{mp}^{att} + \sum_{q=1}^{Q} \beta_{mq}^{pred} z_q^{pred} \tag{5}$$

The modeling framework of this research is shown in Figure 1.

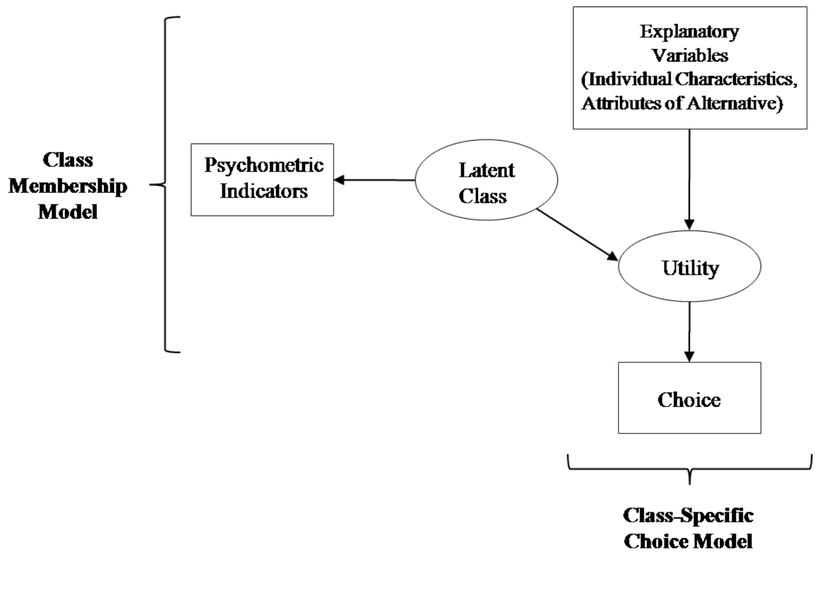


Figure 1: Latent Class Choice model framework in this research

The LCC model framework simultaneously estimates parameters of the class-membership model and the class-specific choice model. Simultaneous estimation of the model structure is an improvement over sequential methods because it produces consistent and efficient estimates of the parameters (Ben-Akiva et al., 1999). Because of the simultaneous estimation of the parameters, we can colligate each trait of latent class and mode choice together. The class-membership model provides information as to who is likely to be in each class, whereas the class-specific choice model gives details of how each latent class behaves.

There are various advantages in a LCC model. First, it can consider unobservable segmentation, such as psychometric traits and latent attitudes. Through analysis of latent class, we can take individual heterogeneity into account. Second, the LCC model conjointly estimates parameters of the class-membership model, as well as the class-specific behavior. It can explain a connected meaning between latent class traits and the mode choice model. Finally, we can know that the estimated size of each (Walker & Li, 2007).

3. Data Used

Data were obtained from a survey to understand citizens' attitudes toward a new water transit system. Seoul, Korea plans to construct a new 30 km water transit system on the Han River located in the middle of the city. To investigate travel pattern changes because of the new water transit system, a survey was conducted for residents along the Han River in Seoul in June 2009. One thousand respondents, who had experienced trips along the Han-river recently, were selected from the sample of "Household Travel Diary Survey" in 2006, which is carried out by Seoul development institute (SDI). We expect that they will be possible users of a new water transit system on the Han-river if it is operated. The questionnaire form was divided into three parts: individual and household characteristics, latent behavior questions, and stated preferences. The first part is summarized in Table 1.

Table 1: Household and individual characteristics

Characteristics		Type	Ratio (%)	Characteristics		Type	Ratio (%)
Household Attributes	Household size	≥ 3 < 3	60.1 39.9	Individual Attributes	Gender	Male Female	36.3 63.7
	Dwelling type	Apt. Else	57.2 42.8		Occupation	Yes No	72.5 27.5
	Number of cars owned	≥ 1 = 0	80.6 19.4		Student	Yes No	7.9 92.1
	Number of pre-school children	≥ 1 = 0	11.9 88.1		Education	College Else	61.2 38.8
	Number of children	≥ 1 = 0	69.5 30.5		Marriage	Yes No	73.3 26.7
	Household income (\million/year)	≤ 20 20~40 40~60 ≥ 60	13.4 30.6 41.1 14.9		Age (year)	≤20 20~40 40~60 ≥60	3.1 44.6 47.3 5.0

3.1. Psychometric Indicators Survey

The second part of survey was designed to identify psychometric latent traits of respondents. The questions addressed attitudinal and behavioral traits for mode choice, such as environmental preferences and preferences for a new water transit system (Table 7). These were used for analysis of latent class. We referred to research survey questions of Ellaway et al. 2003, Steg, 2005 and Sohn & Yun, 2009 and composed 15 items about water transit systems. The psychometric indicators part of the survey was important for determining the preference and traits of a person and his/her choice specific mode. Five-point Likert scales (1 to 5) were used for every question to rate using “disagree strongly,” “disagree somewhat,” “neutral,” “agree somewhat,” and “agree strongly.” Respondents rated aspects related to individual preference and attitude.

3.2. Mode Choice Behavior Survey

The last part of the questionnaire was a Stated Preference (SP) survey designed for mode preference. The SP choice set included private car (auto), transit and a new water transit system on the Han-River. The SP survey was designed using the principles of fully factorial design. Three attributes, in-vehicle and out-of-vehicle travel times and total cost, along with each of the three levels for each of the three modes, were selected. Thus, 81 possible combinations were constructed, and five combinations were administered as one set of SP questions for one respondent in a random sampling. Therefore, based on responses from 1,000 individuals, 5,000 samples were in the SP survey data. Results of the SP survey indicated that 10.9% of the sample population would choose to travel via personal auto, 45.6% of survey participants would use current public transit, and 43.5% of the sample population would choose water transit. Auto cost used in the analysis included gas and parking costs. Transit and water transit costs were computed by fare.

Various individual-specific variables and alternative-specific variables were used for the mode choice models. Variables to compose the utility function and their type are shown in Table 2.

Table 2: Variables for mode choice models

Variables		Type
Individual and household variables	Age	Integer (Years)
	Gender	Binary (Male: 1, Female: 0)
	Occupation	Binary (Yes: 1, No: 0)
	Student	Binary (Yes: 1, No: 0)
	Education	Binary (College: 1, Else: 0)
	Marriage	Binary (Married: 1, Unmarried: 0)
	Number of Children	Binary (Over 1 person: 1, Else: 0)
	Household Size	Binary (under 3 persons: 1, Else: 0)
	Number of Pre-school Children	Binary (Over 1 person: 1, Else: 0)
	Number of cars owned	Binary (Over 1 car: 1, Else: 0)
	Dwelling Type	Binary (Apt.: 1, Else: 0)
	Household Income (Annual)	Float (₩10,000,000 ≈ $1,000)
Mode variables	In-Vehicle Time	Float (min)
	Out-Vehicle Time	Float (min)
	Auto Cost	Float (₩100 ≈ $0.1)
	Transit Fare	Float (₩100 ≈ $0.1)
	Water Transit Fare	Float (₩100 ≈ $0.1)

4. Empirical Application and Results

The LCC models were comprised of class-membership models and class-specific choice models in which parameters were simultaneously estimated. Detailed specifications were required to develop the class-membership and class-specific choice models. The class-membership model constructed latent class using psychometric indicators in the survey questions. We used an exploratory approach to develop class-membership models in which each class had similar preferences and attitudes. Class segmentation can represent individual heterogeneity. The class-specific choice model incorporated individual-specific variables and alternative-specific variables in the mode choice process across classes. To examine the effect of latent class, we compared results of the model with latent class to the model without latent class. It is interesting to note that in this empirical case, there were differences between the model with latent segmentation and the model without latent segmentation. Latent GOLD Choice 4.5 by Statistical Innovations Inc was used for model estimation.

4.1. Number of Latent Classes

The number of classes plays a crucial role in LCC models. The number of class is not predetermined, but is determined by several statistics criteria. Models with 1~4 classes are shown in Table 3. Statistics, such as BIC, AIC, and $\bar{\rho}^2$ in Table 3 provide important information in the selection of the optimal number of latent classes. Such statistics are mostly based on log-likelihood, which is a general principle of weighing the fit of the model. The BIC (Bayesian Information Criterion) is often used in LCC models and is equal to $(2\times \mathrm{LL}(\beta) - \ln(\mathrm{N})\times \mathrm{K})$ where N is the number of respondents, and K is the number of parameters. The AIC is also often used in LCC models and its formula is equal to $(2\times(\mathrm{LL}(\beta) - \mathrm{K})$. The $\bar{\rho}^2$ is a function of the AIC and is equal to $1 - (\mathrm{LL}(\beta) - \mathrm{K})/\mathrm{LL}(0)$ where LL(0) is the log-likelihood of a naive model with no parameters. BIC and AIC are widely used to determine the number of latent classes in LCC models (Vermunt & Magidson, 2005). Model fitting is best when the BIC and the AIC are low and the $\bar{\rho}^2$ is high.

Table 3: Overview of model estimation results

Number of Classes	Number of parameters	LL (Log-likelihood)	BIC (LL)	AIC (LL)	$\bar{\rho}^2$
1	31	-4230.5198	8725.0726	8523.0369	0.114
2	78	-3890.4643	8445.2697	7936.9286	0.175
3	125	-3727.3073	8519.2638	7704.6147	0.199
4	172	-3595.2749	8655.5070	7534.5498	0.216

First, all statistics preferred a model with segmentation over one without segmentation. However, the BIC suggested that the 2-class model was superior, whereas the AIC and suggested the 4-class model. The 4-class model was selected in this study because behavioral interpretation in the model was more acceptable. In the model estimation results section, we discuss the class-membership model and the class-specific choice model of the 4-class model. To compare the model with classes to the model without classes, a non-segmented model was discussed first.

4.1.1. Class-Specific Choice Model Without Latent Class

The class-specific choice model without latent class is shown in Table 4. The choice model was estimated with individual and household variables, such as age, gender, number of children, and household size, and mode variables, such as in-vehicle time, out-vehicle time, and fare. Alternative specific constants of both transit and water transit were statistically significant and had positive signs indicating that travelers who experienced trips along the Han River recently tended to prefer transit in general and water transit to auto in general. Resulting models indicated that characteristics, such as gender, student, education level, number of cars owned and household income affected mode-choice behavior. Females and students tended to prefer transit and water transit to cars. Higher income citizens tended to prefer cars to transit, which agreed with general expectations. For mode-specific variables, time and cost variables were statistically significant with negative signs, indicating that a mode's likelihood of being chosen decreased when modal cost and time increased. This result was consistent with common expectations. While the statistics in Table 3 show that the model with latent class is a significant improvement over the model without latent class, detailed results in Table 5 enabled us to see how behavior varied across classes.

Table 4: Class-Specific Choice Model without Latent Class

Variables		**Mode**	**1 Class**	
			Estimate	**t-statistic**
Alternative-specific constant		SP T	***4.169***	10.855
		SP W	***4.275***	11.057
Individual and household variables	Age	Transit	0.002	0.309
		Water	0.000	0.022
	Gender	Transit	***-0.514***	-4.460
		Water	***-0.489***	-4.198
	Occupation	Transit	*0.199*	1.433
		Water	*0.221*	1.579
	Student	Transit	***0.629***	2.188
		Water	***0.490***	1.678
	Education	Transit	***-0.243***	-2.056
		Water	***-0.257***	-2.154
	Marriage	Transit	0.100	0.337
		Water	-0.101	-0.334
	Number of children	Transit	-0.282	-0.970
		Water	0.103	0.348
	Household size	Transit	***-0.310***	-2.813
		Water	-0.114	-1.030
	Number of pre-school children	Transit	-0.084	-0.515
		Water	***-0.357***	-2.144
	Number of cars owned	Transit	***-1.418***	-6.814
		Water	***-1.307***	-6.256
	Dwelling type	Transit	***0.235***	2.085
		Water	0.057	0.503
	Household income	Transit	***-0.060***	-2.716
		Water	***-0.052***	-2.314
Mode variables	In-vehicle time	All	***-0.030***	-12.066
	Out-vehicle time	T&W	***-0.046***	-13.608
	Auto cost	Auto	***-0.011***	-10.502
	Transit fare	Transit	***-0.103***	-14.968
	Water transit fare	Water	***-0.121***	-17.255
Number of observations			5,000	

Note: Estimates whose t-statistics were higher than the critical value of the 5% significance level are marked in bold and the 10% significance levels are italicized.

4.1.2. Class-Specific Choice Models With Latent Class

Mode choice literature incorporating psychometric traits and individual's attitudes show that an individual's attitude has an important relationship with mode choice behavior (Johansson et al., 2006; Sohn & Yun, 2009). In our research, people who responded similarly to Likert scale questions in the psychometric indicators survey were likely to be affiliated with the same latent class. Estimated parameters of the class-specific choice model with latent class are shown in Table 5. Granted that the parameters of other classes are estimated simultaneously with latent class, parameters across classes have distinct effects on mode choice behavior.

Parameters across classes have different signs, indicating significant heterogeneity across classes. Estimated alternative specific constants of both transit and water transit were significant, except for latent Class 4. Alternative specific constants of Class 1 and 3 were positive, while signs of Class 2 were negative. These results indicated that travelers who experienced trips along the Han-River recently tended to prefer auto to transit and water transit, except in Class 2. In estimates of Class 1, student and citizens of high levels of education tended to prefer cars to transit, unlike the other classes. In Class 2, older citizens and job holders preferred transit and water transit to cars. In the estimation results of Class 3 and Class 4, variables such as education level, household size, and dwelling type significantly impacted mode choice behavior in Class 3. Variables, such as age, gender, occupation, student, number of pre-school children, and household income, had significant impacts on mode choice behavior in Class 4. In alternative specific constants and individual and household variables, signs of parameters and significant results were different across the classes.

The value of time across the classes was calculated to analyze mode choice behavior related to microeconomic principles. The value of time measures express change in utility caused by changes in modal attributes in monetary terms. The estimated parameter of cost and various time components provided information on the value of time. By Train's (2003) definition, the value of time is the extra cost that a person would be willing to incur to save time. It is estimated as a proportion of the time coefficient divided by the cost coefficient. In-vehicle time and out-vehicle time variables estimated in Class 4 were not statistically significant. Therefore, they do not fully support an explanation. Except for Class 4, the value of time across classes can be seen in Table 5, which shows significantly different values of time between the classes. In-vehicle time in Class 1 had higher values than other classes, and people in Class 1 tended to pay more to save time. Also, there was little difference between in-vehicle time and out-vehicle time, and waiting time savings was not valued by people of Class 1. The value of time in Class 3 was higher for out-vehicle time than for in-vehicle time and had a lower value for in-vehicle time, as compared to another group. There were differences across classes through the value of time analysis.

Another helpful method of examining class-specific choice model results is an 'importance rating' of variables within latent classes shown in Table 6. The top seven most important variables are listed for each class. This ranking was determined by taking the difference between the maximum and minimum value of each variable as observed in the dataset and multiplying this difference by the coefficient for that variable, as follows in Eq. 6.

$$\mathrm{maxeff}_{xp} = \max(\hat{\eta}_{a|xp}) - \min(\hat{\eta}_{a|xp}) \tag{6}$$

Let *a* denote a level of attribute *p*, and $\hat{\eta}_{a|xp}$ the utility associated with level *a* for latent class *x*. The variables were rank ordered based on the absolute value of this product, which reflects the order of potential impact on the utility (Vermunt & Magidson, 2005; Walker & Li, 2007).

We can explain variables affecting mode choice by examining the estimation results and variables important to each class. Auto cost, water transit fare, transit fare, age, out-vehicle time, as well as student and marriage status, were regarded as the important variables in Class 1. Important variables in Class 1 included time and cost variables, unlike other classes. Class 2 had only socioeconomic characteristic variables, such as age, income, occupation, number of pre-school children and so on. Important variables for Class 3 included number of pre-school children, age, student, auto cost, dwelling type, water transit fare, and marriage. Heterogeneity across classes was expected as the important variables within class differently turned out.

Table 5: Class-Specific Choice Model with Latent Class

Variables		Mode	Class 1		Class 2		Class 3		Class 4	
			Estimate	**t-statistic**	**Estimate**	**t-statistic**	**Estimate**	**t-statistic**	**Estimate**	**t-statistic**
Alternative-specific constant		SP T	***4.2354***	5.2876	***-23.7064***	-2.6196	***4.7171***	3.7814	13.2685	0.6923
		SP W	***3.6052***	4.4387	***-23.0421***	-2.5506	***6.3959***	4.6139	-22.4457	-1.0852
Individual and household variables	Age	Transit	0.0106	0.6655	***0.8243***	3.3912	-0.0201	-0.879	***0.4282***	1.8248
		Water	0.0203	1.2573	***0.8567***	3.4901	*-0.0429*	-1.4685	***-0.5121***	-3.2126
	Gender	Transit	0.0372	0.1631	***-7.3844***	-2.0295	-0.2777	-0.7044	***-2.3852***	-1.8805
		Water	0.2283	0.966	***-7.3961***	-2.0301	-0.2419	-0.612	***-24.3357***	-3.9558
	Occupation	Transit	***-0.3572***	-1.1781	***15.6392***	2.5748	*0.6576*	1.3522	***-6.5709***	-2.172
		Water	-0.376	-1.2107	***14.7593***	2.4451	0.2841	0.6141	***28.6573***	4.0107
	Student	Transit	***-1.0998***	-2.1894	***14.0303***	2.9074	***2.8781***	2.0439	***25.7378***	2.5623
		Water	***-1.0934***	-2.1202	***13.7167***	2.8597	1.2251	0.8612	***47.7387***	3.0461
	Education	Transit	***-0.7364***	-2.8652	***6.5278***	3.487	***-0.7943***	-1.9973	***5.2205***	1.6158
		Water	***-0.5015***	-1.9065	***6.5885***	3.5499	-0.467	-1.2165	***-7.9387***	-2.9396
	Marriage	Transit	-0.7025	-1.2665	1.612	0.0512	-0.5217	-0.5684	***9.5355***	2.4992
		Water	***-1.0019***	-1.7589	2.5222	0.0801	*-1.4557*	-1.5217	*12.3322*	1.4386
	Number of children	Transit	-0.0687	-0.1279	-11.1704	-0.3537	***-1.4174***	-1.8478	-1.7971	-0.4421
		Water	0.1959	0.3513	-12.0172	-0.3804	-0.1297	-0.1556	***20.3782***	2.0921
	Household size	Transit	***-0.5789***	-2.584	1.1846	0.5868	***-1.3455***	-3.2028	***7.1061***	2.0455
		Water	*-0.343*	-1.4662	1.2518	0.6439	***-1.0611***	-2.5869	***21.0539***	3.6756
	Number of pre-school children	Transit	***0.6928***	1.7787	15.0131	0.8289	*0.6243*	1.3218	***-35.3709***	-2.9125
		Water	0.4026	1.0006	15.5822	0.8597	-5.8699	-0.6735	***-5.4278***	-2.4513
	Number of cars owned	Transit	***-0.709***	-2.3509	2.9148	0.8722	-0.5788	-0.9504	***-52.4858***	-2.5453
		Water	*-0.4301*	-1.4113	2.0659	0.6233	***-1.2105***	-2.0331	-21.3628	-1.1912
	Dwelling type	Transit	0.1159	0.5002	***3.1501***	1.8912	***-1.8695***	-4.5062	***15.5574***	2.8473
		Water	-0.0374	-0.1566	***2.8822***	1.7418	***-1.2952***	-3.1927	***-3.8702***	-1.7313
	Household income	Transit	0.0509	1.0325	***-1.3528***	-3.79	-0.0124	-0.1815	***-1.3367***	-2.265
		Water	-0.004	-0.0761	***-1.2118***	-3.4256	0.0217	0.3753	***2.7022***	3.8661

Table 5 Continued

Variables		**Mode**	**Class 1**		**Class 2**		**Class 3**		**Class 4**	
			Estimate	**t-statistic**	**Estimate**	**t-statistic**	**Estimate**	**t-statistic**	**Estimate**	**t-statistic**
Mode variables	In-vehicle time	All	***-0.046***	-11.0091	***-0.0382***	-3.8229	-0.0022	-0.2356	0.0062	0.2108
	Out-vehicle time	T&W	***-0.0569***	-10.7632	***-0.081***	-6.1867	***-0.047***	-3.4893	-0.0175	-0.3051
	Auto cost	Auto	***-0.0266***	-9.3006	***-0.0368***	-3.3902	***-0.0126***	-3.8793	*-0.0119*	-1.5668
	Transit fare	Transit	***-0.1326***	-12.1013	***-0.2479***	-7.5781	***-0.0468***	-1.7419	***0.3194***	2.2332
	Water transit fare	Water	***-0.1446***	-13.0693	***-0.2464***	-7.388	***-0.0872***	-3.2219	***-0.248***	-1.7729
Value of Time (₩/hour)	In-vehicle time	Auto		10,376		6,228		1,048		-
		Transit		2,081		925		282		-
		Water		1,909		930		151		-
	Out-vehicle time	Transit		2,575		1,960		6,026		-
		Water		2,361		1,972		3,234		-
Number of observations				3,050		990		505		455

Note: Estimates whose t-statistics were higher than the critical value of the 5% significance level are marked in bold, and the 10% significance levels are italicized.

Table 6: Seven most important variables for each class

Rank	**Class 1**	**Class 2**	**Class 3**	**Class 4**
1	Auto Cost	Age	Number of pre-school children	Number of cars owned
2	Water transit fare	Household income	Age	Age
3	Transit fare	Occupation	Student	Household income
4	Age	Number of pre-school children	Auto Cost	Student
5	Out-vehicle time	Student	Dwelling type	Number of pre-school children
6	Student	Number of children	Water transit fare	Occupation
7	Marriage	Gender	Marriage	Gender

To summarize, class-specific choice model results showed different estimates, values of time, and importance ratings across classes because of factors that have significantly different effects across classes. To analyze factors which segment latent classes, the class-membership model is discussed in the next section.

4.1.3. Class-Membership Model

As previously mentioned, the class-membership model was estimated through psychometric indicators in a survey, and its estimation results are shown in Table 7. Class-membership model is a multinomial logit model that show probabilities, which each person belongs to each of the four classes. The class-membership model indicated the average probability of a person belonging to each class. Corresponding sizes for each class 1~4 were about 61%, 19.8%, 10.1%, and 9.1%, respectively. Parameters for the class-membership model differed considerably between classes, and each class was composed of people with different attitudes.

Examining the parameters of the class-membership model showed that people belonging to Class 1 tend to value travel time and travel cost and do not make many trips every day. People in Class 2 regard the environment, travel time, and travel cost as valuable and have a friendly attitude towards water transit. Class 3 is composed of people who travel day after day and prefer private modes to walking comfortably. People belonging to Class 4 tend to prefer one's own modes and want to travel the fastest path because of the valuable time.

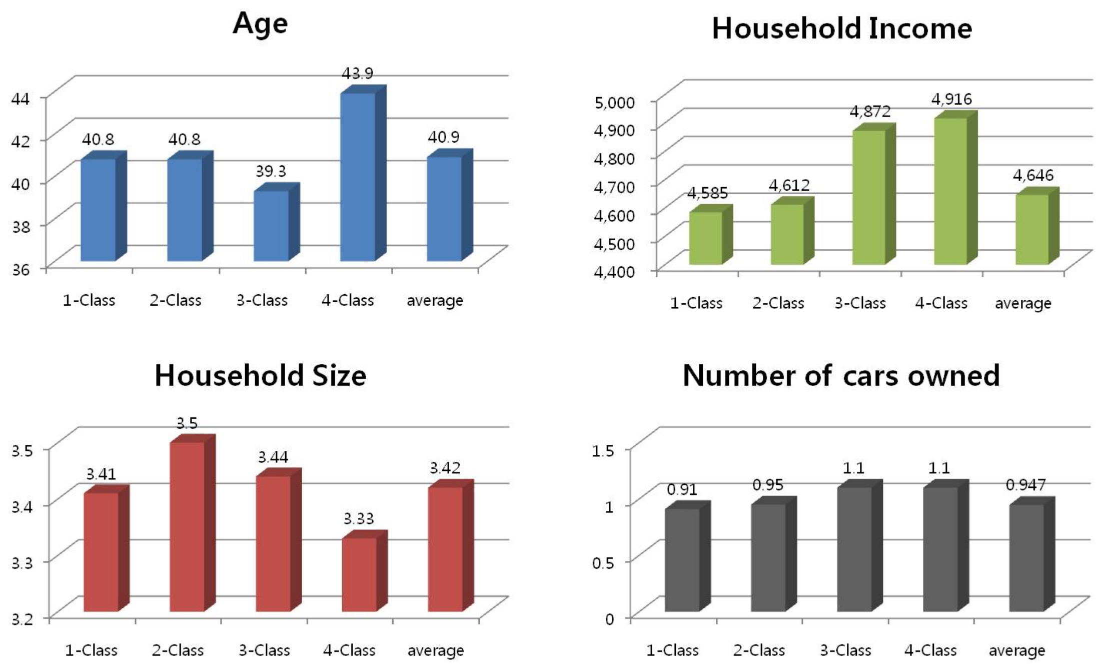
Figure 2 provides another way of examining the class-membership model through class profiling. This figure shows a partial profiling of variables which is the average value of that variable of people within each class, as compared to the total. For example, valuables, such as age, household income, number of households, and number of cars owned is shown. In Figure 2, there are unobserved factors which segment classes and that cannot be explained well by observable socio-economic characteristics.

Table 7: Class-membership model estimation results

	Class Size	**Class 1** **0.6097**		**Class 2** **0.1983**		**Class 3** **0.1011**		**Class 4** **0.0909**	
	Psychometric Indicators Survey Items	Estimate	t-statistic	Estimate	t-statistic	Estimate	t-statistic	Estimate	t-statistic
	Intercept	***7.0809***	5.1148	***-11.6341***	-3.0422	***-5.3394***	-2.148	***9.8927***	6.5073
1	I'm able to change a mode to protect the environment.	0.0071	0.0524	***1.2595***	4.8972	***-1.4817***	-4.6557	*0.2151*	1.4384
2	I'm able to change a mode if travel time is reduced.	-0.1985	-1.2273	***1.0602***	3.4986	-0.034	-0.1282	***-0.8277***	-4.9169
3	I always choose the fastest path despite cheaper alternatives.	***0.5519***	4.11	***-0.4829***	-2.2748	***-0.925***	-3.307	***0.856***	5.6873
4	No stress is more important than arriving early.	*0.1769*	1.3209	***-0.4538***	-2.2506	*0.3268*	1.4848	-0.0499	-0.325
5	Travel time in a mode is not important when the mode is comfortable.	***-0.4914***	-3.4675	0.066	0.2755	***1.3534***	5.0157	***-0.928***	-5.6941
6	I need to make many trips every day.	***-0.9145***	-5.3576	***-0.971***	-4.6036	***2.4574***	5.4011	***-0.572***	-3.3332
7	I travel for equal purpose in the same time zone every day.	***0.7347***	4.7728	*0.2714*	1.4885	***-1.3932***	-3.6343	***0.387***	2.4566
8	Driving makes me uncomfortable.	***-0.65***	-4.4442	0.1288	0.5179	***1.6466***	4.4346	***-1.1254***	-6.572
9	I always choose the most comfortable mode without regard to travel cost.	***-0.6306***	-4.7964	***-0.3808***	-2.1065	***1.0622***	3.263	-0.0508	-0.3732

10	I walk as much as possible.	***1.0906***	5.4752	***1.1016***	4.5949	***-2.9504***	-5.5707	***0.7582***	3.817
11	I prefer a private mode because I like to be on my own.	***-0.4367***	-2.1698	***-1.9038***	-5.8611	***2.4157***	5.2009	-0.0752	-0.3628
12	I am a morning person.	*0.1923*	1.6286	***0.3123***	2.1013	***-0.9419***	-3.5637	***0.4373***	3.4732
13	I will usually use a cruise on the Han-River if its fare is equal to other transit.	***-0.9536***	-4.3199	***1.1382***	2.8254	***1.5817***	2.817	***-1.7664***	-7.1239
14	I will use the water transit if I can get directly to the dock from my house.	***0.8855***	2.6294	***2.1162***	5.4522	***-4.699***	-5.5107	***1.6973***	4.8587
15	I will use the water transit if there are quality commercial equipment and convenient facilities.	***-0.4001***	-2.0398	***-0.528***	-2.2018	***2.6346***	5.1254	***-1.7066***	-7.3655

Figure 2: Latent Class Profiling



People belonging to separate classes differ not only in psychometric traits but also in socio-economic characteristics. Considering both the class-specific choice model and the class-membership model results, Class 1 people were influenced by travel time and cost and consistently regarded mode fare and time as important in mode selection. Class 2 is composed of environment-friendly and water transit-oriented people, as we can see in Table 8. Water transit selection is a large percentage of Class 2. People in Class 3 want to travel comfortably and prefer a private mode. They select largely for autos (27.2%), as compared to the total mode share of 10.9%. In even value of time results, the lower value of time was found than another class, which it is decided that using for selected mode is not bothersome. Also, auto costs were ranked high in importance indicating that people in Class 3 have many trips day after day. In the case of Class 4, people were relatively older than other classes, and they hold to their own modes. Socio-economic characteristics, such as age and income, were considered highly significant in the case of Class 4, but not time and cost.

Table 8: Mode share across classes

	Class	Auto	Transit	Water Transit
Model with segmentation	Class 1	6.8%	51.8%	41.4%
	Class 2	3.4%	31.9%	64.7%
	Class 3	27.2%	37.0%	35.7%
	Class 4	40.2%	40.0%	19.8%
Model without segmentation	Total	10.9%	45.6%	43.5%

5. Conclusions

The focus of this study was to analyze the effect of latent class on mode choice behavior, which can reflect psychometric traits and attitudes. We used SP, a psychometric indicators survey and socio-economic characteristics data to analyze behavior affected by a new water system on the Han River in Seoul, Korea. The framework of a LCC model was used in this study in which the latent classes were the psychometric traits and the choice model was the mode choice. The differentiated analysis of this study used the psychometric indicator survey for latent classes. The LCC model was composed of the class-membership model and the class-specific choice model because it could simultaneously estimate parameters of latent class and mode choice. Also, heterogeneity between classes can be shown through differently estimated choice models across classes.

Results confirmed that psychometric traits, socio-economic characteristics, and mode attributes variables have not only a significantly different impact on mode choice behavior across classes but also on latent traits. We segmented latent classes on the basis of a psychometric indicators survey and estimated the mode choice model across classes. To examine the effects on latent class, we compared the model with segmentation to the model without segmentation. Effects were demonstrated by the estimated parameters of the class-specific choice model. Different signs of parameters across classes showed heterogeneity among individuals. Also, in the class-membership model, psychometric traits and attitudes could be different across classes. People who considered time and cost important showed effects of time and cost on mode choice behavior. The mode share of the latent class that emphasized a comfortable trip and preferred private modes was higher than the total share, which was consistent with results.

From a policy perspective on the introduction of a new water transit system, results suggest that individual latent traits and psychometric indicators were applied to policy analysis. According to individual traits, as well as socio-economic characteristics and mode attributes, mode choice behavior can vary. People who persisted in their own modes were not influenced despite mode fare increases; the only factors affected were socio-economic characteristics variables. On the other hand, the latent class which valued time and cost considered mode choice utility that was affected by variables, such as auto cost, transit fare and water transit fare. Therefore, due to the fare policy change of the government, it is likely to change mode choice. Also, because there were water transit-oriented and environment-friendly people, we must provide appropriate strategies and promotions for each trait and class. However, it is difficult to determine individual traits and psychometric indicators. According to our results, a fundamental profile of each trait was established and if used with socio-economic characteristics, we can suggest a suitable policy for each class.

Mode choice behavior, which is hard to predict due to complex and diverse factors, has been studied in various ways. Recent research in discrete choice models has emphasized the importance of the explicit treatment of psychometric traits and attitudes affecting decision-making. These analyses reflect unobserved factors which could not be captured by conventional methods. Thus, they enhance the explanatory power of mode choice behavior and present detailed results. LCC models with these similar frameworks have advantages of simultaneously estimating a class-membership model and a class-specific choice model. To clearly understand underlying behavior, detailed data on behavioral processes and decision sequences are needed.

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