Binary Probit Model on Drivers Route Choice Behaviors Based on Multiple Factors Analysis

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Abstract This study explores many details of the drivers response to dynamic travel information with variable message signs (VMS) which is the one of the most common advanced traveler information systems (ATIS) deployed in many areas all over the world. A stated preference (SP) survey was conducted to collect various drivers route choice behavior with VMS. Based on the surveys, seventeen potential affecting factors such as city kind, region, gender, age, marital status, degree, job, whether full-time worker, monthly income, crowded level on the current route, vehicle queue length of the current route, delay ratio of the current route, knowledge of an alternate route, length ratio of an alternate route, crowded level on an alternate route, anticipated travel time saving ratio and quality of dynamic travel information were identified and applied to further study. A binary probit model was adopted to evaluate the significance of these seventeen factors. Gender, age, whether full-time worker, delay ratio of the current route, knowledge of an alternate route, length ratio of an alternate route, and crowded level on an alternate route were proved to be significant variables. Then a model for estimating drivers route choice results was build based on the significant variables. The verification results showed that the model estimating precision could reached 76 %.

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1 Introduction

During the last years, traffic congestion has become one of the most common phrases in the daily news. Traffic congestion is a phenomenon caused when a facility is asked to bear a travel demand that is greater than its capacity. This has been caused, in part, by our rapid economic growth. With our rapid economic growth, we have come to expect more mobility in our modem life.

To mitigate this traffic congestion and improve the efficiency of travel in urban areas, various types of advanced traveler information systems (ATIS) have been studied and implemented during the past several decades. ATIS is a major component of intelligent transportation systems (ITS) that include a wide range of new tools for managing traffic as well as for providing services for travelers. Given the continued increase in travel and the difficulties of building new and expanded roads in urban areas, ATIS is essential to maximize the utilization of existing facilities.

One common ATIS that has been deployed is variable message signs (VMS). They are installed along roadsides and display messages of special events that can affect traffic flow such as football games. VMS usually deliver various types of information such as expected delay, cause of incident, lane closure, etc., which can help drivers make smart decisions regarding their trip. It is expected that by providing real-time information on special events happening on the oncoming road, VMS can improve the drivers route choice, reduce the drivers stress, mitigate the severity and duration of incidents and improve the performance of the transportation network.

Unlike other ITS components such as ramp closure, which is part of the advanced traffic management system (ATMS), VMS are not supported by mandatory regulation. That is, the impact of implemented VMS on the transportation network depends to a large degree on the response of drivers. Therefore, it is very important to find and understand those factors that can affect drivers route choice behaviors with ATIS. Many past studies were widely applied to the collection of data and the results were analyzed using statistical methods. However, those individual findings are rarely aggregated to explain drivers route choice behaviors in an effective and efficient manner and there has been no extensive evaluation of those findings [5].

Many researchers, in their attempts to analyze the driver behavior data, have adopted logistic regression models [1–4, 6–8] that is based on regression function and utility models that usually assume the effects of attributes of an alternative are compensatory, which means that increase or decrease of one attribute in a model can be compensated by certain proportional increases or decreases of other variables. However, potential affecting factors were considered too small to reflect the drivers route choice behaviors well.

This study explores many details of the drivers response to VMS. A SP survey was conducted in China to collect various drivers behavior information with VMS. Based on the findings from the surveys, as much as possible potential affecting factors for drivers route choice behaviors with ATIS are identified and applied to further study. A probit model is adopted to evaluate the significance of these factors, and then the primary explanatory factors are adopted to develop the driver compliance model.

2 Stated Preference Survey

The scope of research is usually limited by the availability of data. This study aims to understand the structure of driver compliance with VMS on the urban network. However, driver response associated with VMS is difficult to observe and collect in the field. Thus this study has adopted stated preference (SP) methods involving extensive user surveys. The SP method is a very effective tool to investigate the drivers behavior characteristics under a variety of controlled scenarios. To understand the general drivers response to VMS and to find significant variables that affect the drivers compliance, an online survey was conducted.

Based on the recent enhancement of the internet, online surveys are now generally established as one of the tools for behavior studies. Use of the internet for surveys can improve the reliability of collected data by allowing the researcher to provide more detailed and realistic descriptions to respondents, which allows them to provide answers closer to their behavior under real circumstances. Moreover, it can largely eliminate coding errors and take adaptive designs where the options offered can be modified as a result of the responses to previous answers. However, users of this method should be careful to control the sample population.

The survey was sent to a random sampling of drivers in China based on their travel experiences with a sample size of 1000. A 22-question driver survey questionnaire (see Appendix) was developed in June 2011 to collect the following information: (1) Demographic characteristics of drivers; (2) Perceptions of dynamic travel information; (3) Driver behaviors under dynamic travel information with VMS. Seventeen potential affecting factors are identified as following: city kind (x_1), region (x_2), gender (x_3), age (x_4), marital status (x_5), degree (x_6), job (x_7), whether full-time worker (x_8), monthly income (x_9), crowded level on the current route (x_{10}), vehicle queue length of the current route (x_{11}), delay ratio of the current route (x_{12}), knowledge of an alternate route (x_{13}), length ratio of an alternate route (x_{14}), crowded level on an alternate route (x_{15}), anticipated travel time saving ratio (x_{16}) and quality of dynamic travel information (x_{17}). 540 completed survey forms were returned and used for analysis. Among 490 valid surveys, more than 50 percent of the respondents are somewhat familiar with VMS. The respondents demographic characteristics which present the applicability of research conclusions in this paper are shown in Table 1.

Table 1 Demographic characteristic of survey respondents

Numbers	Characteristics	Options	Percentages (%)
1	Region	Northeast	55.7
		North China	20.6
		East China	11.4
		Central South	4.5
		Northwest	3.3
		Southwest	4.5
2	City kind	Village	5.1
		County	6.7
		Common city	46.9
		Provincial capital	26.3
		Municipality	15.0
3	Gender	Female	36.9
		Male	63.1
4	Age	Less than 20	4.1
		20–29	51.6
		30–39	27.3
		40–49	11.2
		50–59	4.5
		Greater than 60	1.3
5	Marital status	No	44.9
		Yes	55.1
6	Degree	Elementary school	12.0
		Middle school	12.7
		University	52.6
		Master or Doctor	22.7
7	Job	Student	16.9
		Company staffer	31.4
		Civil servant	6.8
		Teacher or Doctor	11.2
		Freelancer	10.4
		Other	23.3
8	Whether Full-time Worker	No	23.1
		Yes	76.9
9	Monthly income (Yuan)	Less than 2000	18.4
		2000–4000	40.6
		4000–8000	26.9
		Greater than 8000	14.1

3 Potential Affecting Factors Analyzing

Binary responses occur in many fields of study. Probit model analysis has been used to investigate the relationship between these discrete responses and a set of explanatory variables. The response, y, of an individual or an experimental unit can take on one of two possible values such as Comply ($y = 1$) or Not Comply ($y = 0$). Suppose x is a vector of explanatory variables and is the response probability to be modeled. The probit model has the form:

$$p(y|x) = f(x) \tag{1}$$

If the following formula is established,

$$f(x) = \Phi(\beta_0 + \beta_1 x_1 + \beta_2 x_2 + \cdots + \beta_{\mathrm{m}} x_m) \tag{2}$$

Then,

$$p(y|x) = \Phi(\beta_0 + \beta_1 x_1 + \beta_2 x_2 + \cdots + \beta_{\mathrm{m}} x_m) \tag{3}$$

where $x_i (i = 1, \ldots, m)$ are the arguments, $\beta_i (i = 1, \ldots, m)$ are the correlation coefficients, β_0 are the constant terms and $\Phi(\cdot)$ is standard normal distribution function.

Total 490 responses were collected and used to develop a probit model. The result based on complete 17 variables is summarized in Table 2. This shows that x_3 (Wald = 4.951), x_4 (Wald = 5.726), x_8 (Wald = 3.262), x_{12} (Wald = 3.968), x_{13} (Wald = 7.306), x_{14} (Wald = 9.284) and x_{15} (Wald = 18.318) have wald-values are significantly greater than the others indicating that the parameters have the greater impacts on driver behavior than others. It is further proved from the result of the probit analysis shown in Table 3 that the driver behaviors under dynamic travel information with VMS depend greatly on their x_3 (Gender), x_4 (age), x_8 (whether full-time worker) and the traffic factors, including x_{12} (delay ratio of the current route), x_{13} (knowledge of an alternate route), x_{14} (length ratio of an alternate route) and x_{15} (crowded level on an alternate route).

4 Probit Model for Driver Compliance

The prediction rates of binary probit model between complete explanatory variables and primary explanatory variables are compared to validate the necessity of potential affecting factors analyzing. To compare the result from the models with the other 100 random samples which were collected by the online survey, it is assumed that if p greater than 0.5, a driver would comply with the given dynamic travel information with VMS. Table 4 shows the aggregated error rates for the binary probit model with complete 17 explanatory variables. Table 5 shows the aggregated error rates for the binary probit model with 7 primary explanatory variables.

Table 2 Probit analysis for driver behavior with complete explanatory variables

Variables	B	S.E.	Wald
x_1	–0.044	0.076	0.339
x_2	–0.043	0.053	0.656
x_3	0.315	0.141	4.951
x_4	–0.205	0.086	5.726
x_5	0.028	0.177	0.024
x_6	–0.066	0.094	0.484
x_7	–0.003	0.045	0.005
x_8	0.318	0.176	3.262
x_9	0.005	0.083	0.003
x_{10}	–0.043	0.084	0.259
x_{11}	0.023	0.050	0.310
x_{12}	0.124	0.062	3.968
x_{13}	0.224	0.083	7.306
x_{14}	–0.181	0.059	9.284
x_{15}	–0.285	0.067	18.318
x_{16}	0.013	0.053	0.065
x_{17}	0.014	0.069	0.042

Table 3 Probit analysis for driver behavior with complete explanatory variables

Variables	Transition variables	B	S.E.	Wald
x_3	X_1	0.328	0.138	5.622
x_4	X_2	–0.186	0.068	7.629
x_8	X_3	0.300	0.156	3.686
x_{12}	X_4	0.124	0.047	6.854
x_{13}	X_5	0.219	0.081	7.285
x_{14}	X_6	–0.166	0.058	8.335
x_{15}	X_7	–0.276	0.059	21.893

Table 4 Classification matrix for probit model with complete variables

		Predicted		
		Y = 0	Y = 1	Percentage errors (%)
Observed	Y = 0	7	16	31.0
	Y = 1	15	62	

Table 5 Classification Matrix for probit model with primary variables

		Predicted		
		Y = 0	Y = 1	Percentage errors (%)
Observed	Y = 0	9	14	24.0
	Y = 1	10	67	

5 Conclusion

Based on the many findings from the SP surveys, seventeen factors are identified that potentially affect drivers route choice behaviors with ATIS. With extensive SP approach, the study revealed many details of driver behavior with VMS. Based on online survey, those factors are evaluated and analyzed. To analyze the impact on driver behavior with VMS, a probit model is adopted. The binary probit model identifies seven significant variables, which are Gender, age, whether full-time worker, delay ratio of the current route, knowledge of an alternate route, length ratio of an alternate route and crowded level on an alternate route. Then the primary variables are used to analyze driver compliance. It showed great flexibility in analyzing the data and identifying the structure of the given data set. It clearly presents the structure of driver compliance behavior while maintaining a reasonable prediction rate of around 76 %. The study has analyzed driver compliance through behavior potential affecting factors analyzing which provides more understanding of driver compliance behavior mechanism while maintaining reasonable estimation accuracy.

The study has found the conditional structure of driver compliance with VMS which means non-homogeneous driver would use different factors to make a route choice decision. This finding can be applied to develop implemental operation strategies for ATIS applications including VMS.

The significant variables that affect driver compliance under the provision of travel information are based on the SP study. However, the study collected 490 samples to analyze and construct the models but considering the complicated structures of driver compliance, extensive research with a larger sample size may disclose many answers more clearly. Especially follow-up survey with non-respondent group will be essential to ensure many findings from this research. To enhance the driver behavior study with VMS, ongoing efforts should be made to find more effective uses of available technologies in SP surveys, including the use of interactive and dynamic surveys based on the computer and the internet. This will help in the development of more reliable and cost-effective methods for behavior data collection.

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