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Modeling commuters' route choice behavior under pre-trip information system

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Abstract: Research about the auto commuter's pre-trip route choice behavior ignores the combined influence of the real-time information and all respondents' historical information in the existing documents. To overcome this shortcoming, an approach to describing the pre-trip route choice behavior with the incorporation of the real-time and historical information is proposed. Two types of real-time information are investigated, which are quantitative information and prescriptive information. By using the bounded rationality theory, the influence of historical information on the real-time information reference process is examined first. Estimation results show that the historical information has a significant influence on the quantitative information reference process, but not on the prescriptive information reference process. Then the route choice behavior is modeled. A comparison is also made among three route choice models, one of which does not incorporate the real-time information reference process, while the others do. Estimation results show that the route choice behavior is better described with the consideration of the reference process of both quantitative and prescriptive information.

Key words: route choice; pre-trip real-time information; bounded rationality theory; logit model

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Traffic congestion during the commuting time of early morning and late evening accounts for the overwhelming proportion of urban traffic congestion. Therefore, it is necessary to examine the influence of pre-trip information on the route choice behavior. The pre-trip information includes historical real-time information, while the historical information often refers to the respondent's historical travel information or all commuters' historical travel information. Many studies have shown the roles of these two types of historical information.

With respect to the route choice models, micro-simulation experiments have been applied in the historical information case. Jha et al. [1] implemented a nested logit model into a simulation system. Yasunori et al. [2] carried out two experiments to examine the relationship between the historical travel information and the route switching behavior. Mahmassani et al. [3] compared the influences of two types of historical information on the route choice behavior. They also found that despite the provision of historical information every day, the congestion period and location still change with time[4]. Ozbay et al. [5] applied the stochastic learning automata (SLA) theory to a road network simulation experiment.

Dynamic process methods have been employed to describe the route choice behavior in the real-time information situation. Mahmassani et al. [6] proposed a multinomial probit model to describe the day-to-day route choice behavior with an implement of the satisfying theory. Dia et al. [7-8] incorporated the Neugent behavioral model and the multinomial logit model respectively into an agent-based simulation system. Hato et al. [9] established a multinomial logit model with an implement of information acquisition and reference process. Khattak et al. [10-11] used a multinomial logit model to examine the factors that affect commuters' travel pattern choices.

Based on the literature review, it can be seen that the existing studies primarily focus the pre-trip information on the respondent's historical information and the real-time information. In this paper, the relationship between all respondents' historical travel information and the real-time information is explored. Besides, many studies have shown that not all commuters accept information. This phenomenon, in this paper, is represented by including the information reference process into the route choice model.

1 Model Development

For the real-time information reference model, the bounded rationality notion is applied based on the assumption that the commuter will refer to the real-time information if the divergence between the traffic situation provided by the real-time information and that provided by the historical information exceeds some threshold value. The entire process can be expressed as

$$y_r^i = \begin{cases} 1 & \text{if } \left| R_{S,r}^{i,\mathrm{R}} - H_{S,r}^{i,\mathrm{H}} \right| > \Delta^{i,r} \\ 0 & \text{otherwise} \end{cases} \tag{1}$$

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where y_r^i is a binary variable which is equal to 1 if the real-time information is referred to, and 0, otherwise; $R_{S,r}^{i,\mathrm{R}}$ is the traffic situation on route S provided by the r-th type of real-time information to commuter i; $H_{S,r}^{i,\mathrm{H}}$ is the traffic situation on route S provided by the historical information to commuter i; $\Delta^{i,r}$ is the threshold value of the r-th type of the real-time information reference for commuter i.

Threshold values are different among commuters, which can be expressed by a utility function determined by the respondent' socio-economic characteristic X^i, normal travel pattern T^i, attitude towards pre-trip information I^i, and variables comparing historical and real-time information D^i. The mathematical formulation for the threshold value is shown as

$$\Delta^{i,r} = f(X^i, T^i, I^i, D^i, \beta) + \xi_{i,r} \tag{2}$$

where $f(\cdot)$ is the systematic threshold which can be a linear function of X^i, T^i, I^i and D^i; β is a parameter to be estimated; $\xi_{i,r}$ is the error component which is assumed to be independently Gumbel distributed.

Then the probability of referring to the real-time information can be expressed by the binary logit model as

$$P(y_r^i = 1) = \frac{\exp\{\,|R_{S,r}^{i,\mathrm{R}} - H_S^{i,\mathrm{H}}, r| - f(X^i, T^i, I^i, D^i, \beta)\}}{1 + \exp\{\,|R_{S,r}^{i,\mathrm{R}} - H_{S,r}^{i,\mathrm{H}}| - f(X^i, T^i, I^i, D^i, \beta)\}} \tag{3}$$

For the route choice model, the multinomial logit model is used and it is expressed as

$$P_{m,r} = \frac{\exp(V_{m,r})}{\sum_{j \in J_r} \exp(V_{j,r})} \tag{4}$$

where $P_{m,r}$ is the probability of choosing the m-th route in response to the r-th type of real-time information; $V_{m,r}$ is the systematic component of the utility function.

Similar to the research of Hato[9], this paper incorporates the real-time information reference result into the route choice utility function, which is shown as

$$V_{m,r} = P(y_r = 1)\lambda_r R_{S,r}^{i,\mathrm{R}} + \alpha_{m,r} Z_{m,r} \tag{5}$$

where $Z_{m,r}$ are the other variables for route m when the r-th type of real-time information is provided; λ_r and $\alpha_{m,r}$ are the parameters to be estimated.

2 Case Study

Data used in this discussion is extracted from a stated preference (SP) behavioral survey carried out in November 2010. A total of 673 auto commuters in Nanjing city, China were randomly selected to finish the face-to-face investigation. Two typical sites in Nanjing city, Yuhuatai and Gulou, were selected as the trip start point and trip end point, respectively. The respondent was told that three routes were under his/her consideration, represented by route 1 (Longpan Road) which is an urban expressway, route 2 (Zhongshan Road) and route 3 (Huju Road), which are two urban arterial roads. Routes 2 and 3 are across the Central Business District (CBD) of Nanjing, while route 1 is not. The respondent was also told that route 1 was his/her usual route to work and on average it takes 20 min to reach the destination.

2.1 Model specification

Based on the variables of the real-time information reference model, Eqs. (2) and (3) can be specified by Eqs. (6) and (7), respectively.

$$\Delta^{i,r} = C + \beta_G G + \beta_D D + \beta_I I + \beta_A A + \beta_T T + \beta_S S + \xi_{i,r} \tag{6}$$

$$P(y_r^i = 1) = \frac{\exp\{\,|R_{S,r}^{i,\mathrm{R}} - H_{S,r}^{i,\mathrm{H}}| - (C + \beta_G G + \beta_D D + \beta_I I + \beta_A A + \beta_T T + \beta_S S)\}}{1 + \exp\{\,|R_{S,r}^{i,\mathrm{R}} - H_{S,r}^{i,\mathrm{H}}| - (C + \beta_G G + \beta_D D + \beta_I I + \beta_A A + \beta_T T + \beta_S S)\}} \tag{7}$$

where C is the constant; G is the commuters' age; D is the commuters' driving age (year); I is the commuters' annual income after tax (yuan); A is the frequency of receiving travel information before commuting during the last week; T is the commuters' decision on whether receiving travel information before the trip or not; S is the binary variable, which is equal to 1 if the traffic situation provided by the real-time information is worse than that provided by the historical information, and 0, otherwise.

Based on the variables of the route choice model, Eq. (5) can be specified by

$$\begin{aligned} V_{m,\mathrm{q}} &= P(y_\mathrm{q} = 1)\lambda_\mathrm{q} C_\mathrm{q} + \alpha_{U,\mathrm{q}} U + \alpha_{B,\mathrm{q}} B + \alpha_{R,m,\mathrm{q}} R \\ V_{m,\mathrm{p}} &= P(y_\mathrm{p} = 1)\lambda_{r,\mathrm{p}} C_\mathrm{r} + P(y_\mathrm{p} = 1)\lambda_{t,\mathrm{p}} C_\mathrm{t} + \\ &\quad \alpha_{U,\mathrm{p}} U + \alpha_{B,\mathrm{p}} B + \alpha_{R,m,\mathrm{p}} R \end{aligned} \tag{8}$$

where $V_{m,\mathrm{q}}$, $V_{m,\mathrm{p}}$ are the systematic components of the route choice utility function for the quantitative information and the prescriptive information, respectively; C_q is the current travel time on three routes provided by the quantitative information; C_r is the binary variable, which is equal to 1 if the route is the suggested alternative by the prescriptive information, and 0 otherwise; C_t is traffic conditions on the three routes provided by the prescriptive information; U is the binary variable, which is equal to 1 if the route is the usual route to work, and 0 otherwise; B is the binary variable, which is equal to 1 if the route passes through the central business district, and 0 otherwise; R is the commuters' attitudes towards this sentence: switching routes according to pre-trip travel information.

2.2 Estimation results for real-time information reference model

The real-time information reference model is estimated by STATA and the result is shown in Tab. 1. As shown in this table, the influence of historical information on the real-time information reference is significant in the case of quantitative information, which can be indicated from the positive and significant parameter value of $|R_{S,r}^{i,\mathrm{R}} - H_{S,r}^{i,\mathrm{H}}|$. It can be inferred from the estimation result that the larger the divergence between the travel time provided by the quantitative information and the travel time provided by the historical information, the bigger the chance commuters get to refer to the real-time information. Commuters will not consider the real-time information if the travel time provided by the quantitative information is almost the same as that provided by the historical information.

Tab. 1 Estimation results for quantitative and prescriptive information reference model

Variable	Parameter	Quantitative information	Prescriptive information
C	1	2.42(2.99)	1.31(1.83)
G	β_G	−0.03(−1.64)	−0.01(−0.64)
D	β_D	0.05(1.90)	0.05(2.13*)
I	β_I	−0.01(−1.90)	−0.01(−1.45)
A	β_A	−0.15(−2.85**)	−0.11(−2.05*)
T	β_T	−0.71(−5.16**)	−0.85(−6.39**)
S	β_S	−3.11(−2.43*)	−0.85(−1.67)
$\lvert R_{S,r}^{i,\mathrm{R}} - H_{S,r}^{i,\mathrm{H}}\rvert$	$\beta_{\lvert R_{S,r}^{i,\mathrm{R}} - H_{S,r}^{i,\mathrm{H}}\rvert}$	0.37(2.33*)	−0.45(−1.52)

Notes: * significant at 5% level; ** significant at 1% level.

For the threshold portion, A, T and S show significant statistical values. The negative parameter values of A and T infer that commuters will refer to the quantitative information even when there is little travel time variation between the quantitative information and the historical information, if they receive the pre-trip travel information many times in the most recent week or believe that the real-time information should be received before commuting. S shows a negative parameter value, which indicates that the reference threshold is much smaller when the travel time provided by the real-time information is longer than that provided by the historical information. Commuters are more sensitive to the worse real-time information.

Compared with the quantitative information, the influence of the historical information on the prescriptive information is not significant. The reason may be that the prescriptive information suggests that commuters take the best route, and commuters do not need to take a lot of time to compare the traffic situations provided by the real-time information and the historical information. The information reference threshold value seems to have little association with the personal information expect for driving years. The reason may be that with the driver license for a longer time, commuters can judge the traffic situation by their rich experience in driving rather than the information.

The reference probability estimation results for both quantitative and prescriptive information are shown in Fig. 1. It can be seen from the results that the reference probabilities for both types of information are high. The reason may be that ATIS has not been widely used by the auto owners in China, and they will be very interested in the new technology if it is available for them.

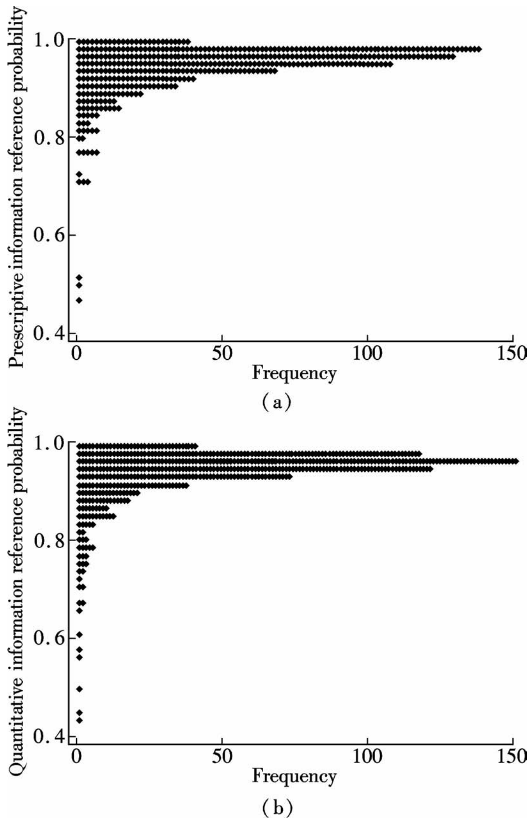

Fig. 1 Estimation results. (a) Quantitative information reference probability; (b) Prescriptive information reference probability

2.3 Estimation results for route choice model

Tab. 2 and Tab. 3 show the estimation results of the route choice model incorporating quantitative information and prescriptive information reference results, respectively. Similar to Hato et al. [9], this subsection presents the comparison of three types of models, which are model 1, assuming that all the commuters refer to the real-time information by replacing $P(y_r = 1)$ in Eq. (5) into 1, model 2, considering the actual information reference choice by replacing $P(y_r = 1)$ in Eq. (5) into 1 or 0, and model 3 which is based on Eq. (8).

In the case of the quantitative information, C_q shows a highly significant z-statistics for the three models and its parameter value is negative which means that commuters are more likely to choose the route if it can take them less time on the route. For the prescriptive information, C_r shows positive parameter values for the three models and its statistical value is much higher than that of C_t. The potential reason is that with the traffic situation information, commuters have to compare the traffic situations on each route before making the route choice decision, while they do not have to do this when the suggested best route

Tab. 2 Estimation results of route choice models for quantitative information

Variable	Parameter	Model 1 ($P=1$)	Model 2 ($P=1/0$)	Model 3 ($P=p$)
C_q	λ_q	−0.28(−2.14*)	−0.15(−5.59**)	−0.46(−3.49**)
U	$\alpha_{U,q}$	4.44(2.28*)	2.89(3.29**)	5.53(3.98**)
B	$\alpha_{B,q}$	/	−0.72(−1.08)	0.62(0.70)
R	$\alpha_{R,2,q}$	0.58(2.66**)	0.58(2.61**)	0.49(2.22*)
	$\alpha_{R,3,q}$	0.61(3.53**)	0.61(3.38**)	0.49(2.73**)
Log-lik intercept only		−705.309	−705.309	−705.309
Log-lik full model		−465.085	−451.164	−458.941
LR		480.448(4)	508.289(5)	492.735(5)
Prob > LR		0.000	0.000	0.000
McFadden's R^2		0.341	0.360	0.349
BIC′		−454.590	−475.966	−460.412

Note: * significant at 5% level; ** significant at 1% level; "/" stands for variables omitted by STATA.

Tab. 3 Estimation results of route choice models for prescriptive information

Variable	Parameter	Model 1 ($P=1$)	Model 2 ($P=1/0$)	Model 3 ($P=p$)
C_r	$\lambda_{r,p}$	0.23(0.27)	1.46(2.78**)	4.59(2.08*)
C_t	$\lambda_{t,p}$	0.40(0.51)	−0.72(−1.74)	2.40(1.04)
U	$\alpha_{U,p}$	/	−1.93(−2.43*)	1.21(0.61)
B	$\alpha_{B,p}$	/	−1.24(−1.87)	−2.74(−2.04*)
R	$\alpha_{R,2,p}$	0.68(3.63**)	0.49(2.46*)	0.65(3.38**)
	$\alpha_{R,3,p}$	0.32(1.51)	0.24(1.09)	0.39(1.76)
Log-lik intercept only		−705.309	−705.309	−705.309
Log-lik full model		−460.898	−439.943	−458.380
LR		488.822(4)	530.732(6)	493.858(6)
Prob > LR		0.000	0.000	0.000
McFadden's R^2		0.347	0.376	0.350
BIC′		−462.964	−491.944	−455.070

Notes: * significant at 5% level; ** significant at 1% level; "/" stands for variables omitted by STATA.

choice information is provided.

Among other variables, U shows a positive parameter value and high statistics for all three models in the quantitative information case. In the prescriptive information case, however, U shows a significant statistical value and a negative parameter value for model 2. Different parameter values suggest that commuters' habits have a considerably positive contribution to the route choice behavior when the quantitative information is provided but a negative contribution to the route choice behavior when the prescriptive information is provided.

Based on the absolute value of BIC′, the overall fit of a model is measured and based on the absolute difference value of BIC′, the comparison of two models can be measured. In the quantitative information case, it can be concluded from the absolute value of BIC′ that model 2 is the best, and model 3 is much better than model 1. The absolute difference value of BIC′ between model 1 and model 3 is 5.822, providing positive support for model 3, while the absolute difference of BIC′ between model 2 and model 3 is 15.554, providing very strong support for model 2. In the prescriptive information case, it can be concluded from the absolute value of BIC′ that model 2 is the best, and model 1 is much better than model 3. The absolute difference of BIC′ between model 1 and model 3 is 7.893, providing strong support for model 1, while the absolute difference of BIC′ between model 1 and model 2 is 28.981, providing very strong support for model 2.

3 Conclusion

This paper presents the influence of historical information on the quantitative and prescriptive information reference behavior, based on which, the route choice behavior is then respectively described for two real-time information cases. The most distinguishing point for this paper is the combination of the real-time information and all respondents' historical travel information. Two foremost conclusions are summarized here. On the one hand, it can be concluded from the route choice estimation results that the route choice behavior is better described by encompassing a real-time information reference framework. On the other hand, it can be deduced from the real-time information reference estimation results that historical information has substantial influences on the quantitative information reference behavior, but not on the prescriptive information reference behavior. For the feasibility of the investigation, the survey about the route choice behaviors in response to the historical and the real-time information is conducted at the same time. This, however, should be a feedback survey. The future work should also focus on the interactive effects of historical information and real-time information.

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出行前信息提供条件下驾驶员路径选择行为建模

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摘要:已有的出行前信息提供条件下的通勤驾驶员路径选择行为通常忽略实时信息和所有出行者历史出行信息之间的相互影响, 针对这一缺点,提出实时信息和历史信息共同作用下的出行前路径选择行为. 通过利用有限理性理论,首先研究了历史信息对定量型和描述型 2 种实时信息的影响,结果发现历史信息对定量型实时信息的参考过程有重要影响,但对描述型信息的影响很小. 在此基础上,基于考虑和不考虑实时信息的参考过程建立了 3 种路径选择模型,预测结果显示,在定量型和描述型信息 2 种情况下,考虑实时信息参考过程的路径选择模型能更好地描述驾驶员路径选择行为.

关键词:路径选择;出行前实时信息;有限理性理论;logit 模型

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