Experimental Analysis and Modeling of Sequential Route Choice Under an Advanced Traveler Information System in a Simplistic Traffic Network

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An experiment to collect sequential route choice data under the influence of an advanced traveler information system was performed using a personal computer–based simulation. The experiment collected information on drivers' pretrip route choice behavior at three levels of information accuracy: 60, 75, and 90 percent. An analysis of variance was performed on the data to investigate the interrelationships among the different variables in an attempt to develop an understanding of what factors significantly influence route choice behavior and learning. An attempt was made to model sequential route choice behavior using a binary logit model formulation; the results were mixed. It was assumed that drivers update their knowledge of the system on the basis of their previous experiences; therefore an information updating function was specified and incorporated into the model. The results indicate that drivers can rapidly identify the accuracy level of information and that they adjust their behavior accordingly. Evidence also indicates that an accuracy threshold level exists below which drivers will not follow advice and above which drivers readily follow advice. It was found that male subjects agreed with advice more often than females, that less experienced drivers agreed more often than experienced drivers, and that a "freeway bias" exists with drivers much more willing to follow advice to take a freeway route. The model of route choice behavior had a prediction rate that was 79 percent accurate, which also indicated that previous experiences had little effect on current route choices. This value may be the result of a misspecified updating function, indicating that further research is required to identify these learning relationships.

The route choice process in the real traffic environment is very complex and there is little experimental evidence of how drivers process information and select their routes (*1*). Therefore, it was decided to analyze route choice behavior in the most simplistic, controlled environment possible. It was believed that this level of control would allow adequate restriction and analysis of the effects of various factors on the route choice behavior. The factor of utmost importance to any analysis of driver behavior influenced by an advanced traveler information system (ATIS) is a measure of the information accuracy. Certainly the future success or failure of ATIS will be highly dependent on the accuracy as well as the quality of advice that can be consistently delivered to the drivers. Previous research (*2–4*) has indicated the influence of system accuracy on compliance with advice. If a system consistently provides bad information it is assumed that drivers will soon begin to ignore the advice, and route choice patterns will remain unchanged. If highly accurate information is consistently provided to drivers it is assumed that drivers will perceive a benefit from following the advice and adapt their behavior to the advice. How do drivers perceive the accuracy of information? Is there an accuracy threshold below which drivers perceive no benefit from following advice? If such thresholds exist are they consistent for all drivers, or do different types of drivers have different thresholds? Can drivers perceive the accuracy of advice, under what conditions, and how rapidly? All of these questions need to be addressed to maximize the potential of ATIS.

The analysis suggests that initially drivers are predisposed to follow the route advice. The average agreement with advice over time shows that for the first few trials drivers accept the advice approximately 78 percent of the time independent of the accuracy level of advice being provided. The findings also suggest that drivers can perceive the level of information accuracy and that they do so rather rapidly. Within the first 8 of 32 sequential trials, the average agreement with advice moved in the direction of the level of accuracy provided. At 75 and 90 percent levels of accuracy, the average agreement with advice increased over the remaining 28 trials, whereas at the 60 percent level of accuracy, the average agreement declined from the initial rate to approximately 60 percent (system accuracy). These findings indicate the importance of the accuracy of information provided by ATIS and show that drivers can quickly discern the level of accuracy being provided.

DESCRIPTION OF ROUTE CHOICE EXPERIMENT

An experiment to investigate drivers' learning and pretrip route choice behavior under ATIS was performed using an

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interactive route choice simulation experiment carried out on a personal computer. The experiment was developed through a collaborative effort between the Institute of Transportation Studies and the Psychology Department at the University of California at Davis.

The simulation begins by presenting a set of instructions to the subject describing how the program operates. The subjects are told that they have purchased a new "traffic watch device" that will provide them with traffic information before they select a route. The subjects are also told that the device will not always be accurate but are not given any indication of its overall accuracy. Before beginning the simulation the subjects are shown examples of the fastest and slowest possible times on each of the routes, and they may repeat the examples as often as necessary to get familiar with the system. Subjects are instructed that their main task is to minimize their overall travel time by deciding when and when not to follow the advice provided by the traffic information system. Subjects are also told that their decisions and response times are being measured and that they should try to respond as quickly as they can make a good decision.

When the subjects are ready to begin the simulation, they are presented with a screen that indicates that it is Trial Day 1; they are instructed to position their hands on the computer keyboard and to press the space bar when they are ready to receive advice. On pressing the space bar, the advice for that day is presented along with a simulated freeway link, a side road link, and an origin and destination. The advice given was either, "Take the Freeway, traffic is moving smoothly" or "Take the side road, there is a problem on the Freeway." The screen display was simple and is approximated in Figure 1.

When the subject selects a route, a red blinking curser (shown by a shaded box on the freeway link) moves across the screen from the starting point (S) to the goal (G). The speed at which the curser moves represents the average travel speed on that link for that travel day. In Figure 1, the double line link represents the freeway and the single line link represents the side road. On completion of each trial subjects were asked to rate their choice satisfaction (e.g., correct, probably correct, don't know, probably incorrect, incorrect) and to provide an estimate of their travel time on their chosen route (e.g., fastest possible, reasonably fast, moderate, fairly slow, incredibly slow).

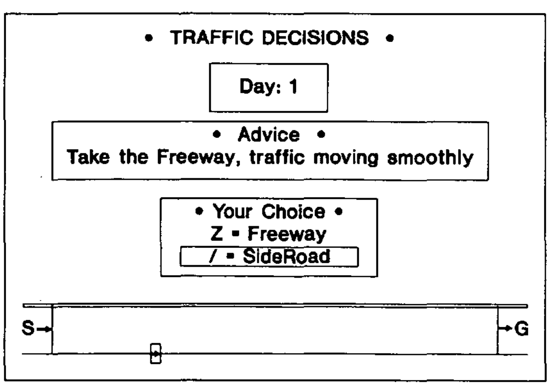

FIGURE 1 Typical screen display of simulator.

The simulation was developed such that various treatments could be applied and then data could be collected under these different conditions. The treatments that could be applied to the simulation included the following:

1. Accuracy: The accuracy level of the advice provided to subjects could take on values of 60, 75, or 90 percent.
2. Stops: A simulated stop on the side road route could be applied.
3. Rationale: A justification statement about why the subject should follow the advice could be provided.
4. Feedback: Feedback could be provided at the end of each trial in the form of actual simulated travel times on the two routes for that trial.
5. Freeway: Identification of the routes as freeway and side road as opposed to simply Routes A and B could be provided.
6. Road: The display could provide the simulated origin and destination with the two route links as shown in Figure 1 or with no network display provided and the travel time simulated by a blinking curser located in the center of the screen.

Three separate experiments were carried out to collect data under various conditions. The three experiments and the conditions under which the simulation has been run to date are shown in Table 1. The first experiment was used to investigate accuracy requirements of ATIS. The experiment was structured as described above but with three levels of information accuracy provided. Three separate groups of 23, 25, and 29 subjects were run through the simulation at three levels of accuracy: 60, 75, and 90 percent. In the second and third experiments the information accuracy was held constant at 75 percent while other experimental conditions were varied. This paper provides an initial analysis of the data collected in the first and third experiments using 4 of the 16 possible initial conditions (Conditions 1, 2, 3, and 7). A forthcoming paper will address the second and third experiments and the effects of varying conditions.

All of the experiments subjected drivers to 32 simulated days in which they were to choose one of two possible routes. For each travel day an amount of delay was randomly assigned to each of the two routes. The units of delay assigned to a particular route are proportional to the travel time experienced on the route. The delay was distributed over the 32 trials such that the mean delay for each route was equal but the variance differed. In this manner, routes with potentially faster travel times but with a greater amount of uncertainty (as one might expect on a freeway) can be compared with routes with slower travel times but with a greater amount of certainty (similar to surface street routes). On completion of 32 sequential simulated days, subjects were asked to rate their potential for purchasing a traffic information device, their perceived accuracy of the device, and their own ability at selecting routes when compared with that of the information device.

The computer program automatically recorded and stored data from each subject for 32 sequential trials. Test subjects were all undergraduate students in the psychology department at the University of California at Davis.

INVESTIGATION OF BEHAVIORAL RELATIONSHIPS USING ANALYSIS OF VARIANCE

Analysis of variance (ANOVA) models are used for studying the relationship between a dependent variable and one or more independent variables for experimental and observational data. The strength of the ANOVA model, and the main reason it is applied here, is that it requires neither that assumptions be made about the nature of the statistical relation nor that the independent variables be quantitative (*5*).

Fixed Effects Model

The goal of this research effort is to develop models of route choice under the influence of ATIS and to capture and incorporate into these models the effects of drivers' learning abilities. The first step in this process is to develop a basic understanding of the factors that influence driver's route choices and how the presence of traffic information systems will affect drivers' route choice decisions over time. The experiment described above was developed explicitly to study drivers' route choice behavior at its most basic level.

The first step in the data analysis was to investigate the interrelationships among the various variables in an attempt to develop an understanding of what factors significantly influence route choice behavior and learning. Three variables of significant interest were selected from the data set for analysis as dependent variables. The first variable of interest is one that indicates a driver's willingness to accept the route choice advice that is provided by the information system. This is a variable that compares the route choice made by Subject i on Travel Day j with the advised route for that day and returns a value of 1 if the subject chose the advised route and a value of 0 otherwise. This variable was analyzed in two different formulations—the first being the average acceptance rate of the advice given and the second being the individual agreement or disagreement. The average acceptance rate is the average acceptance of advice for Subject i on Travel Day j and is given by

$$\text{ACCRATE}_j = \left(\textstyle\sum_{l=1..j} \text{AGR}_l\right)/j \qquad (1)$$

where AGR_l is the level of agreement on day l (1 = agree, 0 = disagree).

The second dependent variable of interest included in the analysis is the subject's decision time. This is the time in seconds that a subject takes to select a route once route information has been provided. The third variable analyzed was a subject's potential use of an information system of the type experienced in the simulation. This variable is a subject's rating of how likely he or she would be to buy such an information system.

The data set used for the ANOVA consists of the 2,464 individual choices made by the 77 subjects from Experiment 1 (Conditions 1 through 3) as shown in Table 1. A software package was used (BMDP 2V) to perform an analysis of variance and covariance on fixed effects factorial designs with

TABLE 1 Experimental Treatments

Experiment	Condition	Treatment Number						Number of
		1	2	3	4	5	6	Subjects
1	1	60%	no	yes	yes	yes	yes	23
1	2	75%	no	yes	yes	yes	yes	25
1	3	90%	no	yes	yes	yes	yes	29
2	4	75%	yes	yes	yes	yes	yes	20
2	5	75%	yes	yes	yes	yes	yes	20
2	6	75%	yes	yes	no	yes	yes	20
3	7	75%	no	yes	yes	yes	yes	20
3	8	75%	no	no	yes	yes	yes	20
3	9	75%	no	yes	no	yes	yes	20
3	10	75%	no	yes	yes	no	yes	20
3	11	75%	no	no	yes	no	yes	20
3	12	75%	no	no	no	no	yes	20
3	13	75%	no	no	yes	no	no	20
3	14	75%	no	no	no	no	no	20
3	15	75%	yes	no	yes	no	no	20
3	16	75%	yes	no	no	no	no	20

two grouping factors (two-way ANOVA). For two-way ANOVA, tests are made of the null hypotheses about equality of main effects for each factor and about interactions between factors. Five variables were selected as grouping variables, and five variables were selected as covariates with three of the variables overlapping. The grouping variables included the percent accuracy of advice (PAADV), the trial block of the choice (TBLOCK), the driving frequency of the subject (NDFREQ), the advised route (ADVROUTE), and the subject's gender (SEX). The covariate or independent variables included SEX, NDFREQ, the individual trial number (TRIAL#), accuracy on previous trial (ADV__N-1), and ADVROUTE. The ANOVA model used in this analysis is the factor effects model for two-way factor studies (*5*). It was decided to use a two-way factor study and include covariate terms as opposed to performing a full multifactor study, which was not feasible because of the relatively small sample size.

The findings indicate that the willingness of subjects to follow advice is strongly influenced by the accuracy of the advice, the experience level of the driver, the gender, and the route being advised. The effects of learning, gauged by the number of trials, were shown to have little effect on the willingness to follow advice. Subjects' decision times were significantly influenced by the accuracy of advice, gender, the advised route, driving frequency, and system experience (trial block). The potential use of an information system was shown to be influenced by the accuracy of advice, the gender, and the driving frequency.

Regression Model

The constant vectors of the ANOVA factor effects model give an indication of the effects of the within-factor levels of the grouping variables on the dependent variable. These factor level constants can be estimated using a regression approach that is equivalent to the ANOVA model (*5*). An in-depth description of the procedures and results of the ANOVA is given elsewhere (*6*).

From the ANOVA, the factors and covariates that had significant effects on the dependent variables were determined. For the dependent variable ACCRATE, the grouping factors PAADV and SEX and the covariate NDFREQ are the most significant. For the dependent variable AGR, the grouping factors PAADV and ADVROUTE and the covariates SEX and NDFREQ are the most significant. For the dependent variable DTIME, the grouping factors PAADV and ADVROUTE and the covariates SEX, NDFREQ, and TRIAL# are the most significant. For the dependent variable USAGE, the grouping factors PAADV and SEX and the covariate NDFREQ are the most significant. For each of these dependent variables a regression analysis was performed to determine the within-factor coefficients of the regression equation. The results of the regression analysis for these four models are presented in Table 2.

The ANOVA results gave an indication of which variables have significant effects on subjects' willingness to follow route advice, their decision times, and their potential use of an information system. The ANOVA regression technique provided insight into how these variables influence route choice decisions. The significant findings of this section are summarized below:

1. Acceptance of advice increases with increasing information accuracy.
2. Males are more willing to accept advice than females and also make their decisions faster than females.

TABLE 2 ANOVA Regression Coefficients

	DEPENDENT= AVERAGE ACCEPTANCE		DEPENDENT= AGREEMENT		DEPENDENT= DECISION TIME		DEPENDENT = USAGE	
INDEPENDENT	COEFF.	T	COEFF.	T	COEFF.	T	COEFF.	T
INTERCEPT	0.78867		0.71504		3.36649		2.7493	
SEX (1=F, 2=M)			0.0382	2.21	-0.1431	-1.87		
DRIVING FREQ. (1=HI, 2=MED, 3=LOW)	0.0115	2.81	0.0195	1.95	0.1905	4.3	0.1532	5.15
TRIAL# (1 - 32)					-0.0768	-19.55		
X1 (65% accuracy)	-0.043	-9.25	-0.0926	-7.99	-0.0787	-1.53	0.6629	19.58
X2 (75% accuracy)	-0.0125	-2.65	0.0033	0.29	0.2239	4.36	0.0447	1.30
X3 (side road advice)	-0.0375	-11.42	-0.0685	-8.36	0.4029	11.11	-0.0879	-3.67
X13 (X1 X3 interactions)	-0.0064	-1.34	-0.0282	-2.43	-0.003	-0.06	-0.1642	-4.70
X23 (X2 X3 interactions)	0.0164	3.44	0.002	0.17	0.0944	1.84	-0.3059	-8.83

3. Experienced drivers are not as willing to accept advice as less experienced drivers, and they also make their decisions faster.

4. A "freeway bias" exists with subjects more willing to accept freeway advice.

5. Although males are more willing to accept advice, they are also less likely to purchase an information system.

6. Whereas less experienced drivers are more likely to follow advice, they are also less likely to purchase an information system.

MODELING SEQUENTIAL ROUTE CHOICE BEHAVIOR

The ultimate goal of this research effort is to develop a realistic model of route choice behavior under the influence of ATIS, which incorporates the effects of drivers' learning abilities. Two modeling approaches are under investigation for the development of a route choice behavioral model as part of this research effort. The first approach, which is described here, is the use of a conventional logit model formulation. The second approach is the use of a neural network model and is described elsewhere (*7*). The use of the logit model and the random utility theory assumes that an individual's choice between two or more alternatives is based on the utility gain experienced by the individual for a particular choice. The reliable estimation of an individual's perceived utility, then, is of primary importance in estimating the overall model. The individual's perceived utility of an alternative is used in lieu of the actual utility because, although the actual utility may be greater or less than the perceived utility, it is an individual's perception of reality that ultimately drives behavioral responses.

It is reasonable to assume that an individual's perceived utility for a specific alternative is a function of the perceived attributes of the alternative, an individual's characteristics (personal biases or preferences), the information available on the alternative, and the perception of the accuracy of such information. There may also be an effect on the perceived utility of an alternative because of a repetitive choice effect. Simply stated, the more times one chooses an alternative the greater the perceived utility becomes for that alternative because of some habitual nature of the individual. This general framework forms the basis for the formulation of specific alternative utility functions within this analysis.

When analyzing sequential choices, the utility functions for each alternative must be updated to reflect the individual's learning processes. Thus, the perceived utility for a specific alternative for a given trial is dependent on the perceived outcome of previous trials or experiences. Each sequential choice results in an experience, which in turn influences the next choice. Just how much this past experience affects the current choice and how rapidly individuals modify their behavior on the basis of their experiences will give an indication of the learning abilities of the individual. Various information updating strategies exist, and finding the most appropriate formulation to apply to drivers' route choice behavior may require a certain amount of trial and error, if an appropriate formulation can be found at all. If the learning and adaptive abilities of drivers vary greatly, then it may be impossible to specify an appropriate updating function that applies to a majority of drivers. The information updating strategy used in this analysis is as follows:

$$x_{ij}(k) = \tau x_{ij}(k - 1) + (1 - \tau)u_{ij}(k - 1) \qquad (2)$$

where $x_{ij}(k)$ is the perceived value of attribute x by individual i for alternative j for trial k, and, likewise, $x_{ij}(k - 1)$ is the perceived value for the previous trial $k - 1$.

Thus defined, $x_{ij}(k)$ becomes an endogenous variable. At this early stage of the modeling effort the issue of endogeneity has been ignored. The variable $u_{ij}(k - 1)$ is the actual value of the attribute as experienced by individual i on the previous trial $k - 1$. The coefficient τ is an experience importance factor whose value gives an indication of the relative importance of an individual's previous experiences in updating perception or expectation on the current trial. Such linear combinations are often used in network assignment.

For an individual who has not performed any trials, no previous experiences exist; therefore a perception of the attribute cannot be developed from previous experiences. Individuals may, however, have preconceived perceptions of certain attributes, in which case initial conditions must be established for the individual attributes. In the route choice simulation used to collect data for this analysis, subjects were given a significant amount of preliminary information about the simulation such that they could develop some initial perceptions of simulation attributes; therefore, initial conditions were established for individuals' perceptions of some attributes.

BINARY LOGIT MODEL

The sequential route choice processes were modeled using the binary logit formulation (*8*). The random utility function is the perceived utility of person i, for alternative route j, on the k^{th} day and is defined as follows:

$$V_{ij}(k) = \beta_0 + \textstyle\sum_{l=1,5}\beta_l X_{ijl}(k) + \varepsilon_{ij}(k) \qquad (3)$$

where

$X_{ij1}(k)$ = a dummy variable indicating which route is the advised route. It is 1 when the advised route is alternative j for day k and is 0 otherwise;
$X_{ij2}(k)$ = the perceived delay on alternative j for individual i for day k;
$X_{ij3}(k)$ = the perceived accuracy level of the information provided for the advised route;
$X_{ij4}(k)$ = a dummy variable, 1 if the subject is male for the advised route; and
$X_{ij5}(k)$ = a dummy variable, 1 if the subject is an inexperienced driver for the advised route.

The utility function for alternative j then is simply a linear combination of an alternative-specific coefficient β_0, the above variables, and an independent extreme-value distributed error term $\varepsilon_{ij}(k)$. The first variable represents the increase in utility of the advised route over the remaining alternative. This formulation assumes that, by advising a subject to take a specific route, the perceived utility for that route increases, thus increasing the probability of choosing that route. On the basis of the ANOVA results that showed an individual agreement with advice of about 72 percent, this variable should contribute significantly to the utility function and have a positive coefficient.

The second variable is an experience variable that represents an individual's perception of the delay to be experienced on either the side road or the freeway. This perception of delay must be updated for each sequential trial to incorporate the learning process on the basis of previous experiences. This variable is updated using the previously described updating function. At the beginning of the route choice simulation, subjects are allowed to view the fastest possible travel times on the freeway and side road, and likewise the slowest possible times. This in effect creates an initial perception of the delay to be experienced on the individual routes. For this analysis, the average of the minimum and maximum possible delay, as displayed to the subject, was used as the initial perceived delay for the two alternative routes.

The third variable is another experience variable representing an individual's perception of the accuracy level of the information being provided. Subjects are told at the start of the simulation that their "traffic watch" device will not always be accurate but are not given any indication of the overall accuracy of the device. It is reasonable to assume that in the absence of any other information, subjects will assume that the information being provided is correct until, through an accumulation of their experiences, they develop a perception of the accuracy of the information system. For this analysis, subjects are initially assumed to perceive the information as being 100 percent accurate, and then their perception is updated using the updating function to account for the effects of their experiences.

The fourth and fifth variables are personal attribute variables that the ANOVA indicates have strong effects on the individual's acceptance of advice. These variables result in increasing the utility of the advised route for male subjects and inexperienced drivers, thus increasing the probability that the subject will accept the advice. It was shown in the ANOVA that these two characteristics resulted in a higher average acceptance rate of advice for subjects with these characteristics.

An alternative specific coefficient was included for the freeway alternative. The ANOVA results indicated a preference or bias toward the freeway indicating that, all else being equal, the perceived utility for the freeway alternative should be greater than that for the side road. It is expected then that this freeway coefficient should be positive.

The model specified above was estimated over a range of experience importance factors with $0 \leq \tau \leq 1$ and with 0.2 increments. The data set for this model included 1,376 individual choices made by 43 subjects (23 from Experiment 1, Condition 2, and 20 from Experiment 3, Condition 7) all of which were subjected to the same experimental conditions. The model estimation technique uses the maximum log-likelihood method. The estimated model coefficients and log-likelihood values are presented in Table 3.

RESULTS

Of the six models estimated and presented in Table 3, the model with the greatest log-likelihood value is the model for which τ was set equal to 0.8. Of the models that incorporate some amount of utility on the basis of experience ($\tau < 1.0$), this model is also the only model in which all the coefficients have the appropriate sign. For the first variable, which represents the effects of route information, the positive value of 0.409 indicates that there is an increase in utility for the advised route and thus an increase in the probability that this route will be selected. The t-statistic for this variable indicates that the coefficient is not individually significantly different from 0 ($t < 1.96$ @ $\alpha = 0.05$), indicating caution in the interpretation of this variable. The second variable, which is

TABLE 3 Logit Model Coefficients

	$\tau = 0$		$\tau = 0.2$		$\tau = 0.4$		$\tau = 0.6$		$\tau = 0.8$		$\tau = 1.0$	
	ß	t	ß	t	ß	t	ß	t	ß	t	ß	t
$X_{ij1}(k)$ Advised route dummy entering alternative 1 and 2	1.199	7.15	1.136	6.06	0.998	4.61	0.741	2.75	0.409	1.01	1.135	9.90
$X_{ij2}(k)$ perceived delay entering alternative 1 and 2	0.059	1.67	0.065	1.49	0.065	1.18	0.047	0.62	-0.039	-0.33	-	
$X_{ij3}(k)$ perceived accuracy of advice entering alternative 1 and 2	-0.094	-0.58	-0.009	-0.05	0.174	0.71	0.511	1.59	0.922	1.86	-	
$X_{ij4}(k)$ male gender dummy entering alternative 1 and 2	0.294	2.00	0.293	2.00	0.292	1.99	0.294	2.00	0.296	2.02	0.290	1.98
$X_{ij5}(k)$ inexperienced driver dummy entering alternative 1 and 2	0.331	2.41	0.328	2.39	0.326	2.38	0.327	2.38	0.334	2.43	0.325	2.37
$ß_0$ freeway alternative specific coefficient	0.514	7.21	0.514	7.21	0.514	7.20	0.513	7.17	0.503	6.87	0.510	7.17
L(ß) log-likelihood at convergence	-670.03		-670.40		-670.46		-669.91		-669.79		-671.52	
L(0) log-likelihood with all coefficients equal to zero	-953.78											
L(C) log-likelihood with all coefficients equal to zero except $ß_0$	-936.11											

an updated perception of the delay on the alternative routes, has a coefficient value of -0.039, indicating that as the perceived delay on a route increases, the utility of that route decreases. Again, the t-statistic indicates that this coefficient is not individually significantly different from 0. The third variable, which is an updated perception of the accuracy of the information, has a coefficient value of 0.922, indicating that as the perceived accuracy of the system increases, the utility of the advised route increases. The t-statistic for this variable as well indicates that this coefficient is not individually significantly different from 0. The last two coefficients, which are indicators of the subject's sex and driving experience level, both have positive values and have t-statistics that indicate individual significance, as was expected on the basis of the ANOVA results. The freeway alternative-specific coefficient has the expected sign and is individually significant, again reiterating the "freeway bias" of subjects. This coefficient and its associated t-statistic remained relatively constant across all estimated models.

The overall fit of this model is not significantly different from the fit of any of the other models, as indicated by the relatively small variation in the maximum log-likelihood values. This brings into question the collective significance of coefficients β_2 and β_3 and the relative importance of the effects of previous experiences on current choices. When $\tau = 1.0$ in the updating function, there is no effect of previous experiences included in an individual's perception of information and route attributes for the current choice. The model for $\tau = 1.0$ was estimated by dropping these two variables from the analysis. The model estimated for $\tau = 1.0$ can then be used to test the collective significance of β_2 and β_3. If the $L(\beta)$ for this last model is defined as the log-likelihood for which coefficients β_2 and β_3 are constrained to 0 ($\beta_2 = \beta_3 = 0$) and is identified as $L(\beta_c)$ then the value $-2[L(\beta_c) - L(\beta)]$ has a chi-square distribution with two degrees of freedom and can be used to test the collective null hypothesis. From the values in Table 3, this chi-square value can be calculated as 3.46, which does not provide evidence to reject the null hypothesis ($X^2 > 5.99$, df $= 2$, $\alpha = 0.05$).

These results indicate two possibilities. The first is that drivers' perceptions of attributes, based on previous experiences, have little effect on route choice behavior under the influence of ATIS or it may be simply that the updating function used in this analysis is flawed and does not accurately describe the updating processes of drivers. The statistical tests of the coefficients for the updated variables, indicating collective insignificance, support both of the above hypotheses. The model with $\tau = 1.0$ includes only the system advice, personal attributes, and the alternative-specific coefficient, yet still predicts the route choice behavior fairly well with 79.2 percent of the 1,376 choices accurately predicted. The prediction rates for this model are presented in Table 4.

These results indicate that an accurate model of route choice behavior, exclusive of learned attributes, may be possible. The model prediction rate of 79.2 percent is approximately the same as the average acceptance rate of advice and the accuracy of the advice. The model then may be simply predicting that the route chosen is the route advised, and this is evidenced by the strong significance of the advice variable ($t = 9.9$) and the relative size of its coefficient. Counter to this argument is the fact that the model prediction rate is much better for the side road than for the freeway and that the prediction rate for the side road is significantly higher than the acceptance rate for the side road, which indicates that the model is not only predicting what is advised. Although excluding experience effects seem to be a gross simplification of the route choice behavioral process, it may be an accurate simplification. If it can be determined that drivers will follow route advice consistently at a rate equivalent to the accuracy of the advice being provided, this simple model of route choice may be adequate for use in a traffic assignment model. Only one possible updating function was used in this analysis, which may be why there were no significant effects as a result of updated perceptions. Continued modeling efforts will be undertaken using various updating schemes to determine the significance of drivers' learning experiences.

SUMMARY AND CONCLUSIONS

Previous research by the authors (*1*) has shown that a basic understanding of drivers' route choice behavior is necessary to develop predictive models of drivers' en route diversion choice. To study the basic underlying factors that contribute to diversion behavior, an interactive computer simulation experiment was developed in an attempt to capture drivers' sequential learning processes. Analysis of these experimental data resulted in the discovery of some interesting relationships. The ANOVA findings provide evidence that males will accept route advice more often than females over a range of accuracies and that inexperienced drivers will follow route advice more often than experienced drivers. In contrast to these findings, when asked about potential use of such an ATIS device, females were more likely to purchase an information device when accuracies were at 60 and 75 percent, but at 90 percent accuracies, males were more likely to purchase a device. These findings indicate that although males accept advice more readily at all accuracy levels, they are not as willing to purchase such a device unless the system is very accurate. A similar finding related to driving experience also

TABLE 4 Model Prediction Rate

		Predicted Choices		Total	% Correctly
		Freeway	Side Road	Number	Predicted
Actual Choices	Freeway	600	198	798	75.2%
	Side Road	88	490	578	84.8%

exists. Although inexperienced drivers were more likely to follow the advice being given, they also reported being less likely to purchase such an information device. This may be the result of less frequent drivers feeling that the savings gained from such a device would not outweigh the costs because of their limited driving. Conversely, more experienced and more frequent drivers perceive a net gain and respond as more likely to purchase a device although they do not follow the advice as often. The ANOVA also revealed that drivers will follow advice to take the freeway more readily than advice to take the side road and that they are quicker to respond to freeway advice, indicating that a "route bias" exists.

Analysis of the route choice decision times of drivers found that there was a very rapid drop in the decision times over the first 8 of 32 trials and that the times remained relatively constant over the remaining 24 trials. This finding and the fact that average acceptance rates of advice approximated the accuracy of the system indicate that drivers could sense and adapt quickly to the level of accuracy being provided by the system. Average decision times were the greatest for information provided at 75 percent accuracy. This indicates that subjects were more readily able to identify the level of accuracy for low levels as well as high levels but took a greater amount of time to discern the moderate level of accuracy.

The efforts to develop a model of route choice behavior that incorporates the learning processes of drivers had mixed results. A model was developed that included drivers' updated perceptions of route delay and information accuracy, but the model was not significantly different from a model that excluded these perceived attributes. The model includes the advised route as a variable. Because subjects followed the advice so readily, the model may simply be predicting that subjects will select the advised route, therefore predicting about 79 percent correct, which is equivalent to the average acceptance rate of advice. More analysis is required using different updating schemes before conclusive results can be made about the effects of experiences on sequential trials. Future research efforts will include attempts to formulate more realistic information updating schemes and to extend the research and modeling effort to a more realistic traffic network environment.

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REFERENCES

1. M. A. Abdel-Aty, K. M. Vaughn, R. Kitamura, and P. P. Jovanis. *Impact of ATIS on Drivers' Travel Decisions: A Literature Review*. Research Report. UCD-ITS-RR-92-7. Institute of Transportation Studies, University of California, Davis, 1992.
2. P. Bonsall and M. Joint. *Driver Compliance with Route Guidance Advice: The Evidence and its Implications*. Society of Automotive Engineers, Warrendale, Pa., Oct. 1991, pp. 47–59.
3. P. Bonsall. The Influence of Route Guidance Advice on Route Choice in Urban Networks. Special Issue. *Proc., Japanese Society of Civil Engineers*, Feb. 1991.
4. P. Bonsall and T. Parry. A Computer Simulation Game to Determine Drivers' Reactions to Route Guidance Advice. *Proc., 18th PTRC Summer Annual Meeting*, London, 1990.
5. J. Neter, W. Wasserman, and M. H. Kutner. *Applied Linear Statistical Models*. IRWIN, Homewood, Ill., 1990.
6. K. M. Vaughn, M. A. Abdel-Aty, R. Kitamura, and P. P. Jovanis. *Experimental Analysis of Sequential Route Choice Behavior Under ATIS*. Research Report UCD-ITS-RR-92-16. Institute of Transportation Studies, University of California, Davis, 1992.
7. H. Yang, R. Kitamura, P. P. Jovanis, K. M. Vaughn, and M. A. Abdel-Aty. Exploration of Route Choice Behavior with Advanced Traveler Information Using Neural Network Concepts. In *Transportation*, Kluwer Academic Publishers, 1993.
8. M. Ben-Akiva and S. R. Lerman. *Discrete Choice Analysis Theory and Application to Travel Demand*. The MIT Press, Cambridge, Mass., 1985.

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