Available online at www.sciencedirect.com

ScienceDirect

Procedia Engineering 137 (2016) 786 – 795

Procedia Engineering

www.elsevier.com/locate/procedia

GITSS2015

A Travel Mode Choice Model Using Individual Grouping Based on Cluster Analysis

Ling Ding*, Ning Zhang

Intelligent Transportation System Research Center, Southeast University, 35 Jinxianghe Road, Nanjing, 210008, China

Abstract

This study aims to estimate travel behaviors by dividing individual travelers into several groups based on their personal characteristics. The individual grouping was achieved using the cluster analysis with the aid of the statistical analysis system (SAS) software. The trips to the central business district (CBD) in Nanjing City of China were taken as a case study. Two travel mode choices were investigated: the transit (bus and metro) and car. Travelers' personal information and travel information were collected through a reveal preference (RP) survey and a stated preference (SP) survey. The personal information include gender, occupation, income, and car ownership, while the travel information include the mode choice, walking time, waiting time, in-vehicle time, fare, comfort, etc. There were 524 valid respondents in the RP/SP survey. These 524 individuals were categorized into three groups using cluster analysis based on their personal information. It was found that people from the three groups had very different characteristics, indicating the cluster analysis worked well. In addition, six travel scenarios were designed for each respondent to ask their travel mode choice. Then, the travel mode choices were estimated using a discrete choice model and compared with the mode choices in the RP/SP survey for each group. It was found that the accuracy rate of the mode choice estimation using individual grouping were remarkably higher than that without grouping, indicating that the individual grouping improved the travel behavior estimation.

Peer-review under responsibility of the Department of Transportation Engineering, Beijing Institute of Technology

Keywords: Travel Mode Choice; Individual Grouping; Cluster Analysis; Discrete Choice Model

* Ling Ding. Tel.: +86-13805159632.
*E-mail address:*dinglingseu@gmail.com

Peer-review under responsibility of the Department of Transportation Engineering, Beijing Institute of Technology
doi:10.1016/j.proeng.2016.01.317

1.Introduction

Travel mode choice have been widely investigated based on the random utility maximization theory and choice behavior theory, such as discrete choice model [1-3]. The essential concept of travel mode choice models is to understand the relationship between traveler's choice and the contributing factors, such as the social-economic level and service level of modes [4-7]. The factors that contribute to travel behaviors mainly fall into two categories: the macroscopic and microscopic factors [8,9]. The macroscopic factors are normally determined by the characteristics of the society, which include economic level, urban land use, etc. The microscopic factors are related to the individual traveler's characteristics and travel attributes. They include travelers' age, income, travel time, travel cost, etc. In regard to the macroscopic factors, Dowing and Gollner [10] investigated the effects of economic level, culture and environment on female's mode choice and found that female motor vehicle use is increasing at a disproportionate rate to men's. In terms of the microscopic factors, many previous studies found that traveler age is a significant contributing factor to the travel behavior [8, 11-13]. It was found children's increasing car travel are probably the most easy-changeable because their travelling are likely to be highly dependent upon the household's social-economic characteristic. In addition, age, income and life stage have significantly different and interactive influences on the travel mode choices [14]. Nicolau [15] found income, family size and education have great effects on travel decision c. Bowman and Ben-Akiva [16] took age, income, travel time and cost as the mode choice variables to predict passengers' travel behavior. Syam et al. [17] studied the mode choice behavior of travelers with a multicultural society and found that face took an effect on mode choice, for example, New Zealand Europeans are the largest group in car use. Compared with the microscopic factors which are individual dependent, the macroscopic factors are much more stable in a specific region and a certain period of time. In regard of the relative stability of the macroscopic factors, this study mainly focuses on the effects of the microscopic factors on the travel mode choice.

According to the existing researches and surveys, the microscopic factors affecting travel choice behavior can be categorized as personal attributes and service of travel mode [8, 10, 18, 19]. Travelers' social-economic attributes include race, age, income, car ownership and occupation. Overall, travelers with higher income would like to choose a more comfortable mode. The car ownership largely determine if a traveler need to choose a public mode. In addition, it is likely commuters prefers travel modes with punctuality, such as the metro. The service of travel mode include travel cost, travel time, comfort and accessibility. For transit users, the cost is ticket fare, while the cost includes the fuel cost and the parking fee for car travelers. The travel time of transit users include the walking time to the station, waiting time, the time on board, transfer time, and the walking time to the destination. For car travelers, travel time include the walking to the parking lot and the in-vehicle time. It is regarded that car travel is more comfortable than the transit. Normally private traffic has a higher accessibility than the transit except for some special regions for personal vehicle forbidding.

The attitudes on travel time, cost, and the service level of the trip normally vary for travelers from different groups. For example, females and elders may regard comfort as the primary concern, while punctuality is the most important factor for commuters. Kevin [20] and Abolfazl [21] investigated females' mode choice behavior and found that females have lower commuting use rate compared to male. Their findings are consistent with other studies showing that females have higher rates of leisure travel [22]. The study by Cutler [23] showed that elders' accessibility reduces with the increase of age, and the reducing rate of elder females is fast than elder males. That is a possible reason why elder males prefers to drive but elder females prefer the transit by community [24].

In addition to the group division based on personal characteristic, group divisions based on other contributing factors have also been investigated. Tsamboulas [25] divided travelers into two groups based on parking payment type (hourly parking payment and monthly parking payment) to study the travel behavior. The study found that: 1) there are similar characteristics within the group; 2) travelers in the group of hourly parking payment are easier to change travel behavior than the other group. Trip behaviors in Chicago, divided into two groups (work trip and non-work trips) were also studied [26]. They found there are similarities between commuters' and non-commuters' travel behavior. However, a number of attributes such as station/stop security, lighting/safety and proximity to services et al. are considered more important by non-commuters (compared to commuters).

2.Motivations and objectives

While some existing studies investigated the travel mode choice based using traveler grouping, the grouping concept is simply based on one or two contributing factors. Therefore, the effect of other contributing factors are not reflected in the analysis. With the aid of cluster analysis, the traveler grouping can take account into more contributing factors that affect travel behaviors. The objective of this study is to predict travel mode choice with individual grouping based on cluster analysis. All the travelers are divided into a few differential groups based on their personal characteristics. It is also expected that the proposed model can improve the predictive accuracy and better describe travelers' mode choice behavior.

3.Research plan

To achieve the goal in this study, the travel behavior in the central business district (CBD) of Nanjing City in China was investigated. First, a survey containing travelers' revealed preference (RP) and Stated-Preference (SP) was conducted to obtain the travelers' characteristics, their actual and preferred travel mode choice. Then, cluster analysis was employed to categorize all the travelers into a few groups based on their characteristics. Afterward, the travel mode choices of all the travelers are predicted based on the utility maximization theory and choice behavior theory. The predictive accuracy using the proposed model was also be verified at the end.

3.1 Travel data collection

The CBD of Nanjing City in China is named Xinjiekou business district. It is a transit-rich region surrounded by business, shopping and entertainment venues, which is attracting large amount of travelers for working, shopping, entertainment, etc. The daily passenger flow in the CBD is more than 600,000 in weekdays and more than 1 million in weekends. Three main travel modes are served in the district, which are metro, bus and car. In terms of the metro, there are currently two metro lines crossing at the CBD in Nanjing under operation. For the ground traffic, the CBD is the intersection of a few urban roads. The hourly traffic flow of an urban freeway is as high as 2,000 at peak periods. The highest daily number of passengers taking the metro is more than 1.4 million.

The data collection was aiming at the travel mode choices of travelers going to the CBD. As mentioned above, a RP survey was taken to collect social-economic information and related travel data of travelers. The individual grouping was based on the social-economic information. The survey was taken through the internet and interview on the travelers who live in Nanjing. In addition, the data collection targeted travelers who had been to the CBD at least once before. Information of 524 respondents was collected for the SP and RP survey. The RP collected the respondent's social-economical information including gender, occupation, income, and car ownership. It should be noticed that the age was not regarded as an attributes because the survey results showed that all the respondents' ages fall into the range of 20 to 45 years old. As a result, the age variance was not high enough for a categorization. The SP survey collected the information of the respondents' preferred mode to the CBD. On the other hand, the SP survey collected the mode choice decisions of the respondents under six travel scenarios. The detailed survey information is shown in Table 1.

3.2 Cluster analysis of individual travelers

Cluster analysis is a multivariate statistical method for the classification of samples or indexes [27, 28]. The primary objective of cluster analysis is to collect data and to achieve the individual grouping based on the character similarity of the study objects. Samples with similar characters are grouped together. The cluster analysis on individual travelers was achieved by an analysis process to categorize all travels into several classes based on the characteristics of these individuals. In this study, 524 individuals with four social-economic attributes were determined, which were gender, occupation, car ownership, and income.

The statistical analysis system (SAS) software is a widely used for hierarchical clustering analysis [29]. Thus, the SAS software was employed for the individual grouping in this study. There are two types of hierarchical cluster: Q-mode analysis and R-mode analysis [28]. Q-mode analysis is sample based. It allows samples of similar characteristics to group together while distinguish samples with significantly different characteristics. R –mode analysis variable based. It assembles the similar variables while separates the very different variables. In this study, the Q-mode analysis was used considering the cluster objects were the individual travelers.

Table 1 The description of the SP and RP survey

Surveys	Information to collect	Description	
RP Survey	Social-economic information (personal attributes)	Gender; occupation; income; car ownership	
RP survey	Travel information last time (other contributing factors)	Transit	Walking time; waiting time; fare; in-vehicle time; seat or not
		Car	Travel time; fuel cost; parking fee; comfort
SP survey	Preferred mode choice under six travel scenarios	Transit	Hypothetic walking time, waiting time, in-vehicle time, fare, and comfort
		Car	Hypothetic travel time, fuel cost, and parking fee

The data collected were used to model coefficient estimation and model validation, so data were divided two parts: data1 and data2. Data 1 was 50% of the whole data randomly sampled from RP data, while data was the union of RP data and SP data.

3.3 Travel Mode choice model

A simple Multinomial Logit (MNL) model was applied in this study for the travel mode choice analysis. The variables used in the utility functions include:

- Walking time: only for transit.
- Waiting time: only for transit.
- In-vehicle time: only for transit.
- Fare: only for transit, it is the public transit’s ticket price.
- Comfort: only for transit, including three levels, very comfortable with seat, no seat but with some freedom of movement, no seat also very crowded.
- Travel time: only for car users.
- Cost: only for car users, including fuel cost and parking fee.

An individual traveler is assumed to choose the travel mode with the maximum utility from different travel modes of 1 to J. A utility known by the traveler is expressed as $U_{nj},(j = 1,\dots,J)$, as shown in Equation 1.

$$U_{nj} = V_{nj} + \varepsilon_{nj} \tag{1}$$

where, V_{nj} is a function of the measured attributes which is also called Representative Utility; ε_{nj} is the unobserved attributes.

The variables in the utility function are composed of travelers’ trip attributes. The travel information of the transit users includes waking time, waiting time, in-vehicle time, fare, and comfort; while the travel information of the car users include travel time and cost. Normally, the utility function is linearly correlated with its variables. The utility function for traveler n, alternative mode j is expressed as Equation 2 [30, 31].

$$V_{nj}\left(X_{nj}\right) = \sum_k \beta_k X_{knj} = \beta_1 X_{1nj} + \beta_2 X_{2nj} + \dots + \beta_K X_{Knj} = \beta' X_{nj} \tag{2}$$

where, $X_j = (X_{1j}, X_{2j}, L, X_{Kj})$, is a vector of attributes for alternative j, and $b_j = (b_{1j}, b_{2j}, L, b_{Kj})'$, is a vector of estimation coefficients.

Based on the travel information from the RP/SP surveys, the estimation coefficients of each attributes can be obtained through the regression using Biogeme. This procedure was taken for each group. The estimated mode choice can also be obtained based on the comparisons of the utilities of the transit travel and car travel. The estimated mode choice of each traveler was compared with the mode choice he/she claimed in the RP/SP survey to understand the accuracy of the prediction model. In addition, the estimation results of the proposed model using individual grouping was compared with that without grouping to know if individual grouping improves the estimation accuracy.

4.Results and discussion

4.1 Data Collection

The four personal attributes of the 524 respondents was collected. The percentages of the male and female travelers are 51.2% and 48.8%, respectively, indicating the gender distribution is balanced. In terms of the income, 16% of the respondents' annual income is lower than 20,000. This is because a good amount of the respondents are college students, many of which have relatively lower incomes. The commuters made up more than 60% of all the respondents. About 45% of the respondents claimed they have one or more cars.

In addition to the personal attributes, the travel information was also obtained from the SP/RP survey. It was found that traveler numbers of the transit and car were 105 and 26, respectively. In another word, the mode choice percent of the transit travel and car travel were 80.15% and 19.85%.

Distributions of the reported transit trip (walking time, waiting time, seat, in-vehicle time and transfers) are got. A reasonable walking time distribution was obtained. The percentage of the walking time higher than 20 minutes was only 11.43%, indicating that the acceptable walking time for most travelers to take the transit was within 20 minutes. Similar, most of the waiting time was within 10 minutes, indicating the acceptable waiting time for most travelers was about 10 minutes. A reasonable in-vehicle time distribution was also observed with a mix of short and long time. More than 60% of trips by transit have no seat because of limited seat. It is noted that most of the trips did not need to transfer.

Travel attributes of car trips such as travel time, fuel cost and parking fee are also obtained. A wide range of travel time was observed varied from within 10 minutes to more than 40 minutes. It was noticed that a 30.77% of the travel time was higher than 40 minutes. This is much higher than of the transit travel, indicating that more travelers preferred a car to transit for a long trip. About half of fuel cost fell into the range of ¥10 - ¥20, which is consistent with the relatively high travel time. All of the parking fee was lower than ¥20. The possible reason of this is that the data collected shortly after the parking price increased, while the last trip to Xinjiekou may be before the parking increased when the parking fee was much lower.

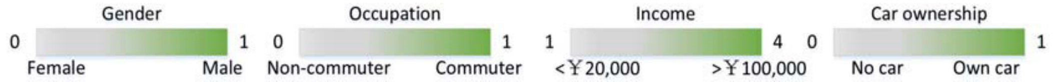
4.2 Individual grouping

The cluster analysis was conducted for the individual grouping of the travelers based on their personal attributes, which are gender, occupation, income, and car ownership. The SAS software was employed for this purpose. Table 2 illustrates the cluster results of the 524 respondents. Three clusters were obtained and their proportions are 27.5%, 25.9%, and 46.6%, respectively. The three clusters were labeled as Group 1, 2, and 3, respectively. All the personal attributes were represented by number indexes, which are shown in the last row of Table 2. For instance, the indexes of male and female were 1 and 0, respectively.

It was found that the average indexes of three groups varied visibly from each other, indicating that the personal characteristics are very different. The gender index of Group 1 is 1, indicating that all the members of Group 1 are males. On the contrary, female is dominant in Group 2 as the gender index is only 0.22. It was also found that the income index and car ownership index of Group 1 are much higher than that of the other two groups, indicating many high-income travelers are in Group 1. The higher occupation index also suggests that most of the members in Group 1 are commuters. To summary the members in each group, the Group 1 mainly consists of high-income male commuters; Group 2 manly consists of low-income female; while the personal characteristic in Group 3 are between that in Group 1 and 2.

Table 2 The cluster results of the individuals

Cluster	1	2	3
Label	Group 1	Group 2	Group 3
Size	27.5% 144	25.9% 136	46.6% 244
Average index of personal attributes	Male 1	Male 0.22	Male 0.39
	Occupation 0.83	Occupation 0.43	Occupation 0.67
	Income 3.23	Income 2.08	Income 2.42
	Auto ownership 0.87	Auto ownership 0.21	Auto ownership 0.39



4.3 Model coefficients estimation

Table 3 shows the variables and coefficients obtained of the estimation model for the three groups and the whole sample without grouping by Biogeme.

Table 3 The model estimation results for groups

Variables	**Utility**	**Coefficient**				**Std.Err (t test)**			
		G1	G2	G3	All	G1	G2	G3	All
IVTT_A	Car	-0.385	-0.374	-0.314	-0.344	0.050 (-2.77)	0.038 (-2.15)	0.329 (-1.96)	0.011 (-5.18)
IVTT_T	Transit	-0.677	-0.448	-0.317	-0.389	0.182 (-3.71)	0.079 (-5.44)	0.025 (-3.09)	0.033 (-5.79)
Waiting time	Transit	-0.679	-0.273	-0.161	-0.333	0.341 (-2.08)	0.055 (-2.69)	0.377 (-4.27)	0.469 (-2.73)
Walking time	Transit	-0.264	-0.172	-0.145	-0.279	0.244 (-1.08)	0.015 (-7.51)	0.410 (-3.53)	0.22 (-1.91)
Fare	Transit	-0.79	-0.961	-0.973	-0.973	0.251 (-3.15)	0.023 (-4.75)	0.787 (-6.02)	0.289 (-2.17)
Comfort	Transit	1.03	0.443	0.206	0.401	0.254 (4.05)	0.075 (10.90)	0.021 (1.96)	0.214 (2.71)
Cost-car	Car	-0.442	-0.734	-0.89	-0.857	0.012 (-3.73)	0.023 (-3.61)	0.255 (-4.28)	0.140 (-2.66)
Car constant	Car	0.00	0.00	0.00	0.00	Fixed	Fixed	Fixed	Fixed
Transit constant	Transit	1.19	2.58	1.59	2.19	0.46 (3.13)	0.0175 (-8.07)	0.34 (3.37)	0.654 (4.34)

Group	G1	G2	G3	All
Number of observations	268	209	277	754
Log likelihood	-185.764	-144.175	-187.742	-522.390
Rho-square	0.735	0.722	0.628	0.610
Adjusted rho-square	0.649	0.616	0.581	0.573

*note: G1, G2, and G3: Group 1, Group 2, and Group 3; IVTT_A: in vehicle travel time of auto; IVTT_T: in vehicle travel time of transit

Overall, the coefficients of the variables were different among the three groups. This is supported by the fact that travelers from the three groups have different attitudes at travel characteristics. In terms of the values of the coefficient, it is as expected that all the coefficients of travel time are negative, including the in-vehicle travel time (IVTT), waking time, and waiting time. It was also found that the in-vehicle travel time of transit (IVTT_T) had a higher adverse effect on the travel utility than the in-vehicle travel time of auto (IVTT_A). It is consistent with the conclusion in the data collection that long trips prefer cars. This is because car normally provides a higher comfort than the transit. The possible interpretation that the waiting time has a higher effect on the utility is that it is more boring to wait than walk. In regard to the comfort estimates in three models, coefficient of Group 1 is larger others, indicating the comfort was more important for the travelers in Group 1. One possible reason is the travelers in Group 1 had a higher income who prefer comfortable modes. The walking time includes the access time and egress time, the detailed description of the two types of walking time can be found in a previous study by Hensher and Rose [32]. The walking time and waiting time of car used were zero because the parking lot is at the very center of the CBD. Therefore, the travel time is equal to the IVTT_A. The transit constants of Group 1, 2 and 3 were 1.19, 2.58 and 1.59, respectively. Comparison among the three groups showed that the transit constant of group 2 was much larger than other two groups, indicating that there were more other factors affecting travelers' mode choice in group 2. Another possible reason is that the individuals with relatively low income in group 2 prefer transit modes over the car mode. This is consistent with the results in previous study [26]

4.4 Model validation

The prediction model based on individual grouping was verified using RP/SP data. There were 524 respondents in survey. Six scenarios were designed for each individual respondent in the SP survey. Therefore, the supposed total sample observations were 3144. However, some obvious erroneous samples were not taken account, and the final valid sample observations were 3024. The observations of Group 1, 2 and 3 were 784, 832 and 1456, respectively. The MNL models were applied to predict the travel mode choice of the three groups from the cluster analysis. The utilities of the travel scenarios were calculated based on Equation (2). Then the predicted utilities of taking transit and car were compared and the differences were shown in Fig. 1.

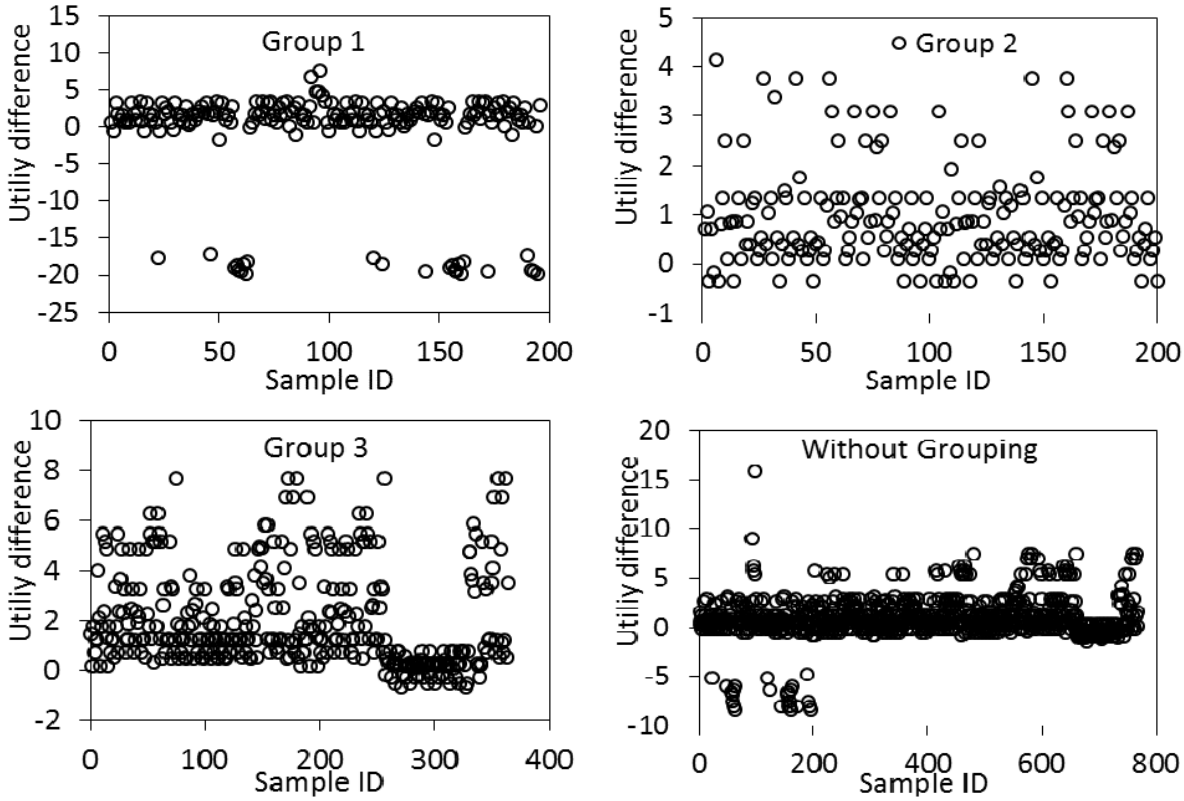


Fig. 1. The differences between the utility of transit and car of the three groups and the whole sample without grouping.

The utility difference was the value of the car travel utility subtracted from the transit travel. Thus, a positive utility difference indicates the transit travel is a better choice. As seen in Fig. 1, most of the utility difference values are positive, indicating a transit travel is more preferred than the car. Some utility differences of Group 1 were pretty low, indicating some individuals with high income were categorized in Group 1. This is consistent with the results of the cluster analysis that the high income travelers were in Group 1. The highest utility difference of Group 2 and 3 are about 4 and 8, respectively. This indicates that people in Group 3 have a relatively lower time value than that in Group2. This is also consistent with the results in the cluster analysis. In terms of predicted results without grouping, a good amount of utility results were negative, indicating a predicted mode choice of car travel. This may be a deviated estimation because the survey results showed that 80.15% of the travelers would like to take the transit. The accuracy of the estimation is discussed below.

The predicted mode choice results were compared with claimed results in the survey. Fig. 2 shows the total sample number, the correctly predicted sample number, and the accuracy rate of the three groups. The accuracy rate of each group was defined as the ratio of the correctly predicted sample number to the total sample number. The prediction accuracy rates of Group 1, 2 and 3 were 89.8%, 85.6% and 78.2%, respectively. On the other hand, the prediction accuracy rate of the entire sample without grouping was 65.6%. This means that there was a significant improvement on the prediction accuracy rate when the individual grouping was applied. This is as expected because the cluster analysis groups travelers of similar personal characteristics. As a result, it is appropriate to use the same coefficient for the individuals in the same group. However, higher deviation may occur in the prediction model without grouping because the same coefficient was used for all the travelers.

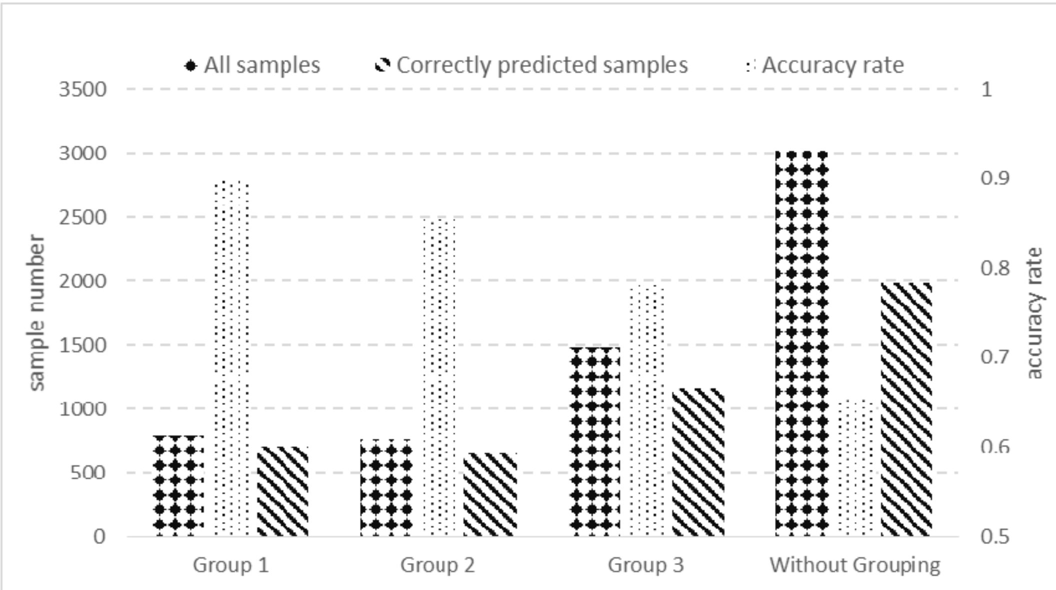


Fig. 2. The prediction results of the three groups and the whole sample without group.

5.Summaries and Conclusions

The paper proposed a prediction model to estimate travel mode choice with individual grouping based on cluster analysis. It is a discrete choice model to estimate the mode choice of individual travelers. Two travel mode options were investigated: the transit and car. A revealed preference (RP) and stated preference (SP) survey were conducted in Nanjing City of China to collect travelers' social-economic information and travel information. The social-economic information was used to classify all the travelers into three groups based on the cluster analysis. The variables in the utility function were from the travel information in the RP/SP survey, including travel time, walking time, fare, etc. The coefficients in the utility functions were obtained through the regression based on the SP/RP survey information. Finally the estimation of the travel mode choice was presented and compared with the survey data. The results showed that the accuracy rates of the estimation of the three groups were 89.8%, 85.6% and 78.2%, respectively. They are remarkably higher than that without grouping, which was 65.5%. This indicates that the individual grouping based on cluster analysis benefits the mode choice estimation.

There are two main contributions of this study. Firstly, the paper shows that it is possible to estimate travelers' mode choice with individual grouping based on the RP/SP data. This estimation strategy involves an easy collection of representative data using SP and RP survey. The results showed that the cluster analysis method is an effective mathematical method to divide individuals into groups. Secondly, by using an approach where individuals are grouped using cluster analysis, individuals' travel behavior estimation can be visibly improved. The advantage of the model with grouping compared to that without grouping is that, it takes full account of the travelers' characteristics. This is important in analyzing travelers' behavior using discrete choice model. The proposed model can also be potentially adopted by the managers to analyze residents' travel behavior and to make necessary strategies. In the future studies, the authors will take account more travel mode choices, personal attributes, and other contributing factors in the model.

References

[1] Anas, A., 1983. Discrete choice theory, information theory and the multinomial logit and gravity models. Transportation Research Part B: Methodological, 17(1), 13-23.
[2] Ben-Akiva, M. and Lerman S. R., 1999. Discrete Choice Analysis: The Theory and Application to Travel Demand. Doctor, MIT.
[3] Walker, J. L., 2001. Extended Discrete Choice Models: Integrated Framework, Flexible Error Structure, and Latent Variables. Doctor, MIT.
[4] Train, K. and McFadden, D., 1976. An Application of Diagnostic Tests for the Independence from Irrelevant Alternatives. Transportation Research Record: Journal of the Transportation Research Board, 637, 39-46.
[5] Train, K. and McFadden D., 1978. The Goods/leisure Tradeoff and Disaggregate Work Trip Mode Choice Models. Transportation Research, 12, 349-353.
[6] Dehghani, Y. and T. A, 1980. Model specification, modal aggregation, and market segmentation in mode-choice models: some empirical evidence. Transportation Research Record: Journal of the Transportation Research Board, 775, 28-34.
[7] Bordagaray, M., d. olio, L., Ibeas, A. and Cecín, P., 2014. Modelling user perception of bus transit quality considering user and service heterogeneity. Transportmetrica A: Transport Science, 10(8), 705–721.
[8] Boisvert, D., 1998. Switching to public transport. Australasian Transport Research Forum, 22(2), 649–666.
[9] Mao, B. H., 2003. Models and application in transportation planning. Beijing, China Railway Press.
[10] Dowling, R. a. A. G., 1997. Women and transport: from transport disadvantage to mobility through the motor vehicle. Australasian Transport Research Forum, 21(1), 337–355.
[11] Romsa, G. and Blenman, M., 1989. Visitor patterns of elderly Germans. Annals of Tourism Research, 16(2), 178-188.
[12] Allan, A., 1999. Making cycling a realistic and practical alternative to the car for urban trips. Australasian Transport Research Forum, 23(2), 805–822.
[13] Morris, J., Wang, F. and Lilja L., 2001. School childrens travel patterns. Transport Engineering in Australia, 7(1), 15–25.
[14] Kattiyapornpong, U. and Miller, K. E., 2009. Socio-demographic constraints to travel behavior. International Journal of Culture, Tourism and Hospitality Research, 3(3), 246 - 258.
[15] Nicolau, J. L. and Más F. J., 2005. Stochastic modeling. A three-stage tourist choice process. Annals ofTourism Research, 32(1), 49–69.
[16] Ben-Akiva, M. and Bowman, J. L., 2001. Activity-based Disaggregate Travel Demand Model System with Activity Schedules[J]. . Transportation Research A, 35(1), l-28.
[17] Syam, A., 2012. Peoples' travel behavior in a multicultural society. Australasian Transport Research Forum, Western Australia.
[18] Samdahl, D. M. and Jekubovich, N. J., 1997. A critique of leisure constraints: comparative analyses and understandings. Journal of Leisure Research, 29(4), 430-452.
[19] Wang, Y., 2014. Modeling traveler mode choice behavior of a new high-speed rail corridor in China. Transportation Planning and Technology, 37(5), 466-483.
[20] Krizek, K. J., 2004. Gender differences in bicycling behavior and facility preferences. Research on women's issues in Transportation. Chicago, Transportation research board of the national academies, 31-40.
[21] Abolfazl, 2004. Gender differences in automobile choice behavior. Research on women's issues in Transportation. Chicago, Transportation research board of the national acadmied. 18-20, 4-8.
[22] Collins, D. and Tisdell, C., 2002. Gender and Differences in Travel Life Cycles. Journal of Travel Research, 41, 133–143.
[23] Cutler, S. and Coward, R., 1992. A vailabily of personal transportation in households of elders: age, gender, and residence differences. The Gerontolist, 32, 77-81.
[24] Ahem, A. and Hine J., 2012. Rural transport-Valuing the mobility of older people. Research in transportation economics, 34, 27-34.
[25] Tsamboulas, D. A., 2001. Parking fare thresholds: a policy tool. Transport Policy, 8(2), 115–124.

[26] Administration, F. T., 2014. Characteristics of Premium Transit Services that Affect Choice of Mode. WASHINGTON, D.C.
[27] Jain, A. K., Murty, M. N. and Flynn, P. J., 1999. Data clustering: A review. ACM Computing Surveys, 31(3), 264-323.
[28] Everitt, B. S., Landau, S. and Leese. M., 2001. Cluster Analysis (4th edition). London, Arnold Press.
[29] Bierbaum, T. J., Case, M. A. and Weston, P. A., 2000. Behavior Recorded: softward to record and analyze behavioral data using SAS and systat statistical softward. Computers and Electronics in Agriculture, 29(3), 233-241.
[30] E.Train, K., 2003. Discrete Choice Methods with Simulation. Cambridge, Cambridge University Press.
[31] Cascetta, E., 2009. Transportation Systems Analysis: Models and Applications (Springer Optimization and Its Applications), Springer.
[32] Hensher, D. A. and Rose, J. M., 2007. Development of commuter and non-commuter mode choice models for the assessment of new public transport infrastructure projects: a case study. Transportation Research Part A, 41, 428-443.