Application of random regret minimization model to route choice considering driving comfort and travel time

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We aim to explore travelers' route choice behavior in the context of driving comfort and route travel time. The driving comfort can be estimated from physiological signal such as heart rate. And route travel time can be collected by GPS trip records. The research framework includes three steps. First, we collect the heart rate during driving from a real-world driving experiment. The driving operation is recorded by CAN data when the test driver faces various traffic events. The driving comfort model related to the heart rate can be developed according to the driving operation such acceleration and braking. Then the heat map of network-wide driving comfort can be obtained for route choice analysis. Second, we generate the route choice set using an experiential road network because local commuters usually choose a route from a limited route set rather than a full route set. We propose to generate k-shortest paths using an experiential road network incorporating link usage frequency. Third, the random regret minimization (RRM) model is applied to estimate the route choice preference. Different from the random utility maximization (RUM) model, RRM model is built on the psychological notion that travelers are regret minimizers selecting the route that makes them less regretful of not having chosen an alternative route. To investigate the impact of individual heterogeneity and journey attributes on route choice preference, we group the OD pairs by gender, age, departure time, and OD Euclidean distance, and then estimate the route choice models respectively.

Key Words : *Route choice preference, choice set generation, driving comfort, travel time, GPS data*

1. Introduction

Route choice modeling is one of the crucial issues in urban transportation system, which plays a core role in both traffic assignment and network simulation. The route choice is a reflection of potential preferences for each available route and we usually assume that traveler chooses the best route by maximizing their utility. There are often multiple routes between an origin-destination (OD) pair. The utility of each route depends on route attributes and individual heterogeneity[1-3]. Generally, the route choice probability can be estimated based on random utility maximization (RUM) theory[4]. And many studies have explored the effect of route attributes such as travel time, distance and cost on the route choice behavior by using discrete choice model based on RUM theory[5]. With the development of regret theory, the interest in random regret minimization (RRM) as an alternative paradigm to RUM has grown in recent years[6, 7]. The discrete choice paradigm of RRM has been applied to various choice contexts such as travel mode, parking route choice, automobile fuel choice ,vehicle type, shopping destination, etc. [6-8]. In contrast with RUM, the criterion of RRM aims to obtain a solution minimizing a user's regret. It is plausible to describe the route choice behavior with the assumption that drivers are regret minimizer who might prefer the route with minimum regret compared with others, rather than choose the route with maximum utility[9)].

However, only limited studies have applied RRM to route choice analysis and comparison between RRM and RUM[10)]. Furthermore, few studies based on RRM theory incorporated the individual heterogeneity due to the difficulty in data collection, though it is widely accepted that individuals have varying tastes for specific attributes. In this study, we aim to model travelers' route choice behavior in the context of average travel time and driving comfort based on RRM. There are two contributions in contrast with previous research. First, we incorporate the individual heterogeneity to the Path-size RRM model, in which the OD pair specific heterogeneity, personal specific heterogeneity, and time specific heterogeneity are considered. Second, the driving comfort represented by heart rate is explicitly incorporated into the route attributes. Previous studies usually regarded driving comfort as an unobserved attribute since it was not easy to capture, even though it should be regarded as an important factor to route choice. We try to fill this gap by modeling the driving comfort that related to driving environment and driving operation in the data collection process.

2. Methodology

In this section, we start with the introduction of the classical RRM model and Path-size RRM model. Next, we formulate the RRM based route choice model that allows for the representation of observed heterogeneity.

(1) The classical RRM model

The concept of anticipated regret is an important determinant of choice behaviour. Regret is what one experiences when a non-chosen alternative performs better than the chosen one, and regret-based choice theories[11)] and models are developed on the notion that individuals aim to minimize their perceived regret when making choices. Following the regret theory, random regret minimization (RRM) models [6, 7, 10)] postulate that decision makers try to minimize their regret when choosing alternatives. The level of perceived regret is associated with the considered alternative i. The regret of alternative i is described by the sum of binary regrets where alternative i is compared to other alternatives on each attribute in the personal choice set. This attribute-level regret can be formulated as follows.

$$R_{i\to j}^{m} = ln\left(1 + exp\left(\beta_m\left(x_{j,m} - x_{i,m}\right)\right)\right) \quad (1)$$

where

$R_{i\to j}^{m}$: the random regret associated with the considered alternative i that is compared to alternative j on attribute m.

β_m: the estimated parameter associated with attribute x_m.

$x_{i,m}, x_{j,m}$: the values associated with attribute x_m for, respectively, the considered alternative i and another alternative j.

This formulation implies that regret is close to zero when alternative j performs worse than i in terms of attribute m, and that it grows as an approximately linear function $\beta_m\left(x_{j,m} - x_{i,m}\right)$ of the difference in attribute values in the case when i performs worse than j in terms of attribute m. Hence, the RRM based model postulates that when a decision maker considers alternative i as compared to alternative j he or she experiences almost no regret with regard to attribute m when the attribute m of alternative i performs considerably better[12, 13)].

The overall regret is conceived to be the sum of all binary regrets associated with the binary comparisons between a considered alternative i and its competitor alternatives j for all attributes m.

$$R_i = \sum_{j\neq i}\sum_m ln\left\{1 + exp\left[\beta_m\left(x_{j,m} - x_{i,m}\right)\right]\right\} \quad (2)$$

where

R_i: the observed regret associated with alternative i.

Similar to the RUM based framework, the functional form of the choice probabilities changes as different assumptions on the random error term ε_i are imposed. When the negative of the errors is assumed to be I.I.D. Type I Extreme Value, the choice probability can be derived using a classical MNL-form formulated as follows.

$$P_{n,i} = \frac{exp(-R_i)}{\sum_{j\in C_n} exp(-R_i)} \quad (3)$$

where

$P_{n,i}$: the probability of selecting route i for individual n;

C_n: the choice set for individual n.

(2) The Path-size RRM

Because of the partial overlap of alternative routes in a route choice situation, the classical RRM model is not appropriate for route choice analysis. Prato (2014) expanded the paradigm of classical RRM in the route choice context considering similarities across alternatives[9)]. Three approaches are proposed: (1) adding utility-based corrections; (2) adding a regret-based term that compares the degree of similarity of a route with other alternatives; (3) adding a regret-based term that adjusts for the correlation of each route with any other alternatives. Empirical studies showed that the second and the third approaches performed slightly better than the first approach. Therefore, we follow the second approach to overcome the overlapping problem because of its simple formulation. In the second approach, a path size correction term[14] is added to the regret function, which expresses the pairwise comparison of the degree of independence of alternatives. The Path-size RRM (PS-RRM) can be formulated as follows.

$$P_{n,i} = \frac{exp\left(-\sum_{j\neq i}\sum_m ln\left(1+exp\left(\beta_m(x_{j,m}-x_{i,m})\right)\right)-\sum_{j\neq i} ln\left(1+exp\left(\beta_{ps}(PS_j-PS_i)\right)\right)\right)}{\sum_{j\in C_n} exp\left(-\sum_{k\neq j}\sum_m ln\left(1+exp\left(\beta_m(x_{k,m}-x_{i,m})\right)\right)-\sum_{k\neq j} ln\left(1+exp\left(\beta_{ps}(PS_k-PS_j)\right)\right)\right)} \quad (4)$$

$$PS_i = \sum_{a\in\Gamma_i} \frac{L_a}{L_i}\frac{1}{M_{a,C_n}} \quad (5)$$

where

Γ_i: the set of links in route i;

β_{ps}: the estimated parameter associated with path size;

L_a: the length of link a;

L_i: the length of route i;

M_{a,C_n}: the number of paths in C_n using link a;

Intuitively, the expected sign of the parameter β_{ps} is positive to indicate that the regret for the considered route decreases if this route is more independent than the alternative ones, and increases when this route is less distinct than the alternative ones.

(3) The PS-RRM with heterogeneity

Individual's responsiveness or taste to route attributes affects her or his route choice for a trip. This responsiveness will, in general, vary across individuals based on individual characteristics. The regret an individual associates with a chosen route can be viewed as comprising two components from the perspective of an analyst. The first component can be viewed as the intrinsic bias of the individual toward the route due to individual heterogeneity (e.g., age, gender, trip purpose, departure time). The second component can be viewed as the regret that the individual derived from perceived or observed attributes of route (e.g., travel time, distance, the number of signalized intersection, cost, and driving comfort). Therefore, we should obtain individual heterogeneity for the regret evaluation on route attributes.

In the PS-RRM model, we assumed that individuals are homogeneous and tastes β_m are fixed coefficients. To incorporate individual heterogeneity, as applied by Bhat (2000) [15] and Li et al. (2016) [3] in RUM based models, β_m are assumed to have a linear relationship between individual characteristics and route attribute coefficients. Therefore, β_m in the PS-RRM model can be reformulated as follows.

$$\beta_{n,m} = \sum_p \alpha_p y_{n,m,p} + \gamma_m \quad (6)$$

where

$y_{n,m,p}$: the observed variable p that related to individual n's tastes on route attribute m;

α_p: the estimated parameter associated with heterogeneity;

γ_m: the estimated parameter associated with the constant term on route attribute m.

For route choice analysis, the individual heterogeneity can be divided to three categories: personal-specific (e.g. age and gender), OD pair specific (e.g. OD distance) and time specific (e.g. peak/off peak hours and day of week). We discuss the effect of heterogeneity on route attributes in section 4.

3. Data

The GPS and OBD data used in this study was collected from private vehicles. In recent years, benefiting from the popularity of vehicle navigation system, GPS data has become an important resource and has been used in route choice analysis and route-finding problems [16-18]. The data is collected from 150 private cars in Toyota city, Japan in 2011 as a part of the Green Mobility project supported by Toyota Motor Corporation. On-board equipment (e.g., OBD device) installed in their private cars recorded the GPS trajectory as well as the driving behaviour such as brake and acceleration operation second by second. The data are uploaded to the internet server by the participants every week. In this study, the GPS data can be used for travel time estimation and the driving behaviour data recorded by OBD can be used for driving comfort estimation.

(1) Road network

A road network with 4072 nodes and 12,877 links in Toyota city, Japan, is used to analyse the route choice behaviour. This is a dense network. It covers an area of about 320 km^2.

(2) Observations

The 150 drivers who made trips every day in the period March to December of 2011 are selected as the subjects for this study. Because the data set is large-scale, we only select 4312 OD pairs in March for this empirical analysis. As shown in Fig. 1, the OD pairs with only one trip account for 69.29% of the total trips, while the OD pairs with 2-3 trips, 4-5 trips, 6-10 trips and 11 above trips only account for 14.49%, 5.59%, 2.94%, 7.70%, respectively. For the OD pairs with large number of trips (e.g., more than 10 trips), it is possible to extract the experienced routes to generate the choice set from the trip record if the driver used more than one routes. However, it is difficult to obtain the route choice set for most of the OD pairs with sparse trips. To fill this gap, it is necessary to generate the route choice set for each OD pair.

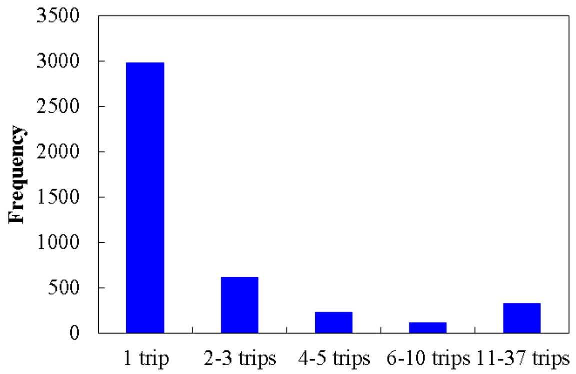

Fig. 1 The distribution of the number of trip for each OD pair

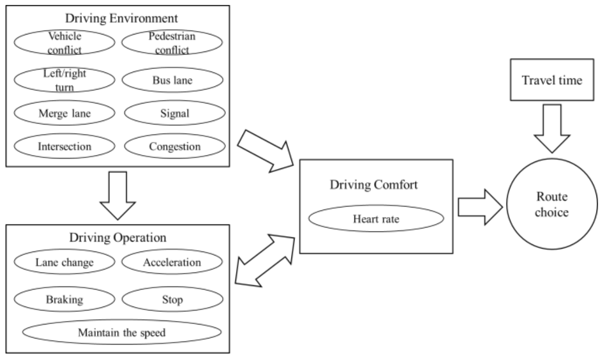

Fig. 2 Influence factors related to driving comfort and route choice

Fig. 3 A ring route for driving comfort modeling

Because the travel time and driving comfort are considered in our route choice model, we need to estimate the route travel time and quantify the driving comfort for each candidate route. The average route travel time can be obtained by using GPS data after map-matching process[19], and the driving comfort is quantified by heart rate increase which is estimated by easy-to-measured variables such as driving condition and driving operation collected by GPS and OBD.

(3) Driving comfort estimation

Travel time, distance, cost, value of time, the number of signalized intersection were usually regarded as the important route attributes in route choice analysis. However, driving comfort has not been explicitly considered due to the difficulty in data collection, although it is an important influence factor when drivers choose the best routes. Some drivers may wish only to minimize travel time. Others may feel uncomfortable making difficult maneuvers, and therefore avoid lane changes, freeways, heavily-congested roads or left turns (right turn traffic) at intersections without protected signals[20]. Elder drivers might be more insensitive to travel time and distance, given the comfort and better driving conditions that they enjoy. Some studies have shown that driving comfort or stress can be indicated by physiological signals such as heart rate, respiration, muscle activity, and skin conductance[21, 22, 18]. As shown in Fig. 2, drivers adjust their operation to accommodate the change of driving environment. And the driving environment and operation will cause the change of driving comfort; meanwhile the driving comfort also reacts on the driving operation. Heterogeneous drivers are assumed to choose the best routes based on their feeling of driving comfort and travel time in the past driving experience. In this study, we use heart rate increase as an indicator for driver comfort because it is convenient to collect by portable device such as Polar monitor[23, 24]. Driving comfort can be quantified by the heart rate increase compared with the heart rate in calm down situation. Large heart rate increase usually indicates nervous and stressful mental state when the driver needs to deal with complex situation. As shown in Fig. 3, the link-based driving comfort was detected in a ring route[18]. Totally 21 variables related to driving environment and driving operation, such as speed, acceleration, brake, vehicle confliction, pedestrian confliction, lane change, are collected for driving comfort analysis. Our previous study[18] has applied machine learning approach such as Random Forest to estimate the driving comfort and found that the top four easy-to-measured variables, i.e., average link speed, standard deviation of link speed, average brake frequency and average acceleration frequency, make a contribution of 72% to the driving comfort. Therefore, it is possible to estimate the link-based driving comfort based on these four variables. One of the significant advantages is that these four variables can be easily collected by the in-vehicle devices such as OBD and GPS. Since these four variables can represent most of the traffic condition and driver operation, it is not necessary to install the camera and physiological devices to capture the traffic condition and driving comfort in a large-scale data collection procedure. Following our previous study, we apply the machine learning approach to estimate the link-based driving comfort in the whole network. And the route-based driving comfort can be represented by the sum of the link-based driving comfort

Algorithm 1. Route choice set generation

Step 1: Initialization
Set S_n= “empty” for all OD pairs n;
Set $K_n = 1$;
Find the least travel time route P_{n,K_n} for all OD pairs with A-star algorithm;
Compute the route travel time T_{n,K_n};
Save P_{n,K_n} to S_n;
Step 2: Iteration
For each OD pair n, set iteration number $m = 0$;
  Step 2.1: Link weight penalty
  For each link on a path in S_n, their weights were penalized by w_i, where
  $w_i = \alpha^m W_i$ with $0 < \alpha < 1$, and W_i is the original weight of link i;
  $K_n := K_n + 1$;
  $m := m + 1$;
  Step 2.2: Find the candidate paths
  Calculate the shortest path P_{n,K_n} based on $\alpha^m W_i + W_i$;
  Step 2.3: Path checking
  Compute the path travel time T_{n,K_n} based on the sum of W_i in the path P_{n,K_n}
  If $T_{n,K_n} < 1.5T_{n,1}$ and $P_{n,K_n} \notin S_n$
    Save P_{n,K_n} to S_n;
  Else
    $K_n := K_n - 1$
  Step 2.4: Termination
  If $K_n < N$, where N is the upper number of candidate path
    Go to **Step 2.1;**
  Else
      Add the observed path into S_n
    End;

after calculating the average link speed, standard deviation of link speed, average brake frequency and average acceleration frequency for each link.

(4) Route choice set generation

Since the road network used in this study is a relatively large-scale network, the population of available routes for an OD pair (the universal set) is very large and mostly not known. The identification of distinct relevant route alternatives in such a network is not straightforward and requires model-based approaches such as repeated shortest path search[25)]. Some studies used the Monte Carlo simulation for searching the shortest path with distance as criterion where link distances were repeatedly randomized using a normal distribution[3, 26, 27)]. However, a driver would not recognize the difference among the similar routes with highly partial overlap. Generally, the universal route set will not be known by the driver due to the large number of potential paths and his or her limited cognitive abilities. The driver cognition is usually associated with his or her travel experiences

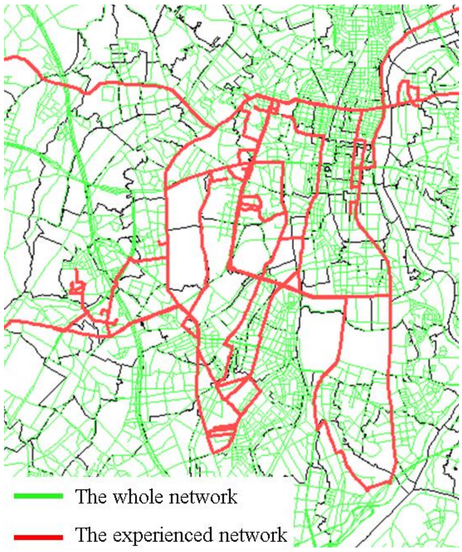

Fig. 4 The whole network and personally experienced network

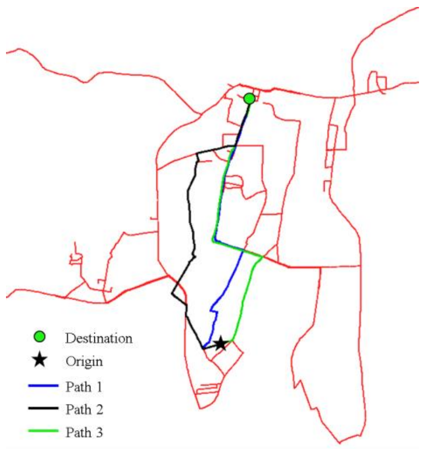

Fig. 5 The route choice set based on personally experienced network

in this network and his or her manner of acquiring information. Therefore, we propose to generate the route choice set on the experienced road network but not on the whole network. As shown in Fig. 4, we extract the links that the driver experienced in the past one month to build the individual network for generating the route choice set. This procedure can greatly reduce the number of possible routes and guarantee that all the routes in the experienced network can be cognized by the driver. Then, the route choice set is generated by using a link penalty method which is similar to Chen et al. (2007) [28)]. As shown in Algorithm 1, we first generate the shortest route based on the average travel time, then the selected links are given a penalized weight and the next shortest route based on the penalty network will be generated. We iteratively penalty the selected links and generate k routes until the travel time of the last route exceed 1.5 times of the first shortest route. Finally, we add the observed route into the choice set if the observed route is not included. Fig. 5 gives an example of the individual route choice set.

4. Empirical results

(1) Model specification

Two route attributes, average travel time and driving comfort are included into the regret function. Travel time and distance are two highly similar and correlated attributes, so only one of them would be sufficient to the regret function. The cost is not considered because almost all of the roads are free in the urban road network. Since driving comfort should be highly correlated with the number of intersections, signal control and road grade, these variables are not considered. To illustrate the performance of the PS-RRM model with heterogeneity (PS-RRMH), three other models, i.e., Path-size logit (PSL), Path-size logit with heterogeneity (PSLH), and PS-RRM, are also estimated in this analysis. A summary of the different structures is shown in Table 1. The systematic part of the regret with observed heterogeneity in Eq. (6) is given as:

$$\beta_{n,m} = \alpha_1 DayOfWeek_{n,m} + \alpha_2 DepartureTime_{n,m} + \alpha_3 Young_{n,m} + \alpha_4 Old_{n,m} + \alpha_5 Gender_{n,m} + \alpha_6 Ln(OD\_distance) + \gamma_m \quad (7)$$

The PSL model is given as follows.

$$P_{n,i} = \frac{exp\left(\sum_m \beta_m x_{i,m} + \beta_{ps}\ln(PS_i)\right)}{\sum_{j\in C_n} exp\left(\sum_m \beta_m x_{j,m} + \beta_{ps}\ln(PS_j)\right)} \quad (8)$$

Accordingly, the PSLH model is given as follows.

$$P_{n,i} = \frac{exp\left(\sum_m \beta'_{n,m} x_{i,m} + \beta_{ps}\ln(PS_i)\right)}{\sum_{j\in C_n} exp\left(\sum_m \beta'_{n,m} x_{j,m} + \beta_{ps}\ln(PS_j)\right)} \quad (9)$$

where $\beta'_{n,m} = \beta_{n,m}$.

(1) Estimation result

The estimation results and goodness of fit of the four models are shown in Table 1. The Constant_T, Constant_C and Constant_P are fixed parts of the tastes on route attributes. The Constant_C and Constant_P have a negative sign as expected. However, Constant_T has a positive sign, which would be expected to have a negative sign because longer travel time should reduce the utility or increase the regret. To further explain the unusual estimation result, we estimate two PS-RRM models by considering travel time and driving comfort separately. As shown in Table 2, all of the parameters have expected signs. Interestingly, it is found that the likelihood of PS-RRM only considering driving comfort and path size is greatly better than the likelihood of PS-RRM only considering travel time and path size. That means the effect of driving comfort is much stronger than the effect of travel time on the model fitness. Therefore, we guess the unexpected sign of Constant_T is caused by the dominated effect of driving comfort.

Then, we look at the performance of the four models. As expected, the PSLH model and PS-RRMH model are better than their original form without considering the observed heterogeneity. The PS-RRMH model is better than the PSLH model, which confirms our assumption that drivers are more likely to choose routes by minimizing their anticipated regret instead of maximizing their utility.

The OD pair specific heterogeneity is reflected by the logarithm of OD distance. The negative sign and t-statistic suggest that OD distance will affect the taste for average travel time and driving comfort significantly. Drivers are more sensitive to average travel time and driving comfort when they need to drive longer distances. It is reasonable because drivers usually need to make a travel time schedule for a long distance trip on one hand and they prefer to comfortable driving that prevents fatigue on the other hand.

The personal specific heterogeneity is represented by age and gender. All of these variables are significant. It is found that young drivers (age<=35) are less sensitive to travel time and driving comfort; while elder drivers (age>60) are less sensitive to travel time but they are more sensitive to driving comfort. It also indicates that the middle age drivers are more sensitive to travel time than the young and elder drivers, while they are less sensitive to driving comfort than elder drivers.

The time specific heterogeneity is represented by departure time (depart at peak/off-peak hours) and day of week (weekend/weekday). The negative sign of departure time indicates that drivers are more sensitive to travel time and driving comfort at peak hours, because the travel time may be unstable and the congestion and frequent traffic conflict may cause uncomfortable driving at peak hours. It is also found that people are more sensitive to travel time when they depart at weekend, while they are less sensitive to driving comfort.

The positive sign and t-statistic for the path size indicates that the regret will reduce and the utility will increase if the route has less overlap than the alternative ones.

5. Conclusion and future work

This study developed a route choice model based on RRM approach. In contrast to RUM approach, RRM enables to minimize the anticipated regret of not having chosen another route when making choices. Comparing with RUM based models, RRM based models show better fitness, which indicates the assumption that drivers choosing the best route by minimizing their anticipated regret are more appropriate, even though the assumption of maximizing the user utility is still reasonable.

The first contribution of this study is the application of PS-RRM model that explicitly captures the heterogeneity which includes the OD pair specific heterogeneity, personal specific heterogeneity, and time specific heterogeneity. Second, the driving comfort represented by heart rate increase is explicitly incorporated into the route attributes. Previous studies usually regarded driving comfort as an unobserved attribute, even though it should be regarded as an important factor to route choice. We estimate the driving comfort by using four easy-to-measured variables which can be captured by OBD and GPS. The estimation results confirm that the incorporation of observed heterogeneities such as OD distance, age, gender, departure time and day of week enables to improve the performance of the RRM and RUM based models. The t-statistic indicates that the observed heterogeneities have significant effects on taste of travel time and driving comfort. For example, drivers are more sensitive to average travel time and driving comfort when they need to drive longer distances. The middle age drivers are more sensitive to travel time than the young and elder drivers, while elder drivers show more sensitive to driving comfort

Table 1 Estimation results of four models

Parameter	PSL		PSLH		PS-RRM		PS-RRMH	
	Est	t-stat	Est	t-stat	Est	t-stat	Est	t-stat
Average travel time								
Constant_T	0.0081	25.55	0.0067	3.44	0.0014	30.25	0.0096	2.49
Day of week (1, weekend; 0, weekday)			-0.000027	-2.04			-0.00052	-5.60
Departure time (1, peak hour; 0, off-peak hour)			-0.0024	-3.71			-0.00040	-4.59
Young (1, age<=35; 0, age>35)			0.00020	2.02			0.00042	2.99
Old (1, age<=60; 0, age>60)			0.0027	2.70			0.00033	2.00
Gender (1, male; 0, female)			-0.00167	-2.07			-0.0011	-3.7
Logarithm of OD distance			-0.00127	-2.13			-0.0018	-2.05
Driving comfort								
Constant_C	-0.26	-39.51	-0.17	-3.27	-0.075	-41.73	-0.33	-16.85
Day of week (1, weekend; 0, weekday)			0.056	4.08			0.051	15.92
Departure time (1, peak hour; 0, off-peak hour)			0.040	3.03			0.011	3.80
Young (1, age<=35; 0, age>35)			0.0025	2.14			0.018	3.37
Old (1, age<=60; 0, age>60)			-0.0027	-2.12			-0.037	-4.32
Gender (1, male; 0, female)			0.037	2.26			0.060	4.69
Logarithm of OD distance			-0.046	-7.42			-0.046	-10.65
Path size								
Constant_P	14.74	20.50	14.85	15.24	1.57	21.29	1.11	16.89
Sample size	4312							
Null LL	-8482.39							
Final LL	-2956.31		-2908.55		-2868.46		-2759.13	
Rho_sq	0.651		0.657		0.662		0.675	

Table 2 Effects of travel time and driving comfort on model fitness

Path Attributes	PS-RRM (with driving comfort and path size)		PS-RRM (with travel time and path size)	
	Est	t-stat	Est	t-stat
Travel time	--	--	-0.00047	-21.33
Driving comfort	-0.057	-41.11	--	--
Path size	2.10	28.98	1.75	31.19
Sample size	4312			
Null LL	-8482.39			
Final LL	-3461.08		-7578.29	
Rho_sq	0.592		0.107	

than young and middle age drivers. The time specific heterogeneity shows that drivers are more sensitive to both travel time and driving comfort at peak hours and weekend, while they are more sensitive to travel time but less sensitive to driving comfort.

In further research, the GPS and OBD data might be combined with questionnaire data so as to take into account for a greater number of behaviour terms such as activity schedule and travel time budget. Further, in this study, the unobserved heterogeneity is not incorporated so as not to make the model too complicated. However, a mixed RRM based model should be formulated to capture the random effects of the unobserved heterogeneity.

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