MODELING DRIVERS' DIVERSION FROM NORMAL ROUTE, LINK CHOICE AND COMPLIANCE UNDER ATIS USING GENERALIZED ESTIMATING EQUATIONS

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Abstract

The objectives of this paper are to model the effect of providing different types and levels of ATIS on; (1) Drivers' diversion from habitual route while information is provided, (2) Drivers' compliance with a pre-trip advised route, and (3) Driver's compliance with en-route short-term traffic information. A travel simulator was used as a dynamic data collection tool. The simulator uses realistic network, real historical volumes, and different weather conditions. It provides five different types and levels of traffic information/advice, one at a time, and collects dynamic pre-trip and en-route route choices. The Generalized Extreme Equations (GEE) technique was used to account for correlation between repeated choices made by the same subject. The modeling results showed that travel time and familiarity with the device that provides the information had significant effects in the three models. Expressway users are shown as the most travel-time savers who would divert if they are guided to less-travel-time alternative. Number of traffic signals on the normal route and advised route affect diversion from the normal route and compliance with pre-trip advised routes. The paper presents a detailed assessment of ATIS on travel decisions.

Keywords: ATIS; Advised route; Normal route; Link choice; Repeated observations; GEE
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1. Introduction

Advanced Traveler Information Systems (ATIS) have gained wide acceptance among researchers and practitioners as a promising technology for improving traffic performance. In order to evaluate the benefits of ATIS, drivers' accessing and benefiting from traffic information/advice provided must be fully understood. The objective of this paper is to understand the effect of providing different types and levels of traffic information/advice to travelers on different route choice paradigms; (1) modeling drivers' diversion from normal route, (2) modeling drivers' compliance with pre-trip advised route, and (3) modeling driver's compliance with en-route short-term (link) traffic information choice.

The simulator OTESP (Abdel-Aty and Abdalla, 2002) was used to collect dynamic route choices under ATIS. OTESP is an interactive windows-based computer simulation tool. It simulates commute home-to-work morning trips. A realistic 25-node and 40-link urban network from Orlando was used. The network has a fixed origin-destination pair and comprises different types of highways. It includes two toll expressways, 6-lane and 4-lane principle arterials, 4-lane and 2-lane minor arterials, and local collectors. OTESP's code was fed with real historical traffic volumes. OTESP provides different levels of traffic information to the subjects in five different scenarios (levels of information) including: no information (scenario #1), pre-trip information without and with advice (scenarios #2 and #3, respectively), and en-route information (in addition to the pre-trip information) without and with advice (scenarios #4 and #5, respectively). During the actual experiment, OTESP presents ten simulated days (two days for each scenario). The first 5 trial days of each subject are run under scenarios #1 to 5, respectively, and named “first-trial-days”. Similarly, the last 5 trial days are run under scenarios #1 to 5, respectively, and named “last-trial-days”. There is no difference in the travel time computations across the scenarios. The differences between the five scenarios are only in the level of the information/advice provided to subjects and whether they are pre-trip or en-route. OTESP also provides three different weather conditions (clear sky, light rain, and heavy rain). The simulator accounts for delays caused by intersections, recurring congestion, non-recurring congestion (incident), queuing at toll plazas, and weather condition effects. The Moore’s shortest path algorithm (Pallottino et al., 1998) has been employed in the code of OTESP to determine the travel-time-based shortest path, which is introduced as advice to the subjects in scenarios 3 and 5. A four-table database is created to capture all the information/advice provided and the traveler decisions. For detailed design and description of the simulator, the reader is referred to Abdel-Aty and Abdalla (2002).

In OTESP, which provides animation capabilities, the subject has the ability to move his/her vehicle on different segments of the network using the computer’s mouse. When approaching any node (intersection), the subject is required to make a decision on selecting the following link. At the beginning of each trial day, the subject is provided with the current travel-time for the two bus routes and that of the shortest-path on the network in case of driving. OTESP is unique in its ability to collect dynamic data for different route choice paradigms. First, before starting the actual experiment, OTESP presents a Normal-Route form in which the subject is required to provide his/her normal link-by-link route on a morning-week-day trip from the origin (assumed home) to the destination (assumed work) in normal conditions and with no information provided. This can be used to model drivers’ diversion from normal routes. Second, scenarios 3 and 5 of OTESP present an advised route from the origin to the destination, based on a shortest path algorithm. This can be used to model drivers’ compliance with an advised pre-trip route. Finally, scenarios 4 and 5 of OTESP provide en-route short-term (link) information which dynamically changes every time the subject reaches an intersection, the link information is provided in a quantitative and qualitative forms. This can be used to model drivers’ compliance with en-route short-term traffic information.

The statistical problem of repeated observations arose in this study because each subject made multiple choices. These choices are correlated. This correlation must be taken into account. Otherwise, the model would underestimate the standard errors of the modeling effects (Stokes et al., 2000). In this paper the correlation between repeated choices was taken care of by using the Generalized Extreme Equations with binary probit link function.

2. Background

2.1. Benefits of ATIS

A considerable number of studies have examined the potential benefits of providing pre-trip and en-route real-time information to travelers. Researchers are interested in the effects of ATIS on all types of travel decisions. ATIS is empirically shown to result in reducing travel time, congestion delays, and incident clearance time (Wunderlich, 1996; Abdel-Aty et al., 1997; Sengupta and Hongola, 1998). There is empirical evidence supporting the hypothesis that travelers alter their behavior in response to ATIS (Bonsall et al., 1991; Zhao et al. 1996; Mahmassani and Hu, 1997; Vaughn et al., 1995). Reiss et al. (1991) have reported travel time savings ranged from 3% to 30% and reduction in incident and congestion delays of up to 80% for impacted vehicles. However, other studies argued that providing information might not necessarily reduce congestion (Arnott et al., 1990).

2.2. Route choice and switching under ATIS

Pre-trip and en-route route switching is a direct response to ATIS. Network conditions, travel time, travel time variability, delays associated with congestion and incidents, and traveler attributes are significant determinants of route choice (Spyridakis et al., 1991; Adler et al., 1993; Mannering et al., 1994; Abdel-Aty et al., 1995a, b, 1997). Some studies proved that information provision induces greater switching in route choice behavior (Mahmassani et al., 1990; Conquest et al., 1993; Abdel-Aty et al., 1994a). For example, Conquest et al. (1993) reported that 75% of commuters change either departure time or route in response to information. Liu and Mahmassani (1998) concluded that travelers were more likely to change route when their current choice would cause them to arrive late. They also concluded that drivers exhibited some inertia in route choice, requiring travel time savings of at least one minute on the alternative route.

2.3. Drivers' familiarity with the network and diversion from habitual route

Polydoropoulou et al. (1996) and Khattak et al. (1996) concluded that drivers exhibit some inertia for using their habitual route, especially for home-to-work trips. Polydoropoulou et al. (1996) found that drivers are more likely to divert to another route when they first learn of a delay before the trip. Drivers are less likely to divert during bad weather, as alternative routes might be equally slow. Prescriptive information greatly increases travelers' diversion probabilities, although similar diversion rates are attainable by providing real-time quantitative or predictive information about travel times on usual and alternative routes. The authors suggested that drivers would prefer to receive travel time information and make their own decisions. Abdel-Aty et al. (1994b) showed that ATIS has a great potential in influencing commuters' route choice even when advising a route different from the usual one.

It is also shown that traffic information should be provided with alternative route information as well. Streff and Wallace (1993) reported differences in information requirements between commuting, non-commuting trips, and trips in an unfamiliar area. Khattak et al. (1996) found that travelers who are unfamiliar with alternative routes are particularly unwilling to divert. This conforms with the study of Kim and Vandebona (2002), which concluded that drivers who are familiar with alternative routes have a high propensity to change their pre-selected routes. However, accurate quantitative information might be able to overcome this behavioral inertia. Further, the commuters were generally willing to comply with advice from a prescriptive ATIS (Khattak et al., 1996; Lotan, 1997). Adler and McNally (1994) found that travelers who are familiar with the network are less likely to consult information. Bonsall et al. (1991) found that user acceptance declined with decreasing quality of advice in an unfamiliar network. As familiarity with the network increased, drivers were less likely to accept advice from the system. However, Allen et al. (1991) found that familiarity does not affect route choice behavior.

2.4. Travelers' characteristics and ATIS

Recognizing the nature of ATIS information in dynamic environments, some analysts argued that trip choice decisions are based not only on objective information supplied by ATIS, but also on subjective information as perceived by travelers (Ben Akiva et al., 1991; Zhao et al., 1996). For example, Mehndiratta et al. (2000) proved that interest in travel information is a function of complex travel behavior, demographics, attitudinal characteristics, and technology interest related factors. Khattak et al. (1993) concluded that commuters' diversion behavior varied with their personal characteristics and the characteristics of the trip they were making at the time when the choice arose. Mahmassani and Chen (1993) concluded that there is no clear measure of information effect on travelers that is independent of user choice behavior, prevailing traffic conditions, and network interactions. Conquest et al. (1993) noted that commuters provided with information from ATIS could be classified as route changers, route and time changers, non-changers, and pre-trip changers. Polak and Jones (1995) found that traffic information use depends on a range of personal, travel related and contextual factors.

These observations reinforced the need to model judgment processes of travelers under ATIS. Abdel-Aty et al. (1994a) mentioned that women tend to listen to pre-trip information, while more men receive en-route information. Freeway users who perceive heavy congestion on their route are more likely to receive pre-trip information. Only 15 percent of the commuters use more than one route to work; these people tend to have high income. The authors estimated a negative correlation between pre-trip information users and use of multiple routes. The correlation between en-route information users and use of multiple routes was insignificant. Pre-trip and en-route information usage have a positive influence on the number of route changes. Those who use pre-trip information are likely to make more route changes. Khattak et al. (1995) concluded that males or wealthier drivers are more likely to switch from the usual route if congested. Vaughn et al. (1995) found that male and less experienced drivers are more likely to agree with traffic advice. Viswanathan et al. (2000) showed that technology use influences travel decision-making in different ways for three analyzed stages of travel; before leaving home, en-route, and returning home. They concluded that the stated action taken by travelers is also influenced by personal and household factors. Viswanathan et al. (2000) used information technology use as predictors for traveler decision-making behavior but did not explore factors affecting information access and use. Some researchers indicated that drivers personal characteristics do not affect route choice process. For example, Abdel-Aty et al. (1997) found that gender was the only significant socioeconomic factor in the route choice process. Mahmassani et al. (2000) indicated that gender, age (greater than 40), level of education (with college degree) and high income (greater than $50,000) are not statistically significant in explaining route switching.

Based on the above review, it is clear that research directed at investigating decision processes underlying route choice paradigms is not sufficiently understood. The literature is in need to a study that provides most of the previously discussed factors in one analysis and collects different route choices from the same subjects. The analysis presented in this paper studies how routes choices are affected by travelers' socioeconomics, driving experience, driver's familiarity with pre-trip/en-route traffic information, the existence of five different levels of ATIS, different weather conditions, familiarity with the network, familiarity with the device that provides the information (the learning effect), number of traffic signals, the travel time, and routes characteristics.

Moreover, most related analyses, with few exceptions, ignored the correlation between repeated decisions made by the same traveler. It has been concluded also that there is a need for more efficient and statistically approved methodologies to handle this problem, which may bias the results. Gopinath (1995) demonstrated that different model forecasts result when heterogeneity of travelers is considered. Delvert (1997) argued that models of travel behavior in response to ATIS must address heterogeneity in behavior. If correlation is ignored by using a model that is too simple, the model would underestimate the standard errors of the modeling effects (Stokes et al., 2000). In this paper, GEE is used and different correlation structures are tried to account for correlation between repeated choices.

3. Methodology: Generalized estimating equations

Generalized Estimating Equations (GEEs) provide a practical method with reasonable statistical efficiency to analyze discrete and correlated data. GEEs were introduced by Liang and Zeger (1986) as an extension of the Generalized Linear Models (GLM), which are extension of traditional linear models (Nelder and Wedderburn, 1972). The GEE methodology models a known function of the marginal expectation of the dependent variable as a linear function of the explanatory variables. With GEE, the analyst describes the random component of the model for each marginal response with a common link and variance function, similar to what happens with a GLM model. However, Unlike GLMs, GEEs account for the covariance structure of the repeated measures. This covariance structure across repeated observations is managed as a nuisance parameter.

The GEE methodology provides consistent estimators of the regression coefficient and their variances under weak assumptions about the actual correlation among a subject's choices. The GEE method relies on the independence across subjects to consistently estimate the variance of the proposed estimators even when the assumed working correlation structure is incorrect. In GEEs, the analyst has to specify and feed the model with a correlation structure (in the form of a symmetric matrix) for every subject in estimating the covariance of the parameter estimates. For simplicity, one form for the correlation matrix is specified for all subjects. Different structures for the correlation matrix can be used. Liang and Zeger (1986), Zeger et al. (1988) and Liang et al. (1992) provide further details on the GEE methodology.

3.1. Modeling correlation in GEEs

Suppose a number of n_i choices are made by subject i, total number of subjects is K, and y_{ij} denotes the j^{th} response from subject i. There are $\sum_{i=1}^{K} n_i$ total choices (measurements). Let the vector of choices made by the i^{th} subject be $Y_i = (y_{i1},\ldots, y_{in_i})'$ and let V_i be an estimate of the covariance matrix of y_i. Let the vector of explanatory variables for the j^{th} choice on the i^{th} subject be $X_{ij} = (x_{ij1}. .. , x_{ijp})'$.

The GEEs for estimating the $(1 \times p)$, where p is the number of regression parameters, vector of regression parameters β is an extension of the independence estimating equation to correlated data and is given by

$$\sum_{i=1}^{K} \frac{\partial \mu_i^{'}}{\partial \beta} V_i^{-1} (Y_i - \mu_i(\beta)) = 0 \qquad (1)$$

Since $g(\mu_{ij}) = x_{ij'}\,\beta$, the p x n_i matrix of partial derivatives of the mean with respect to the regression parameters for the i^{th} subject is given by

$$\frac{\partial \mu_i'}{\partial \beta} = \begin{bmatrix} \frac{x_{i11}}{g'(\mu_{i1})} & \ldots\ldots & \frac{x_{in_i1}}{g'(\mu_{in_i})} \\ \vdots & & \vdots \\ \frac{x_{i1p}}{g'(\mu_{i1})} & \ldots\ldots & \frac{x_{in_ip}}{g'(\mu_{in_i})} \end{bmatrix} \tag{2}$$

Where:

g is the link function $g(\mu) = \Phi^{-1}(\mu)$. This function is the inverse of the cumulative standard normal distribution function, which is:

$$\Phi(x) = (2\pi)^{-\frac{1}{2}} \int_{-\infty}^{x} e^{-\frac{x^2}{2}}\, dx \tag{3}$$

3.2. Working correlation matrix

Let $R_i(\alpha)$ be an n_i x n_i "working" correlation matrix that is fully specified by the vector of parameters α (the correlation between any two choices). The (j, k) element of $R_i(\alpha)$ is the known, hypothesized, or estimated correlation between y_{ij} and y_{ik}. The covariance matrix of Y_i is modeled as

$$V_i = \phi A_i^{\frac{1}{2}} R(\alpha) A_i^{\frac{1}{2}} \tag{4}$$

Where:

A_i is an n_i x n_i diagonal matrix with $v(\mu_{ij})$ as the j^{th} diagonal element.

ϕ is a dispersion parameter and is estimated by

$$\hat{\phi} = \frac{1}{N-p} \sum_{i=1}^{K} \sum_{j=1}^{n_i} e_{ij}^2, \quad N = \sum_{i=1}^{K} n_i \tag{5}$$

R is the working correlation matrix. It is the same for all subjects, is not usually known and must be estimated. It is estimated in the iterative fitting process using the current value of the parameter matrix β to compute appropriate functions of the Pearson residual $e_{ij} = \frac{y_{ij} - \mu_{ij}}{\sqrt{v(\mu_{ij})}}$.

If $R_i(\alpha)$ is the true correlation matrix of Y_i, then V_i is the true covariance matrix of Y_i. If the working correlation is specified as $R=I$, which is the identity matrix, the GEE reduces to the independence estimating equation. Four different structures for the working correlation matrix are used:

1- Independent R, it assumes independence between the repeated choices within a subject

$$Corr(y_{ij}, y_{ik}) = \begin{cases} 1 & j = k \\ 0 & j \neq k \end{cases} \tag{6}$$

2- Exchangeable R, it makes constant the correlations between any two choices within a subject.

$$Corr(y_{ij}, y_{ik}) = \begin{cases} 1 & j = k \\ \alpha & j \neq k \end{cases} \quad Where, \ \widehat{\alpha} = \frac{1}{(N^{*} - p)\phi} \sum_{i=1}^{K} \sum_{j \neq k} e_{ij} e_{ik} \quad and \quad N^{*} = \sum_{i=1}^{K} n_i (n_i - 1) \qquad (7)$$

3- Auto-regressive *R (AR-1)*, it weighs the correlation within two choices by their separated distance (order of choice). As the distance increases the correlation decreases.

$$Corr(y_{ij}, y_{i,j+t}) = \alpha^{t}, \ t = 0,1,2,.....,n_i - j \quad Where, \ \widehat{\alpha} = \frac{1}{(M - p)\phi} \sum_{i=1}^{K} \sum_{j \leq n_i - 1} e_{ij} e_{ij+1} \quad and \quad M = \sum_{i=1}^{K} (n_i - 1) \qquad (8)$$

4- Unstructured *R*, it has $n_i(n_i - 1)/2$ parameters to be estimated. It assumes different correlation between any two choices within a subject.

$$Corr(y_{ij}, y_{ik}) = \begin{cases} 1 & j = k \\ \alpha_{jk} & j \neq k \end{cases} \quad Where, \ \widehat{\alpha}_{jk} = \frac{1}{(K - p)\phi} \sum_{i=1}^{K} e_{ij} e_{ik} \qquad (9)$$

It is worth mentioning that the criteria for assessing goodness of fit do not apply to the GEE (SAS/STAT, 2003). In this paper, comparing the expected vs. the actual results was used to compare the four correlation structures.

4. Subjects recruitment

Subjects were recruited based on an experiment to guarantee the inclusion of groups of drivers that represent different income (2 levels), age (3 levels), gender, level of familiarity with the network (2 levels), and level of education (2 levels). Subjects were instructed that their main task is to minimize the overall trip travel time by deciding when and when not to follow the information and/or advice provided. Subjects have been asked not to go through the simulation unless they had at least 30 minutes of spare time (the average simulation time was found to be 23.77 minutes) and were willing to concentrate and do their best in their choices. Moreover, during the simulation, the subjects' response time was measured without notifying them, to insure that they are serious. A total of 65 subjects had run the simulation, 10 trial days each. Two subjects out of the 65 have been excluded from this study because their response time were found outliers in the normal distribution plotting of subjects' response time (Z=3.21 and 3.78, Zcr = 2.57).

5. Long-term route choice analyses

A total of 630 trial days (trips) have been completed by the 63 qualified subjects. Out of these 630 trial days, 539 were in the drive mode and 91 were in the transit (bus) mode. This paper focuses only on the drive mode. The 539 chosen routes that were chosen in the drive mode were identified and categorized by the sequence of links that were traversed on a given trial day. Then, they were ranked and numbered by the frequency of use. These numbers were used as routes' IDs. Using the same way of identification, both the shortest-path/advised routes (calculated by the program in all 5 scenarios, and provided to the subjects in scenarios 3 and 5 as advice) and the subjects' normal routes (provided by subjects before they started the actual experiment) were handled. The results showed that there were 44 distinct routes that have been chosen during the 539 experimental trial days. The shortest-path/advised routes' classification showed that there were 11 distinct routes representing the 539 trips. Similarly, the results showed that there were 17 distinct routes representing the 63 subjects' normal routes. To compare between the chosen route and the normal route or the pre-trip advised route, a subject's chosen route is considered matching with his/her normal route if all subsequent origin-to-destination links of the two routes are identical. The same criterion applies to match a chosen route with a pre-trip shortest-path/advised route. It was noticed that there are correlations between the subjects' chosen and normal routes and between the chosen and the advised routes. This was expected because some drivers follow the advised routes while others have inertia towards their normal routes. In order to relate this correlation to the traffic information/advice availability and other effects, Model #1 and Model #2 were developed and discussed hereinafter.

6. Modeling diversion from habitual route (Model 1)

Data collected from the 539 trial days completed in the drive mode were used. The GEE was the statistical methodology used. The four correlation structures were also tried. The response variable was the subject's diversion from his/her normal route. This response variable is binary with the value of "1" if the subject has diverted and "0" otherwise. The analysis of this model did not distinguish between pre-trip and en-route diversion from normal route. Therefore, the diversion may happen before or while driving. Table 1 shows parameter estimates of the main effects and one interaction effect and comparisons between the four structures of the correlation matrix (independent, exchangeable, auto-regressive, unstructured). The maximum number of repeated observations for the same subject was found 10. Therefore, the correlation matrix is a 10*10 symmetric matrix with 1's as diagonal elements. The model correctly expected the response variable for 406, 407, 414, and 438 observations out of the 539, for the independent, exchangeable, auto-regressive, and unstructured, respectively. This means that the last three correlation structures were favored over the independent case (similar to the above model). Again, the unstructured correlation was also favored over the exchangeable and autoregressive structures (81.26% classification). The results (Table 1) showed that ten main effects and one two-level interaction term were significantly correlated with the dependent variable. The travel time of the normal route (positively) and that of the diverted route (negatively) are correlated with the likelihood of diversion from the normal route. High-educated drivers were less likely to divert from their normal routes. The model estimates also showed that drivers who usually use the expressway system are more likely to divert. This indicates that expressway users may divert from the expressway if they are guided to a temporarily less-travel-time surface-street alternative. Drivers were found more likely to divert in the last-trial-days when compared with the first-trial-days of the experiment. This shows a learning effect. The number of traffic lights in the normal route has a positive influence on diversion, which indicates that drivers try to minimize their stops and interruptions by diverting to other routes. Drivers were less likely to divert in scenario 1 where no information was provided. Drivers were more likely to divert in any scenario of the four scenarios with information/advice. This was concluded because the coefficient parameters of the four dummies representing scenarios 2 to 5 compared to the base scenario 1 were found positive. Moreover, adding advice to pre-trip and/or en-route advice-free information increases the diversion probability (compare coefficients 0.89 vs. 0.66 and 1.61 vs. 0.83). In addition, providing en-route information in addition to the pre-trip only information increases the diversion probability (compare coefficients 0.83 vs. 0.66 and 1.61 vs. 0.89).

Table 1. Diversion from Habitual Route Model

Parameter	Correlation Structure: Indep. coeff.	Indep. t-stat	Exch. coeff.	Exch. t-stat	Autoreg. coeff.	Autoreg. t-stat	Unstruc. coeff.	Unstruc. t-stat
Intercept	-2.714	-4.47	-2.612	-4.19	-2.549	-4.26	-2.236	-3.85
Education; 1 if graduate school or higher, 0 otherwise	-0.343	-1.89	-0.349	-1.90	-0.323	-1.76	-0.381	-2.00
Expressway freq.; 1 if subject uses pre-trip and/or en-route traffic information usually or everyday, "0 otherwise	0.763	2.21	0.770	2.14	0.793	2.24	0.767	2.21
Travel time of the normal route	0.087	6.14	0.082	5.90	0.080	6.01	0.075	5.74
Travel time of the diverted route	-0.039	-2.83	-0.036	-2.87	-0.035	-2.86	-0.034	-2.89
Pre-trip information; 1 for scenario 2, "0 otherwise	0.697	4.05	0.693	4.11	0.688	4.15	0.655	3.92
Pre-trip information/advice; 1 for scenario 3, "0 otherwise	0.931	5.11	0.939	5.22	0.920	5.25	0.887	5.06
En-route information; 1 for scenario 4, "0 otherwise	0.848	4.69	0.862	4.89	0.857	5.01	0.827	4.85
En-route information/advice; 1 for scenario 5, "0 otherwise	1.691	5.83	1.670	5.91	1.662	5.48	1.608	5.31
System learning: 1 for the last-trial-days of the experiment, 0 for the first-trial-days	0.370	2.47	0.370	2.49	0.339	2.25	0.314	2.10
Number of traffic signals on the normal route	0.136	2.22	0.853	2.70	0.130	2.20	0.115	1.92
Number of traffic signals on the normal route * En-route information/advice	0.834	2.55	-2.612	-4.19	0.819	2.41	0.762	2.22
Model evaluation; number of correctly expected observations divided by the total number of observations	406/539 = 75.32%		407/539 = 75.51%		414/539 = 76.81%		438/539 = 81.26%	

Only one two-level interaction term was found significant and indicated the positive joint effect of the number of traffic signals on the drivers' normal route and providing en-route information/advice on the en-route diversion decision. Other variables including; age, gender, income, driving experience represented by the number of years a subject had a driver's license, different weather conditions, and familiarity with the network were tested and found uncorrelated with drivers' diversion from the normal route decision.

7. Modeling compliance with pre-trip advised route (Model 2)

The 63 subjects have chosen 218 routes in scenarios 3 and 5, where pre-trip advised route is provided, and in the drive mode. These 218 chosen routes were the data for the GEE model. As in the above two models, a binomial probit link function and four correlation structures were tried. The response variable was the subject's compliance with the pre-trip advised route. This response variable is binary with the value of "1" if the subject complied with the pre-trip advised route until the destination and "0" otherwise. Table 2 shows parameter estimates with comparisons between the three structures of the correlation matrix. The maximum number of repeated observations for the same subject was found four. Therefore, the correlation matrix is a 4*4 symmetric matrix with 1's as diagonal elements. The model correctly expected the response variable for 137, 138, 139, and 139 observations out of the 218, for the independent, exchangeable, auto-regressive, and unstructured, respectively. This indicates that no significant difference was found between the four different correlation structures. A reason for that might be because the number of subjects was relatively greater than the maximum number of repeated observations per subject (63 vs. 4). This led to lesser role to the correlation in the model.

The modeling estimates show that highly educated drivers (graduate school or higher) are less likely to comply with the pre-trip advised route. Drivers who usually receive traffic information have a high propensity to comply. Non-familiars with the network are more likely to comply. The travel time of the advised route (negatively) and that of the chosen route (positively) affect the likelihood of compliance with the advised route. Drivers were found more likely to comply in the last-trial-days than the first-trial-days of the experiment. This means that, familiarizing drivers with an information-device have a positive effect on their compliance. In heavy rain conditions (vs. light rain or clear sky), drivers are more likely to comply with the advice. High number of traffic lights in the advised route has a negative influence on compliance. No interaction term between the main effects was found significant in this model. Other variables including; age, gender, income, driving experience represented by the number of years a subject has a driver's license, and frequency usage of expressways were tested and found uncorrelated with the response variable.

8. En-route short-term route (link) choice analysis (Model 3)

In OTESP, at each node, the subject is required to make a decision and choose between the two coming links. This choice is considered, in this model, positive if the subject chose the link that had a better level of congestion (its delay is less than the other's; delay of a link is equal to the difference between its actual travel time at a specific movement and its free flow travel time). While, the choice is considered negative if the subject made a bad short-term decision by choosing the link with a worse level of congestion. The delay on a link at a certain movement was considered instead of its travel time because the links are different in length. Only in scenarios #4 and #5, en-route short-term information is provided to the subjects in two forms; first, giving each link a color that represents its congestion (green, yellow, or red for free, moderate, or congested flows, respectively). Second, the travel time of every link is given. These two forms represent qualitative and quantitative information, respectively. Scenario 5 also provides a long-term advised route from the driver's location to the destination.

Throughout this study, 5572 movements (decisions) have been done through the 40 links of the network. Out of them, 4753 decisions (en-route short-term choices) were made in

Table 2. Compliance with Pre-trip Advised Route Model

	Correlation Structure							
	Indep.		Exch.		Autoreg.		Unstruc.	
Parameter	coeff.	t-stat	coeff.	t-stat	coeff.	t-stat	coeff.	t-stat
Intercept	1.080	1.42	1.172	1.57	1.086	1.44	1.486	2.10
Education; 1 if graduate school or higher, 0 otherwise	-0.585	-2.77	-0.618	-2.96	-0.591	-2.81	-0.524	-2.73
Info familiarity; 1 if subject uses pre-trip and/or en-route information everyday or usually, "0 otherwise	0.284	1.78	0.279	1.78	0.289	1.82	0.258	1.78
Network familiarity; 1 if subject is familiar with the network, 0 otherwise	-0.966	-3.72	-0.959	-3.71	-0.968	-3.73	-1.059	-3.96
Travel time of the advised route	-0.036	-2.04	-0.040	-2.26	-0.038	-2.18	-0.040	-2.30
Travel time of the chosen route	0.034	1.70	0.034	1.73	0.034	1.74	0.027	1.52
System learning: 1 for the last-trial-days of the experiment, 0 for the first-trial-days	0.482	2.37	0.475	2.34	0.475	2.35	0.377	1.84
Heavy rain: 1 for heavy rain condition; 0 for light rain or clear sky	0.445	2.01	0.454	2.10	0.454	2.07	0.379	1.92
Number of traffic signals on the advised route	-0.190	-2.47	-0.183	-2.43	-0.183	-2.40	-0.204	-2.88
Model evaluation; number of correctly expected observations divided by the total number of observations	137/218 = 62.84%		138/218 = 63.30%		139/218 = 63.76%		139/218 = 63.76%	

the drive mode and 819 movements in the bus mode. Out of the 4753 drive decisions, 1667 movements were excluded from the analysis because the driver had no choice but to proceed on to the unique coming link. This happens at the most east, west, and north nodes of the network. Out of the remaining 3086, 1650 decisions were found to be positive while 1436 decisions were negative.

The 3086 link choices were the data used. The GEE was employed. The response variable is binary with the value of "1" for positive choices and '0' for negative choices. Table 3 shows the parameter estimates with a comparison between exchangeable and autoregressive correlation structures. The maximum number of repeated observations was 71. Therefore, the correlation matrix dimensions are (71 * 71). The unstructured correlation matrix is not appropriate for this case because the number of response pairs for estimating correlation was less than the number of correlation parameters to be estimated (2485 = 71 * 70/2). The model correctly expected the response variable for 2128, 2365, and 2139 observations out of the 3068, for the independent, exchangeable, and autoregressive correlation matrices, respectively. This indicates that the last two correlation matrices were favored over the independent case. Also, the exchangeable correlation structure was favored over the autoregressive structure (76.64% classification). In the autoregressive correlation structure, the correlation between two repeated choices is not fixed and depends on the time-gap between them. For example the correlation between observations #1 and #5 was found almost zero. On the other hand, the exchangeable correlation structure assumes equal and fixed correlation between any repeated choices. This might lead to the reason why the exchangeable correlation structure was favored over the autoregressive structure for this model.

Table 3. Results of Modeling En-route Short-term (Link) Choice

	Correlation structure					
	Indep.		Exch.		Autoreg.	
Parameter	Coeff.	t-stat.	Coeff.	t-stat.	Coeff.	t-stat.
Intercept	-2.191	-23.77	-2.282	-23.97	-2.022	-23.75
Info-familiarity; 1 if subject uses pre-trip and/or en-route traffic information usually or everyday, 0 otherwise	0.246	10.12	0.244	10.30	0.247	10.45
Info-provision: 1 for scenario 4 where en-route information is provided without advice, 0 otherwise	0.150	2.23	0.166	2.19	0.139	2.14
Same color: 1 if the two coming links were with the same color (qualitative congestion level), 0 otherwise	-0.267	-4.03	-0.282	-3.96	-0.246	-3.87
System learning: 1 for the second 5 trial days of the experiment, 0 for the first 5 trial days	2.057	17.61	2.141	17.64	1.894	17.18
Heavy rain: 1 for heavy rain condition; 0 for light rain or clear-sky	0.236	3.19	0.241	3.26	0.250	3.50
Number of movements since the origin	0.368	10.30	0.365	10.50	0.323	9.65
Interaction terms						
Heavy rain * Same color	0.269	2.23	0.280	2.33	0.286	2.45
Number of movements since the origin * System-learning	0.241	6.35	0.238	6.44	0.206	5.74
Model evaluation; number of correctly expected observations divided by the total number of observations	2128/3086 = 68.96%		2365/3086 = 76.64%		2139/3086 = 69.31%	

The modeling results showed that, in general, the provision of en-route information increases the likelihood of making a positive link choice. This means that the en-route short-term information has a good chance to be used and followed. When the two coming links had the same qualitative level of congestion, drivers were less likely to make a positive choice. Then, the qualitative information is more likely to be used than the quantitative information. The following effects/interactions increase the likelihood of obeying the en-route short-term information:

- Being familiar with traffic information
- Learning and being familiar with the system that provides the information
- Heavy rain condition
- Being away from the origin, i.e. close to the destination (presented by the number of movements since the origin)
- Providing qualitative information in heavy rain conditions
- Being away from the origin and being familiar with the device that provides the information

9. Summary and conclusions

This paper presented models of 3 route choices under different types and levels of ATIS. A real network/conditions travel simulator was used to collect dynamic data for the 3 models using same subjects and same experiment. The paper presented the following models; (1) Drivers' diversion from habitual route given information is provided, (2) Drivers' compliance with a pre-trip advised route, and (3) Driver's compliance with en-route short-term (link) traffic information. Binomial Generalized Extreme Equations were used to account for correlation between repeated choices made by same subject. The correlation was found significant in two models out of three. This depicts the importance of understanding the nature of correlation between mode/route choices in the transportation field.

Table 4 summarizes the modeling results for the above 3 models. In Table 4, effects 2 through 5 are subject-related variables. Effects 6 through 12 are related to level of information/advice provided, familiarity with the system that provides the information, network conditions, or weather conditions (both network and weather conditions are provided by the information system). Effects 13 through 18 measure the effect of travel time on all 3 models of this paper. Effects 19 through 21 are two-level interaction terms. By comparing the first group of effects over the 3 models, the following findings are concluded:

1. Highly educated drivers are more likely to divert from habitual route and/or comply with pre-trip advised route. Education level does not affect en-route compliance.
2. Expressway users are more likely to divert (they do not affect other paradigms though).
3. Traffic information users are more likely to follow the pre-trip and en-route traffic information provided.
4. Drivers familiar with the network are less likely to comply with pre-trip information. Network familiarity does not affect drivers' en-route compliance.

By comparing the second group of effects over the 3 models, the following findings are concluded:

5. Providing pre-trip and/or en-route traffic information/advice assists drivers and drivers in their route decisions. As the level of information/advice increases the benefits increase.

6. Qualitative is more beneficial than quantitative information in assisting drivers' en-route short-term (link) choices.
7. Severe weather conditions increase the compliance with pre-trip and en-route traffic information while they do not affect drivers' diversion from habitual route.
8. Being away from the origin or close to the destination increases drivers' compliance with the en-route information provided.
9. As drivers get more familiar with the device that provides the information their compliance with traffic information before and while driving increases, also, diversion from habitual route increases.
10. Less number of traffic signals on an advised pre-trip route increases the probability of compliance.
11. High number of traffic signals on a habitual route increases the probability of diversion.
12. The information provision increases the probability of diversion from a habitual route. In particular, adding advice to pre-trip and/or en-route advice-free information increases this diversion probability. Providing en-route information in addition to the pre-trip information, also, increases the diversion probability.

By comparing the third group of effects over the 5 models, the following main finding is concluded:

13. Travel time was shown in all models as significant effect in travelers/drivers choices.

A methodological conclusion is the need to account for the repeated observations in the route choice modeling. Otherwise, the results will be biased. All the three correlation structures presented in this paper were favored over the independence case especially when the number of repeated choices is relatively high compared to the number of subjects or the total number of observations. The best correlation structure was not fixed to the three models. Choosing the best correlation structure depends on the nature of the correlation, total number of subjects, maximum number of repeated choices per subject, and available degrees of freedom in the modeling process. Modeling the unstructured correlation type needs high number of degrees of freedom. The autoregressive structure may not be favored for cases with relatively high number of repeated choices. Exchangeable structure relaxes the need for extra degrees of freedom but it has the restriction of equaling correlation between any pair of choices made by the same subject, which might be reasonable in many cases.

Table 4. Summary Modeling Results for all 5 Models

#	**Effect**	**M1**	**M2**	**M3**
1	Intercept	-2.24	1.49	-
2	Education; 1 if graduate school or higher	-0.38	-0.52	
3	Expressway freq.; 1 if uses expressway usually or everyday	0.77		
4	Info familiarity; 1 if uses information usually or everyday		0.26	0.24
5	Network familiarity; 1 if subject is familiar with the		-1.06	
6	Pre-trip information; 1 for scenario 2	0.66		
7	Pre-trip information/advice; 1 for scenario 3	0.89		
8	En-route information; 1 for scenario 4	0.83		0.17
9	En-route information/advice; 1 for scenario 5	1.61		
10	Same color: 1 if two coming links were with same			-
11	System learning: 1 for the last-trial-days, 0 for the first-	0.31	0.38	2.14
12	Heavy rain: 1 for heavy rain condition; 0 for light rain or		0.38	0.24
13	Number of traffic signals on the normal route	0.12		
14	Number of traffic signals on the advised route		-0.20	
15	Number of movements since the origin			0.37
16	Travel time of the normal route	0.08		
17	Travel time of the advised route		-0.04	
18	Travel time of the chosen route	-0.03	0.03	
	Interaction terms:			
19	Number of traffic signals on the normal route * En-route	0.76		
20	Heavy rain * Same color			0.28
21	Number of movements since the origin * System-learning			0.24

Model 1 (M1): modeling diversion from normal route (1=diverts vs. 0=uses normal route)
Model 2 (M2): modeling compliance with pre-trip advised route (1=comply vs. 0=not complies)
Model 3 (M3): modeling compliance with en-route short-term (link) information (1=complies vs. 0=not complies)
Effects 2-12 are binary and take the value "1" as specified in the table and take the value "0" if otherwise.
An empty cell in the table means that either the effect is not applicable to the corresponding model or it is insignificant.

References

Abdel-Aty, M. and Abdalla, F. 2002. Design and Development of a Computer Simulation Tool to Collect Data that Support Hybrid Travel Models under ATIS. Proceedings of the Annual Conference of the Canadian Society for Civil Engineering, Montreal, Quebec, Canada.

Abdel-Aty, M., Kitamura, R., and Jovanis, P., 1997. Using Stated Preference Data For Studying The Effect of Advanced Traffic Information on Drivers' Route Choice. Transportation Research, Part C, Volume 5.

Abdel-Aty, M., Kitamura, R., and Jovanis, P., 1995a. "Investigating Effect of Travel Time Variability on Route Choice Using Repeated Measurement Stated Preference Data" Transportation Research Record, 1493, 39-45.

Abdel-Aty, M., Vaughn, K., Kitamura, R., Jovanis, P., and Mannering, F., 1995b. Models of Commuters' Information Use and Route Choice: Initial Results Based on Southern California Commuter Route Choice Survey. Transportation Research Record, 1453, 46-55.

Abdel-Aty, M., Vaughn, K., Jovanis, P., Kitamura, R., and Mannering, F., 1994a. Impact of Traffic Information on Commuters' Behavior: Empirical Results from Southern California and their Implications for ATIS. The Proceedings of the 1994 Annual Meeting of IVHS America, 823-830.

Abdel-Aty, M., Kitamura, R., Jovanis, P., and Vaughn, K., 1994b. Investigation of Criteria Influencing Route Choice: Initial Analysis Using Revealed and Stated Preference Data. Report No: UCD-ITS-RR-94-12, California University, Davis.

Adler, J. and McNally, M., 1994. In-Laboratory Experiments to Investigate Driver Behavior under Advanced Traveler Information Systems. Transportation Research, 2C, pp. 149-164.

Adler, J., Recker, W., and McNally, M., 1993. Conflict Model and Interactive Simulator (FASTCARS) For Predicting En-route Driver Behavior in Response to Real-Time Traffic Condition Information. Transportation, 20(2), 83-106.

Allen, R., Ziedman, D., Rosenthal, T., Stein, A., Torres, J., and Halati, A., 1991. Laboratory Assessment of Driver Route Diversion in Response to In-Vehicle Navigation and Motorist Information Systems. Transportation Research Record, 1306, 82-91.

Arnott, R., De-Palma, A., and Lindsey, R., 1990. Departure time and route choice for the morning commute. Transportation Research B. 24, 209-228.

Ben-Akiva, M., De-Palma, A., and Kaysi, I., 1991. Dynamic Network Models and Driver Information Systems. Transportation Research A, 25, 251-266.

Bonsall, P., Firmin, P., Anderson, M., Palmer, I., and Balmforth, P., 1996. Validating VLADIMIR: can the results of a route choice simulator be trusted?. presented at the fourth International Conference on Survey Methods in Transport, Steeple Aston, England.

Bonsall, P., and Parry, T., 1991. Using an Interactive Route-Choice Simulator to Investigate Driver's Compliance with Route Guidance Advice. Transportation Research Record, 1306, 59-68.

Conquest, L., Spyridakis, J., and Haselkorn, M., 1993. The Effect of Motorist Information on Commuter Behavior: Classification of Drivers into Commuter Groups. Transportation Research C, 1, 183-201.

Delvert, K., 1997. Heterogeneous Agents Facing Route Choice: Experienced versus Inexperienced Tripmakers. Presented at IATBR '97, Austin, TX.

Gopinath, D., 1995. Modeling Heterogeneity in Discrete Choice Processes: Application to Travel Demand. MIT, Ph.D. Thesis.

Khattak, A., Polydoropoulou, A., and Ben-Akiva, M., 1996. Modeling Revealed and Stated Pretrip Travel Response to Advanced Traveler Information Systems. Transportation Research Record, 537.

Khattak, A., Schofer, J., and Koppelman, F., 1995. Effect of Traffic Information on Commuters' Propensity to Change Route and Departure Time. Journal of Advanced Transportation, 29.

Khattak, A, Schofer, J., and Koppelman, F., 1993. Commuters' En-route Diversion and Return Decisions: Analysis and Implications for Advanced Traveler Information Systems. Transportation Research Record. 24A, 101-111.

Kim, K., and Vandebona, U., 2002. Understanding Route Change Behavior – A Commuter Survey in South Korea. Presented in Transportation Research Board. 81st Annual Meeting. Washington, D.C.

Liang, K., Zeger, S., and Qaqish, B., 1992 "Multivariate Regression Analysis for Categorical Data" Journal of Royal Statistical Society, Series B, 54, 30-40.

Liang, K. and Zeger, S., 1986. Longitudinal Data Analysis using Generalized Linear Models. Biometrika, 73, 13 -22.

Liu, Y., and Mahmassani, H., 1998. Dynamic Aspects of Departure Time and Route Decision Behavior under Advanced Traveler Information Systems (ATIS): Modeling Framework and Experimental Results. Transportation Research Record, 1645, 111-119.

Lotan, T., 1997. Effects of Familiarity on Route Choice Behavior in The Presence of Information. Transportation Research, Part C, 5, 225-243.

Louviere, J. and Woodworth, G., 1983. Design and Analysis of Simulated Consumer Choice or Allocation Experiments: an Approach Based on Aggregate Data. Journal of Marketing Research XX, 350-367.

Mahmassani, H., Huynh, N., and Srinivasan, K., 2000. Tripmaker Choice Behavior for Shopping Trips under Real-Time Information: Model Formulation and Results of Stated-Preferences Internet-Based Interactive Experiments. Presented at the Transportation Research Board, 80th Annual meeting, Washington, D.C.

Mahmassani, H. and Hu, T., 1997. Day-to-day Evolution of Network Flows under Real-time Information and Reactive Signal Control. Transportation Research C, 5, 51-69.

Mahmassani, H. and Chen, P., 1993. An Investigation of the Reliability of Real-Time Information for Route Choice Decisions in a Congested Traffic Network System. Transportation, 20, 157-178.

Mahmassani, H., 1990. Dynamic Models of Commuter Behavior: Experimental Investigation and Application to the Analysis of Planned Traffic Disruptions. Transportation Research A, 24, 465-484.

Mannering, F., 1987. Analysis of the Impact of interest rates on automobile demand. Transportation Research Record, 1116, 10-14.

Mannering, F., Kim, S., Barfield, W., and Ng, L., 1994. Statistical analysis of commuters' route, mode and departure time flexibility. Transportation Research C, 2, 35-47.

Mehndiratta S., Kemp M., Lappin J., and Nierenberg, E., 2000. Who are the Likely Users of ATIS? Evidence from the Seattle Region. Presented at the Transportation Research Board 79th Annual Meeting. Washington, D.C.

Nelder, J. and Wedderburn, R., 1972. Generalized Linear Models. Journal of the Royal Statistical Society, A, 135, 370 -384.

Pallottino, S. and Grazia, M., 1998. Shortest Path Algorithms in Transportation Models: Classical and Innovative Aspects. In P. Marcotte and S. Nguyen, editors, Equilibrium and Advanced Transportation Modeling, pp. 245-28.

Polak J. and Jones P., 1995. The Acquisition of Pre-Trip Information: A Stated Preference Approach. Transportation 20, 179-198.

Polydoropoulou, A., Ben-Akiva, M., Khattak, A., and Lauprete, G., 1996. Modeling Revealed and Stated En-Route Travel Response to Advanced Traveler Information Systems. Transportation Research Record, 1537.

Reiss, R., Gartner, N., and Cohen, S., 1991. Dynamic Control and Traffic Performance in a Freeway Corridor: a Simulation Study. Transportation Research A, 25A,(5), 267-276.
SAS/STAT, 2003., Technical Support Resources, Version 8.2.

Sengupta, R., and Hongola, B., 1998. Estimating ATIS benefits for the Smart Corridor. Partners for Advanced Transit and Highways" Research report, UCB-ITS-PRR-98-30, Institute of Transportation Studies, University of California, Berkeley.

Spyridakis, J., Barfield, W., Conquest, L., Haselkorn, M., and Isakson, C., 1991. Surveying Commuter Behavior: Designing motorist information system. Transportation Research A,. 25, 17-30.

Stokes, M., Davis, C., and Koch, G., 2000. Categorical data analysis using the SAS system. second edition, Cary, NC: SAS Institute.

Streff, F. and Wallace, R., 1993. Analysis of Drivers' Information Preferences and Use in Automobile Travel: Implications for Advanced Traveler Information Systems. Proceedings of the Vehicle Navigation and Information Systems Conference, Ottawa, Ontario.

Vaughn, K., Reddy, P., Abdel-Aty, M., Kitamura, R., Jovanis, P., 1995. Route Choice and Information Use: Initial results Simulation Experiment. Transportation Research Record, 1516, 61-91.

Vaughn K., Abdel-Aty, M., Kitamura, R., Jovanis, P., Yang, H., Kroll, N., Post, R., and Oppy, B., 1993. Experimental analysis and modeling of sequential route choice behavior under ATIS in a simplistic traffic network. Transportation Research Record, 1408, 75-82.

Viswanathan, K., Goulias, K., and Jovanis, P., 2000. Use of Traveler Information in the Puget Sound Region: A Preliminary Multivariate Analysis. Transportation Research Record, 1719, 94-102.

Wunderlich, K., 1996. An assessment of pre-trip and en route ATIS benefits in a simulated regional urban network. Proceedings of the third world congress on Intelligent Transport Systems at Orlando.

Zeger, S., Liang, K., and Albert, P., 1988. Models for Longitudinal Data: A Generalized Estimating Equation Approach. Biometrics, 44, 1049-1060.

Zhao, S., Harata, N., and Ohta, K., ,1996. Assessing Driver Benefits from Information Provision: A Logit Model Incorporating Perception Band of Information. Proceedings of the 24th annual Passenger Transport Research Conference, London, England.