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DEVELOPMENT OF METHODOLOGY FOR ANALYZING TRAVEL PATTERNS IN THE CONTEXT OF DEVELOPING COUNTRIES

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ABSTRACT

Many cities in developing countries have been suffering from worsening traffic congestion and environmental degradation in city centers and most of radial corridors, which are caused by rapid urbanization trend and unbalanced transportation systems. Under such circumstances, this study attempts to develop a new methodology for 1) identifying representative travel patterns in developing countries based on a data mining approach called Exhaustive CHAID, and 2) clarifying the influential socio-economic attributes and/or mobility factors for the identified travel patterns by combining SEM (Structural Equation Modeling) approach and an aggregate-type logit model. The effectiveness of the methodology was confirmed based on the person-trip data obtained from "Metro Manila Urban Transport Integration Study" in 1996.
Keywords: Travel pattern, Exhaustive CHAID, Structural Equation Modeling, Aggregate-type logit model

1. INTRODUCTION

Many cities in developing countries have been suffering from worsening traffic congestion and environmental degradation in the city centers and most of the radial corridors. The issues are especially serious in capital cities. In fact, most of the capital cities have the highest urbanization rank, sometimes exceeding 10 folds more than the second urbanized city in countries like the Philippines. Concentration of population in these cities is one of the biggest reasons causing serious traffic congestion. On the other hand, reflecting the influence of rapid economic growth and the policies of promoting the automobile industry, more people tend to purchase their own passenger cars. In addition, disordered, unrestricted, and unregulated land development can be found in many placeswithout the proper control by the governments.Due to these uncontrolled polices of economic and urban development, time-consuming and costly construction of new road infrastructure cannot catch up with the increasing traffic demand. As a result, travel demand and transport supply are seriously unbalanced. This urbanization trend and unbalanced transportation systems are the most fundamental threats for the society to overcome and expected to considerably influence people's travel behavior. Under such circumstances, this study attempts to develop a new methodology for 1) identifying representative travel patterns in developing countries based on a data mining approach called *Exhaustive CHAID*, and 2) clarifying the influential socio-economic attributes and/or mobility factors for the identified travel patterns by combining *SEM* (*Structural Equation Modeling*) approach (Jöreskog and Sörbom, 1996) and an aggregate-type *logit* model.

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2. REVIEW OF RELATED LITERATURE

The study aims to determine the individual trip pattern of Metro Manila residents and its immediate environs. Noting that there are more than 21.9 million daily trips in Metro Manila at the time of the study, is there really a representative trip or activity patterns to represent Metro Manila's 21.9 million daily trips? The purpose here is to have a better understanding of the trip making behavior of the residents on a reduced scale, i.e., a few representative trip patterns. These representative trip patterns will be called as the potential *travel markets*.

Researchers have devoted considerable effort to identifying homogeneous travel behavior groups, each of which also has distinctive socio-demographic characteristics. Interest in these efforts has been fueled by both theoretical and applied concerns. From a theoretical perspective, if such behaviorally and socio-demographically homogeneous groups can be identified, we would have an improved understanding of the determinants of travel (Damm, 1983). Kitamura (1988), used trip-chaining as an aid in identifying these distinct groups that manifest the same travel pattern and at the same time have homogeneous socio-economic characteristics. Trip-chaining as a method is base on the fact that a trip is a link-sequence of activities and a continuous process and therefore should be analyzed as such.

This study will identify those homogeneous groups not only having similar socio-demographic characteristics but also in their travel-activity behavior. These groups, which will be called patterns/groups, will be analyzed based on their revealed trip-making behavior of one day. The potential travel markets of these groups will also be analyzed and determine what influenced this travel-activity behavior or the determinants of travel activity pattern.

The demand for travel has long been recognized as a derived-demand that is motivated by the need or desire for activity participation at spatially separated locations. These needs and desires are satisfied within the constraints, which limit the travel opportunities of the individual or household. Some needs and desires for activity participation require satisfaction less frequently than each day. For example, societies where home refrigeration is commonly available, grocery shopping is typically not undertaken each day. Other activities require even more frequent participation, e.g., time spent at home (Pas and Koppelman, 1987).

The Uppsala Household Travel Survey made use of data on out-of-home travel-activity pattern, a self-administered travel diary on movements by the adult members of households over a 35-day period. There are 149 individual samples from 93 households that constitute a representative sample of Uppsala's population (Damm, 1983). The measure that best described an individual's travel-activity pattern were: (1) the proportion of out-of-home time spent on shopping; (2) the proportion of trips that were single-stop trips; (3) the number of trips per travel day; (4) proportion of trips that were made for personal business; (5) the proportion of trips that were made for social purposes; (6) the proportion of trips made on foot; and (7) proportion of stops made for recreation (Damm, 1983).

In this study, the measures for classifying individual travel-activity pattern were: (1) time started form home; (2) time ended at home; (3) number of fixed number of activities such as home, work, and school; (4) time spent at home; (5) time spent at work; (6) time spent at school; (7) time spent for private business; (8) time spent for employer's business; (9) time spent for medical activities; (10) time spent for social activities; (11) time spent for eating activities; (12) time spent for shopping activities; (13) time spent for church activities; (14) time spent for accompanying other household members; (15) time spent for other activities; (16) number of trips; (17) time spent travelling. The foregoing dimensions were selected in an attempt to capture a time-space representation of the total travel-activity pattern undertaken by the individual during a given day.This measure for classifying individual travel activity was based on the study done by Villoria in 1989.

In other related studies, Chung and Ahn's (2002) paper has two objectives in their research: to explore relationships among socio-demographics, activity participation, and travel behavior by using data from a developing country (Korea); and to examine variations in activity patterns on different ways of the week by developing a series of structural equation models. The general findings show that strong relationships were found among socio-demographics, activity participations, and travel behavior, which can be simultaneously captured by the SEMs used in this research. Second, results were very similar to those in existing literature with data from the United States, even though data from Korea were used here. It was temporarily concluded here that there are similar relationships between socio demographics and travel behaviors in developed and developing countries.

3. METHODOLOGY

The analysis of travel patterns is an important research topic in transportation research and urban planning. It provides the background information necessary to better understand the complex relationship between urban structure, the transportation system and household travel patterns (Timmermans et. al,2013). There have been proposed several methods to classify the travel patterns. Most of the existing methods adopt arbitrary pre-defined classification criteria, which are usually selected based on analysts' knowledge and experiences. The task of classification also needs a very time-consuming "trial and error" process. As a result, these existing methods cannot systematically classify the travel patterns.

To overcome the issues of the existing classification methods and to rationally and systematically identify the representative travel patterns, a data mining approach called *Exhaustive CHAID (Chi-squared Automatic Interaction Detector)* is adopted. *CHAID* (Kass, 1980) is one of the most popular methods used in science and businessfor performing classification or segmentation. It uses the given data to automatically build a series of "if-then" rules (in the form of decision tree) that can classify the sample with maximum accuracy, than when using traditional exploratory statistical methods. Decision trees are charts that illustrate decision rules. They begin with one root (parent) node that contains all of the observations in the sample. The process is then applied recursively to subgroups to define sub-subgroups, and so on, until the tree is converged based on certain stopping criteria.

However, sometimes *CHAID* may not find the optimal split for a variable, since it stops merging categories as soon as it finds that all remaining categories are statistically different. Accordingly, the *Exhaustive CHAID* (Biggs *et al,* 1991) was developed to remedy this issue by continuing to merge categories of the predictor variable until only two super categories are left. It then examines the series of merges for the predictor variable and finds the set of categories that gives the strongest association with target variable. Thus, the *Exhaustive CHAID* can find the best split for each predictor variable.

On the other hand, the disadvantage for such a data mining approach is that the resultant classifications (here refers to travel patterns) are deterministic, in the sense that each "if-then" rule only corresponds to a specific travel pattern. To reflect the stochastic characteristics of travel pattern choice behavior, one can establish a disaggregate *logit*-type choice model. However, it is not an easy task to specify the relevant attributes for each alternative travel pattern, especially in the context of developing countries. Considering these matters, this paper first proposes to apply anaggregate-type *logit* model to not only alleviate the task of specifying the attributes for each alternative travel pattern, but also incorporate people's rational choicemechanisms.On the other hand, since choices of different travel patterns are not independent and, the explanatory factors for travel patterns sometimes show the complex cause-effect relationships, this paper further proposes to combine the aggregate-type *logit* model and the *SEM* approach, in order to flexibly reflect these behavioral and statistical mechanisms. This will be explained later.

4. DERIVING REPRESENTATIVE TRAVEL PATTERNS BASED ON EXHAUSTIVE CHAID

In this study, the person-trip survey database of the 1996 "Metro Manila Urban Transportation Integration Study (MMUTIS)" conducted by the Japan International Cooperation Agency (JICA) was used. As an initial attempt to confirm the effectiveness of the proposed methodology, a total of 3,987 individual samples were randomly extracted from the MMUTIS database. The number of samples from Metro Manila is 3,273 (82.09%) and 714 (17.91%) from the adjoining provinces. The total samples represent 6.5% of the total number of households of the MMUTIS data, 6.66% for Metro Manila and 6.22% for the adjoining provinces. The variables used in the Exhaustive CHAID include departure time from home and arrival time at home, number of obligatory activities, number of trips, time spent at home, office ad school, and time for performing private business, employer's business, medical, social, eating, shopping, church activities and accompanying other household members, and time spent traveling. To find the most suitable target variable for deriving the representative travel patterns, each of the above-mentioned variables is assumed to work as the target variable. The following goodness-of-fit index (SPSS, 2001) is used to evaluate the effectiveness of the derived travel patterns.

$$\text{Goodness} - \text{of} - \text{fit index} = \frac{Between\text{-}node\ variance}{Between\text{-}node\ variance + Within\text{-}node\ variance} \qquad (1)$$

One can see that Equation (1) is simply the proportion of variance explained by the Exhaustive CHAID. Clearly, this proportion is always between zero and unity where unity indicates a perfect fit. The goodness-of-fit index for each target variable is shown in Figure 1. Observing the results suggests that the target variable "Time spent at office" has t he highest goodness-of-fit index of 0.7250. there is still some residual variance, but the amount we can account for using the model is enough to convince us that we have captured the most suitable target variable.

To examine the stability of travel patterns by "Time spent at office", the total sample was partitioned into training and test samples, where the former is used to derived the optimal classification rules and the latter is used to examine the validity of derived rules. Goodness-of-fit indices for 5 sets of sample combinations are shown in Table 1. It is obvious that there is no much difference among the different combinations. The correlation between observed and predicted means (Figure 2) of target variable for each travel pattern shows that the rules generated on one part of the data fits the other part as well. The resultant travel patterns are shown in Figure 3. There are at most 3 classification levels and 16 terminal nodes indicating representative travel patterns. The characteristics of the travel patterns are summarized in Table 2.

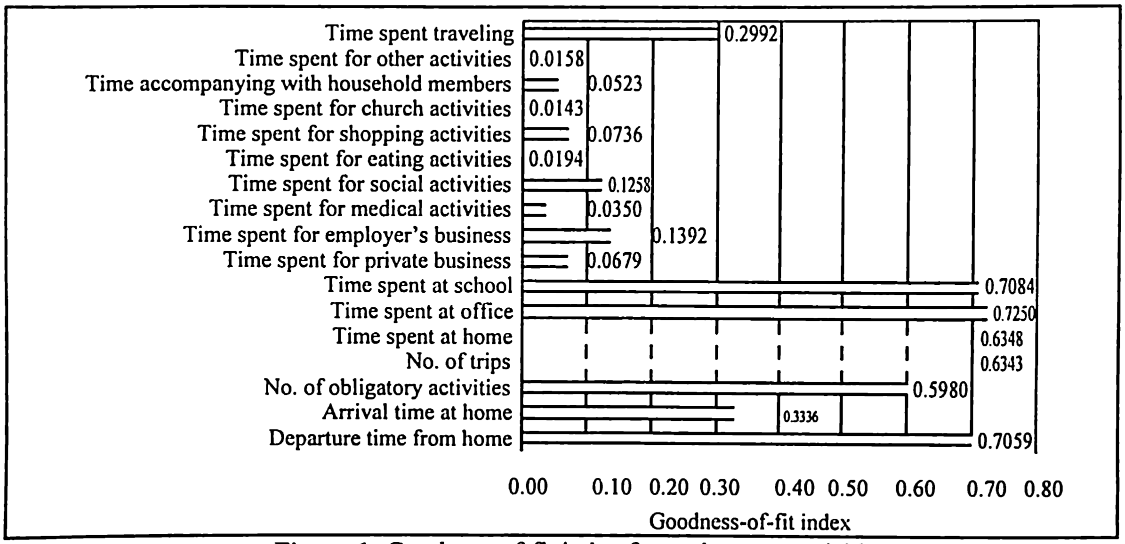

Figure 1: Goodness-of-fit index for each target variable

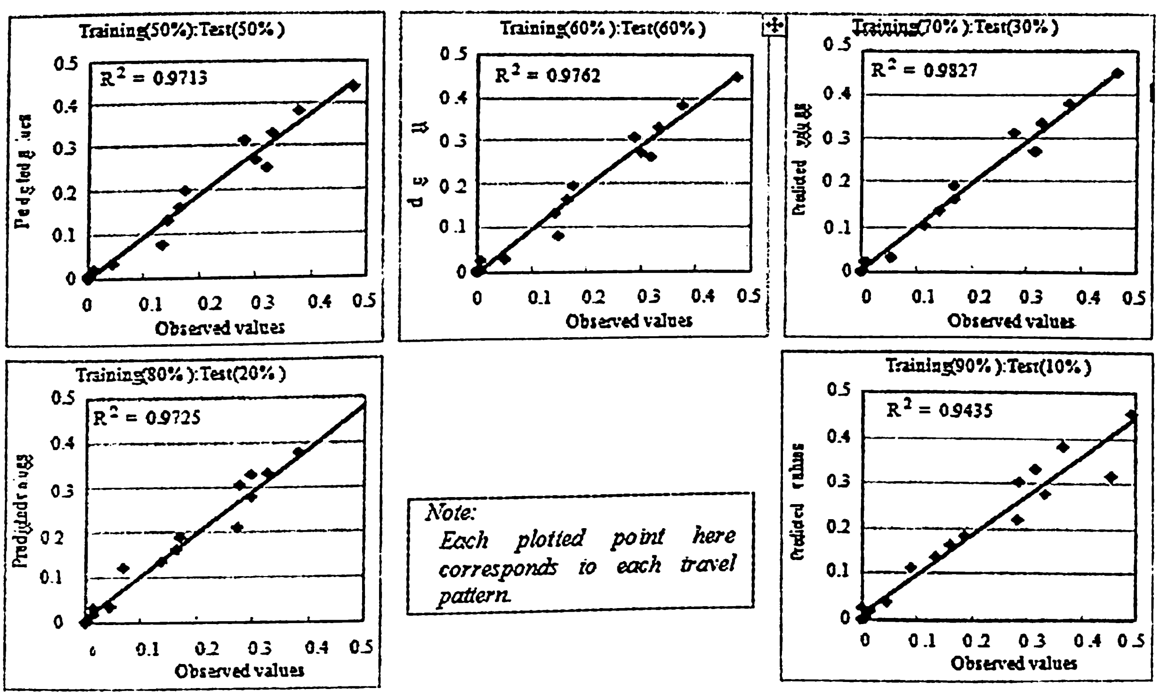

Figure 2: Correlation between Observed and Predicted Means of Target Variable

Table 1: Analysis Results of Stability for the Derived Travel Patterns

Partition Ratio		Goodness-of-fit index		Number of Terminal Nodes
Training	Test	Training	Test	
50%	50%	0.7149	0.7272	12
60%	40%	0.7243	0.7165	12
70%	30%	0.7243	0.7111	13
80%	20%	0.7224	0.7220	14
90%	10%	0.7261	0.7105	15

Table 2: Characteristics of the Derived Travel Patterns (1)

Pattern	Socio-economic Attributes			Dominant Activities	Dominant Travel Modes
	Average Age	Occupation	Dominant Gender		
Pattern 1	39.55	Housewife	Female	Home, Shopping Employer's Business	Walk, Pedicab Bicycle, Motorcycle
Pattern 2	35.66	Housewife	Female	Home, Social Shopping, Private Business	Walk, Pedicab Bicycle
Pattern 3	35.00	Officials of Gov't & Special Organizations Plant & Machine Operators	Male	Home Employer's Business School/Eat/Shopping	Walk, Pedicab Motorcycle, Tricycle
Pattern 4	32.93	Service Workers & Shop & Market Workers	Male	Work Home	Walk, Pedicab Bicycle, Motorcycle
Pattern 5	37.79	Officials of Gov't & Special Organizations Corporate Executives Professionals	Male	Home, Work Employer's Business	Walk, Pedicab Bicycle
Pattern 6	36.89	Housewife Officials of Gov't & Special Organizations Plant & Machine Operators	Female	Home, Employer's Business Social/Shopping	Walk, Pedicab Bicycle
Pattern 7	11.44	Elementary Students, Few High School & University Students	Relatively Equal	Home School	Bicycle, Motorcycle Tricycle, Jeepney
Pattern 8	11.36	Elementary Students, Few High School & University Students	Relatively Equal	Home School	Bicycle, Motorcycle, Tricycle, Jeepney, Bus
Pattern 9	14.14	High School & University Students, Few Elementary Students	Slight dominance of Female	Home School	Pedicab, Bicycle, Motorcycle, Tricycle, jeepney
Pattern 10	14.90	Elementary Students, Few High School & University Students	Slight dominance of Female	Home School	Pedicab, Bicycle, Motorcycle, tricycle, jeepney
Pattern 11	35.76	Laborers & Unskilled Workers Officials of Gov't & Plant & Machine Operators	Male	Work, Home, Employer's Business Shopping Social Activities	Walk, Pedicab Bicycle
Pattern 12	21.85	Elementary Students High School & University Students	Female	School, Employer's Business, Shopping	Walk, Pedicab, Bicycle, Motorcycle, Tricycle
Pattern 13	36.19	Laborers & Unskilled Workers Service Workers Shop & Market Workers	Male	Work, Home Employer's Business	Walk, Pedicab Bicycle
Pattern 14	22.56	Elementary Students High School & University Students	Male	Work, School, Home Few Employer's Business	Walk, Pedicab, Bicycle, Motorcycle, Tricycle
Pattern 15	20.05	Elementary Students High School & University Students	Male	School, Work Home	Walk, Pedicab, Bicycle, Motorcycle, Tricycle, jeepney
Pattern 16	18.43	High School & University Students Few Elementary Students	Relatively Equal	School, Home Work	Walk, Pedicab, Bicycle, Motorcycle, Tricycle, jeepney

From Figure 3, it is obvious that patterns 4, 2 and 8 are the top three in shares among the 16 travel patterns. The dominant activities are the work performed by younger workers of service/shop/market for pattern 4, the private affairs done by middle-aged housewives for pattern 2 and the school for pattern 8 (Table 2). The trip makers in pattern 4 have the longest travel time and consequently depart from home earliest among the top three patterns, while the trip makers in pattern 8 have the shortest travel time (Table 3). One can also observe from Table 3 that these three dominant travel patterns have the similar of trips, but the number of obligatory activities for patterns 4 and 8 is twice as large as pattern 2. Considering the characteristics of these different types of trip makers, the results seem realistic.

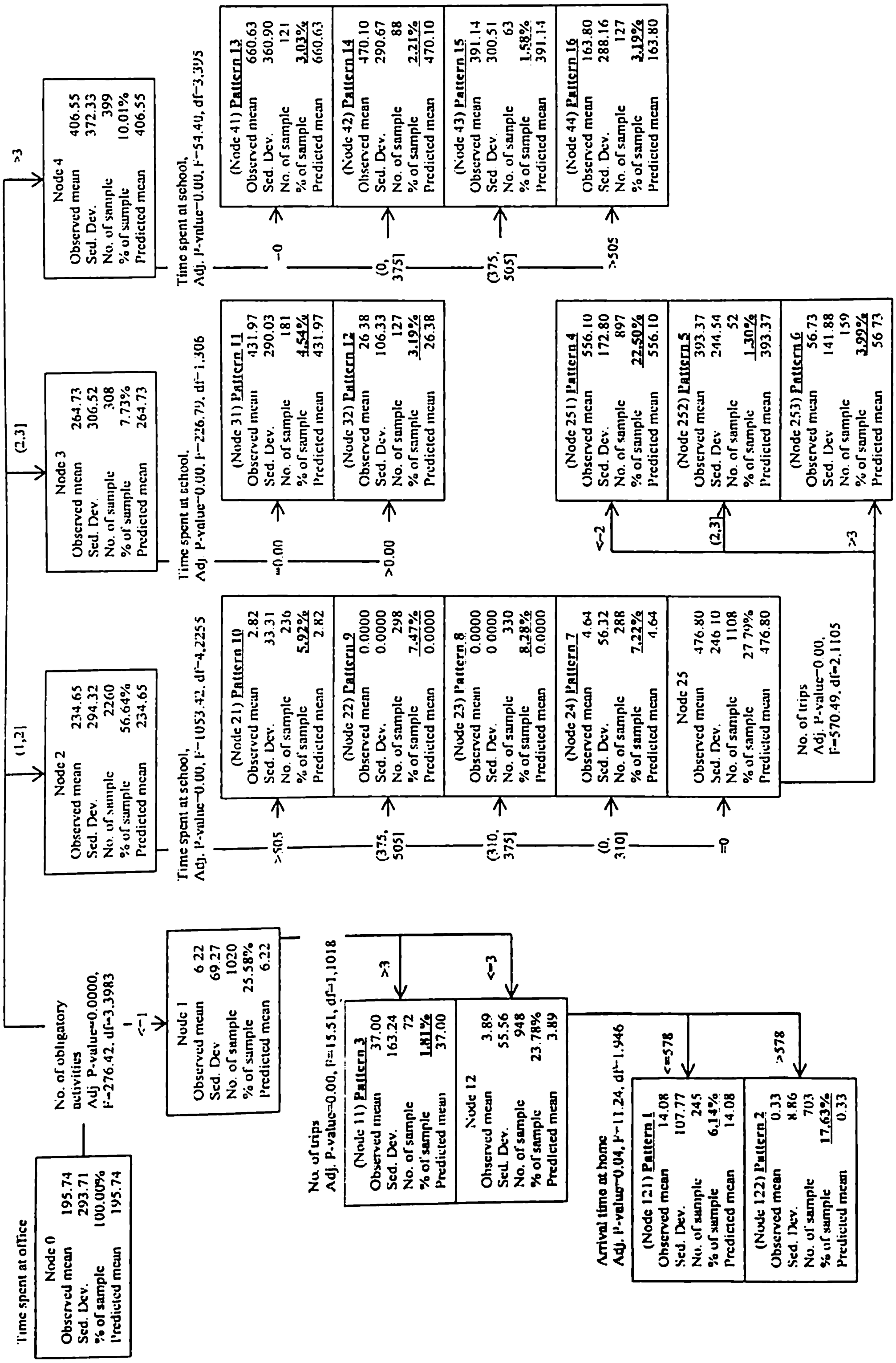

Figure 3: Sixteen Representative Travel Patterns Derived from the Target Variable "*Time Spent at Office*"

Table 3: Characteristics of the Derived Travel Patterns (2)

Travel Pattern	No. of Obligatory Activities	Total Travel Time	Time Departed from Home	Time Arriving at Home	No. of Trips
1	0.99	42	6:50	7:44	2.02
2	1.00	86	10:29	15:18	2.05
3	0.94	229	6:00	14:45	5.35
4	2.00	110	7:43	17:44	2.00
5	2.00	147	7:45	16:55	3.00
6	2.00	134	7:59	15:25	4.40
7	2.00	58	9:30	14:09	2.12
8	2.00	49	8:13	14:46	2.03
9	2.00	68	7:45	16:08	2.06
10	2.00	76	6:28	17:22	2.08
11	3.00	160	8:18	16:09	4.23
12	3.00	134	8:48	15:42	3.97
13	4.20	82	7:40	16:33	4.74
14	4.40	88	8:58	15:44	4.55
15	4.10	96	7:38	16:29	4.46
16	4.46	77	7:16	16:32	4.26

5. ANALYSIS OF TRAVEL PATTERNS CHOICE BEHAVIOR BASED ON A COMBINED MODELING APPROACH

First, define the following aggregate-type *logit* model.

$$P_{ij} = \exp(v_{ij} + e_{ij}) \,/\, \textstyle\sum_{j'} \exp\,(v_{ij'} + e_{ij'}) \tag{2}$$

where, P_{ij} indicates the share of travel pattern j at zone i, v_{ij} reflects the influential attributes of travel pattern j at zone i and e_{ij} is an error term following a normal distribution.

Next, for the ease of model estimation, the logarithm transformation for equation (2) was conducted as follows:

$$y_{ij} = \ln(p_{ij} + l)/\ln(p_{ij_0} + l) = \sigma_j \eta_{ij} + \varepsilon_{ij},\ \sigma_j \eta_{ij} = v_{ij} - v_{ij_0},\ \varepsilon_{ij} = e_{ij} - e_{ij_0} \tag{3}$$

Where, j_0 is the reference travel pattern and ε_{ij} is anew error term following normal distribution. $(P_{ij} + l)$and$(P_{ij_0} + l)$ are introduced to meet the requirement of logarithm function. $\eta_{ij}$is an endogenous latent variable defined below (σ_j is the relevant parameter of η_{ij}).

$$\eta_{ij} = \kappa M_{ij} + \mu S_i + \zeta_{ij} \tag{4}$$
$$x_{ijk} = \sigma_\kappa M_{ij} + \delta_{ijk} \tag{5}$$
$$z_{iq} = \sigma_q S_{iq} + \delta_{iq} \tag{6}$$

Here, M_{ij} is an latent variable representing the mobility factors $\{x_{ijk}: k = 1, \dots, K\}$ (e.g., travel time and license ownership) and is further explained by another latent variable S_i indicating the socio-economic attributes $\{z_{iq}: q = 1, \dots, Q\}$. $\kappa, \mu, \sigma_k, \sigma_q$ are the parameters and ζ_{ij}, δ_{ijk}, δ_{iq} are the error terms. In this study, the following observed variables were also adopted for the model estimation based on a prior analysis.

1) Socio-economic attributes *$\{Z_{iq}\}$*

(1) Age: average age; (2) Male% ratio of male; (3) Housewife%: ratio of housewives; (4) Tertiary%: ratio of tertiary population; (5) LN (income): logarithm value of income; (6) LN (students%): logarithm value of ratio of students.

2) Mobility factors *$\{X_{ijk}\}$*

(1) License%: ratio of driving-license holders; (2) EXP (transfer): exponential value of average transfer times; (3) travel time by mode including walk, tricycle, jeepney, car/jeep and bus).

The variables LN (income), LN (students%) and EXP (transfer) are introduced to reflect the nonlinear influence on the choice of the share of each travel pattern.

Here, the error terms (εij) in equation (3) might be correlated each other, and the mobility factor Mij are probably affected by the socio-economic attribute Si. To flexibly deal with these matters in a much more sophisticatedly statistical and practical way, it is proposed to estimate the aggregate-type logit model (equations (3) ~ (6) min the framework of Structural Equation Modeling approach. The estimation results are shown in Figure 4. The GFI value is 0.747, suggesting that the resultant model estimation results can capture the travel patterns in relatively good accuracy.

The regression weights shows that most of the variables are significant at the level of 90% or 95%, and both socio-economic attributes and mobility factors have positive and statistically significant effects on the choices of travel patterns. Focusing on the weight parameter for each travel pattern, one can see that all of them have positive signs and significant values. Considering the tree structure in Figure 3, we only assumed here that the adjoining error terms are correlated each other. It is found that the error terms between patterns 4 and 5, patterns 9 and 10, patterns 10 and 11, and patterns 11 and 12 are statistically significant. Of course, we can easily extend this structural equation modeling approach to incorporate much more general error structure. On the other hand, the influence of socio-economic attributes on the mobility factors is unexpectedly not significant (t-statistic is 1.52). Since this study is the first attempt of examining the effectiveness of the proposed methodology, and only nearly 7% of the total sample household data was extracted from the original large-scale person-trip data, further discussions on these matters remain as future research issues. On the whole, it can be concluded that the proposed methodology is effective to capture the representative travel patterns and their influential factors.

Concerning the mobility factors, most of the regression weight parameters of travel time by mode have positive influence on the choice of travel patterns, except for the parameters of License% and Car/Jeep-time. This implies that active participation (i.e., the increase in the number of activities) would accompany either longer travel time or more transfer times. Among the mobility-related variables, the parameters of License% and Car/Jeep-time are negative, partially due to the fact that only 2.8% of the samples have driving licenses.

For the socio-economic attributes, most of the parameters have logical signs and statistically significant except for the Male% parameter. Considering the rapid economic growth and the increase of tertiary ratio in Metro Manila metropolitan area, the positive parameters of Tertiary% and LN (income) suggest that it would result in the further increase of individuals' participation on each travel pattern in the future.

Comparing the parameters of socio-economic attributes and mobility factors, the latter is almost twice as large as the former. This mans that the improvement of mobility would further spur people's active participation of performing various activities.

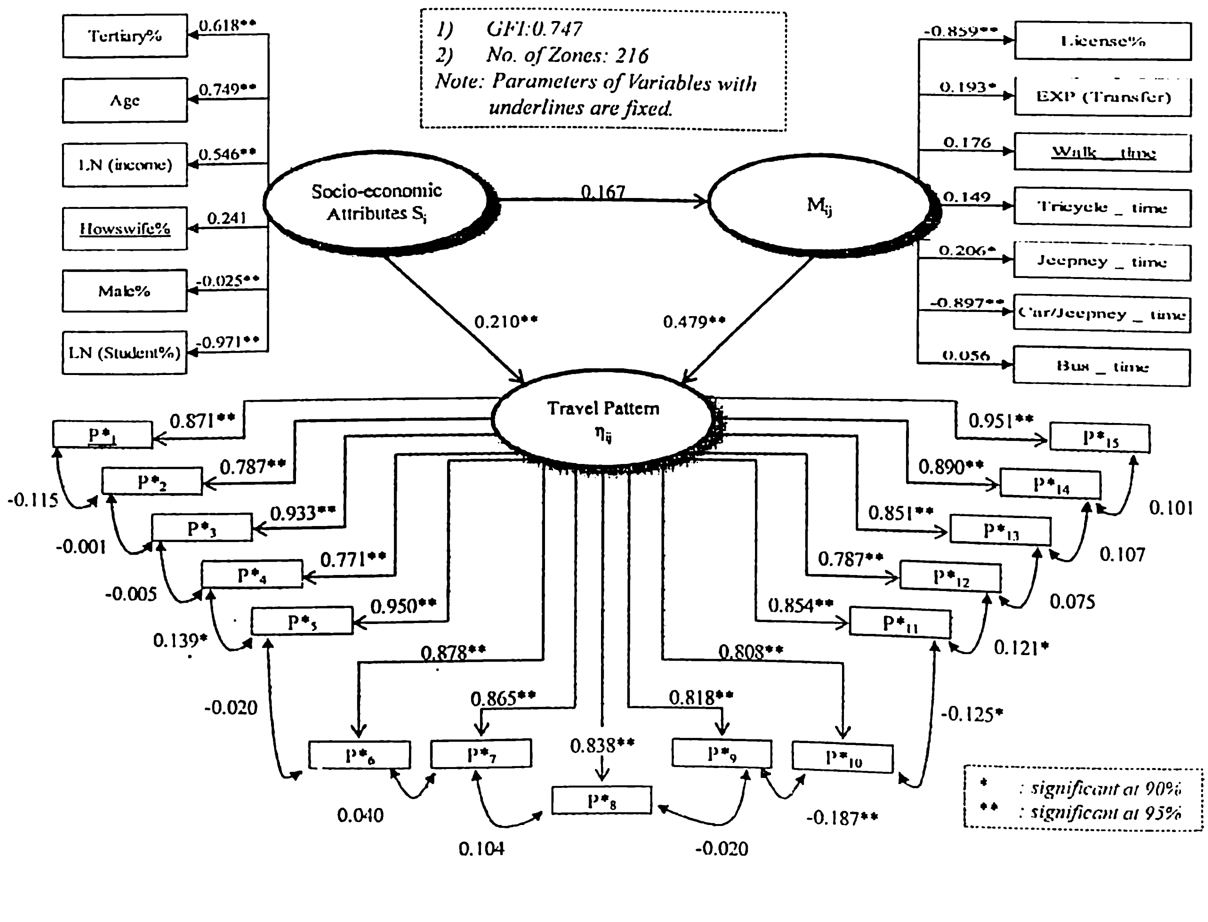

Figure 4: Standardized Estimation Results of Travel Pattern Choice Model

6. CONCLUSIONS AND FUTURE RESEARCH DIRECTIONS

To provide the information necessary to better understand the influence of rapid urbanization, changing socio-economic conditions and levels of transportation services on choices of various travel patterns, this study first proposed a new methodology for analyzing choices of travel patterns. The methodology combines three approaches: an *Exhaustive CHAID* approach, an aggregate-type logit model and a structural equation modeling approach. *Exhaustive CHAID* approach is used to systematically and effectively classify the complex travel patterns. Comparing with conventional classification methods, *Exhaustive CHAID* approach can alleviate the subjective biases of selecting classification criteria as well as the time-consuming classification task. Aggregate-type logit model is used to model people's choice behavior of various travel patterns. Structural equation modeling approach is adopted to flexibly incorporate not only the correlated error structure of travel patterns, but also the influence of socio-economic attributes on mobility factors, in a much more sophisticated statistical and practical way.

By using a person-trip survey database of the "Metro Manila Urban Transportation Integration Study (MMUTIS)", 16 representative travel patterns were first successfully extracted from nearly 4,000 sample household data based on *Exhaustive CHAID* approach. Next, choice mechanisms of the 16 travel patterns were represented by combining the aggregate-type *logit* model and the structural equation modeling approach. A significant result of the study in developing countries (in this case Metro Manila) has shown that the influence of socio-economic attributes and level of service for each travel mode on various decision -making aspects can be easily captured by applying the proposed methodology. The findings in this study reveal some pictures about the travel patterns of a sample developing country that is highly urbanized and experiencing rapid expansion. In recent years, to effectively represent people's travel patterns, activity-based approach becomes more and more popular in the developed world. This is because activity-based approach focuses on the fact that travel is a derived demand from performing various activities. However, it is still difficult to apply such approach in developing countries because implementing such activity survey isproblematic most especially for the budget-scarce developing countries.

This research is just a small stride toward a comprehensive investigation of many urgentissues in analysis of travel patterns. This study can be extended in the future. First, the datamining approach is only applied to derive the representative travel patterns. It seems thatcomparing with the widely used *logit*-type models based on the principle of random utilitymaximization, the data mining approach has some possibilities to explore the complexdecision making mechanisms in a more flexible way. In this case, it should be made clear howto interpret the rationality of the relationship between the derived decision rules and thedecision results. Second, to predict future travel patterns, the proposed methodology shouldbe further improved to incorporate other decision-making aspects like the choices ofdestination and travel modes in spatial context. Finally, considering that most of travel modesavailable in developing countries are ill equipped and their significant influences on choicesof activities seriously arouse environmental concerns, comparative analysis of spatial travelpatterns in different developing countries from the environmental perspective can be expectedto provide useful information for policy-making.

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