# Experimental Analysis and Modeling of Advice Compliance: Results from Advanced Traveler Information System Simulation Experiments

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Computer-based microsimulation is evolving as a useful tool for the collection of travel behavior data. Analysis of the route choice problem in particular demands sequential data to capture the behavioral dynamics involved. The use of microsimulations to collect data of this type is in its infancy, because microcomputers powerful enough for this type of simulation have only recently become available. One such simulation recently completed at the University of California at Davis resulted in a data set that will support dynamic modeling. The simulation collected 32 sequential binary route choice decisions made by 343 subjects under various experimental conditions. The experimental factors included information accuracy, feedback, provision of descriptive rationale for route advice, indication of one route alternative as a freeway, and control for stops on the side road route. An analysis of the experimental treatments used in the simulation is presented, and a dynamic probabilistic model of subjects' advice compliance is developed. A regression approach was used to estimate the factor effects of an analysis of variance model of the experimental treatments. Dynamics were introduced into the model by the development of a perception variable that, when it is incorporated, leads to the adaptive expectations model. A linearized model of relative frequencies incorporating lagged dependent variables to account for behavioral dynamics is formulated and estimated. Econometric methods of pooled cross-sectional, time-series analysis are used to estimate models that account for heteroskedasticity and autocorrelation.

The application of advanced technologies to the traffic environment is an area that will have significant impacts on individual driver behavior. If real-time, accurate information on the characteristics of the travel environment can be provided to travelers before their departure and while they are en route, will behavior be altered in such a way as to improve the individual accessibility of drivers or improve the overall characteristics of the travel environment resulting in accessibility gains for all drivers, or will the individual benefits of such systems conflict with systemwide improvement goals? To accurately model the macrolevel effects of advanced traveler information systems (ATISs) the microlevel effects of these systems on individual driver behavior must be analyzed and understood.

A thorough understanding of behavioral dynamics is critically important when behavior cannot be represented properly on the basis of cross-sectional observation. This arises when time lags exist between a change in the travel environment and a behavioral change in response. Such time lags can be caused by the lack of information; experimentation and learning; the psychological, time, and monetary costs of searching; organized behavior based on planning; perception thresholds; constraints; and apparently irrational preferences for habitual behavior. These would lead to behavioral inertia, resistance to change, and differential speeds of adjustment, which in turn may lead to asymmetric responses to change (*1*).

Dynamic decisions are decisions in context and in time. This means that the decision maker must consider the consequences of each decision for future decisions, that he or she is constrained by earlier decisions, and that he or she may sometimes be able to correct problems caused by earlier decisions in later decisions (*2*). Prediction of the magnitude and timing of behavioral responses to changes in contributing factors demands the use of sequential data. The recognition of behavioral dynamics in the decision process points to the need to observe behavioral units repeatedly over time to accurately predict and forecast behavioral response.

Brehmer (*2*) states that experiments on dynamic decision making simply cannot be made by ordinary experimental methods because of the dynamic and interactive nature of the experimental tasks and claims that experimentation in this area is impossible without interactive computer simulation, which has only recently become available in the laboratory. Computers make it possible to create dynamic simulations and to study how subjects interact with such simulations. Brehmer labels such simulations "microworlds." These microworlds simulate some of the essential features of the dynamic system being investigated and are designed to reflect three main characteristics of real-world decision problems: complexity, dynamics, and opaqueness. They are complex in that they require the subjects to consider many different elements, dynamic in some or all aspects, and opaque in that all characteristics are not automatically revealed to the subject, requiring the formation and testing of hypotheses about their state and characteristics. The use of computer simulation in the framework of a controlled laboratory experiment is the approach that was taken in the present study to analyze the dynamic nature of the route choice process.

## DESCRIPTION OF SIMULATION EXPERIMENTS

An experiment to investigate drivers' learning and pretrip route choice behavior under ATISs was performed by using an interactive route choice simulation experiment carried out on a personal computer (PC) (*3*). 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

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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). The screen display of the simulator is shown in Figure 1. In Figure 1 the double-line link represents the freeway and the single-line link represents the side road. When the subject selects a route, a red blinking cursor (depicted by the small box on the side road link) moves across the screen from the origin (O) to the destination (D). The speed at which the cursor moves represents the average travel speed on that link for that travel day.

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 they 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 decision and response times are being measured and that they should try to respond as quickly as they can make a good decision.

The simulation was developed such that various experimental 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. Accuracy as defined within this experiment means that for any given trial day $i$, the probability that the information on day $i$ is correct ($P_i$) is equal to the accuracy level of the experiment. For example, condition 1 of experiment 1 used an accuracy level of 60 percent; thus, on any given trial day $i$ $P_i$ is equal to 0.6, or on average, over the 32 trial days, subjects experienced 19 trials in which correct information was provided and 13 days in which incorrect information was provided (subjects were not aware of the level of accuracy assigned in the experiment).

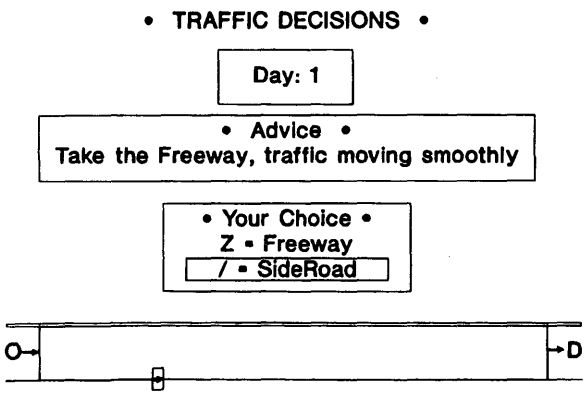


**FIGURE 1 Screen display of simulator.**

2. Stops. A simulated stop on the side road route could be applied.

3. Rationale. A justification statement as to 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. An identification of the routes as freeway and side road as opposed to simply Routes A and B.

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 could be simulated by a blinking cursor 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 discussed elsewhere (*3*). The first experiment was used to investigate the accuracy requirements of ATISs. The experiment was structured as described earlier, 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, respectively. The analysis and results of this first experiment can be found elsewhere (*3*). In the second and third experiments the information accuracy was held constant at 75 percent and other experimental conditions were varied. This paper provides an analysis of the data collected in the second and third experiments. The second and third experiments resulted in data from 266 subjects giving 8,512 individual choices. 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. Although the representativeness of students may be questionable, if the goal is to investigate how humans perceive information, learn, and adapt over time, then this pool of subjects may be as representative as any other within their homogeneous age group. Although some may question the "humanness" of undergraduate students with respect to basic human behavioral characteristics, the sample should be representative; however, it will be biased by age. With regard to other characteristics, 42 percent of the sample was male, which is underrepresentative of the general population. To measure the level of driving experience in the sample, all subjects were asked to rate their driving frequency. One hundred eleven subjects indicated that they either currently commute or do not now but formally commuted, 98 subjects indicated that they do not commute but drive frequently, and 57 subjects indicated that they either drive infrequently or do not drive.

## ANALYSIS OF EXPERIMENTAL TREATMENTS BY ANOVA

In this section the effects of the various treatment combinations are analyzed by analysis of variance (ANOVA) techniques. ANOVA models are used for studying the relation 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 that it is applied here, is that it does not require the investigator to make assumptions about the nature of the statistical

relation (except for covariate terms), nor does it require the independent variables to be quantitative (*4*). The first treatment, accuracy, has three levels, and the effects of this treatment have been documented previously (*3*). Generally, increasing information accuracy results in increased advice compliance, and subjects tend to quickly identify the level of accuracy of the system and accept advice at a rate equivalent to the level of accuracy.

The significant findings from the first data set (*3*) are summarized as follows:

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.
3. Experienced drivers are not as willing as less experienced drivers to accept advice, 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. Although less experienced drivers are more likely to follow advice, they are also less likely to purchase an information system.

In a parallel project that is investigating commuters' acquisition and use of traffic information and its effect on route choice decisions using survey methods (*5,6*), it was found that females were more willing to accept pretrip traffic information than males, which contradicts findings provided elsewhere (*3*). A study by Mannering et al. (*7*) of the influence of traffic information on route, mode, and departure time choice, based on travel surveys, also found that males were less likely to be affected by pretrip traffic reports for all three decisions. These contradictory findings spurred further investigation into the effects of gender. In the data presented elsewhere (*3*) it was found that at information accuracy levels of 65 and 90 percent male acceptance of information was significantly higher than female acceptance, whereas at a 75 percent level of accuracy no significant difference in information acceptance was found between males and females. The net effect that was reported was that males had higher acceptance rates than females, but these results were not independent of accuracy level. In the data from the second and third experiments, which have much larger sample sizes and all observations are at a 75 percent accuracy level, it is found that females do accept pretrip information more than males, which agrees with the similar findings from the surveys.

The analysis by Vaughn et al. (*3*) focused on the effects of accuracy on subjects' agreement with advice, the decision time required to make a route selection, and the subjects' willingness to purchase a system on the basis of their experiences with the simulation. The analysis performed here focuses on these same dependent variables but addresses the effects of four of the remaining experimental treatments as defined earlier: feedback, rationale, freeway, and stops. ANOVA models were estimated for each of the three dependent variables, and the final models that retained the significant main effects and interactions are presented in Table 1. The model of subjects' agreement with advice indicates that the effects of feedback and rationale are individually significant and that the interaction effects of stops and rationale are strongly significant, whereas the individual effects of stops and freeway are only moderately significant. In the model of subjects' decision time, feedback, rationale, and stops are all individually significant, and again, the interaction effects of stops and rationale are strongly significant. In the model of subjects' willingness to purchase an information system, all of the main and interaction effects in the model are strongly significant.

## ANOVA Regression Models

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 by a regression approach equivalent to the ANOVA model.

The factor effects model can be represented in the matrix form

$$\mathbf{Y} = \mathbf{X}\boldsymbol{\beta} + \mathbf{x}\tau + \epsilon \tag{1}$$

where

$\mathbf{X}$ = a matrix of dummy variables that represent the levels of the treatments,
$\mathrm{x}$ = a matrix of covariates,
$\boldsymbol{\beta}$ and $\tau$ = coefficient vectors, and
$\epsilon$ = error vector.

When a background variable (covariate) is strongly related to the dependent variable, an analysis of covariance may increase the precision of comparisons between treatments by reducing the within-group variability in the dependent variable due to the influence of the covariate. Since all treatments in this analysis have only two levels, the ANOVA regression model has the same number of parameters as the parent ANOVA model has effects. For a detailed explanation of the ANOVA regression procedure see Neter et al. (*4*).

The objective is therefore to test appropriate hypotheses about the treatment effects and to estimate these effects. For hypothesis testing the model errors are assumed to be normally and independently distributed with zero mean and constant variance $\sigma^2$. Additional assumptions of the covariate model are that within each group the dependent variable has a linear relationship with the covariate and that the slope of the regression for each covariate is the same in each group.

Because of the sequential nature of these data the method of ordinary least squares (OLS) for estimating the regression is not appropriate. In this data set $\mathbf{Y}$ is a cross-sectional time-dependent vector of observed behavior with elements $Y_i(t)$, which is the observation for individual $i$ at time period $t$, and $i$ is equal to 1 to $N$ and $t$ is equal to 1 to $T$, where $N$ is the number of subjects (266) and $T$ is the number of sequential, equally spaced observations on each subject ($n$ = 32). $\epsilon$ is a cross-sectional time-dependent vector of errors with elements $\epsilon_i(t)$. $\mathbf{x}$ is an $NT \times k$ matrix of $k$, $NT \times 1$ vectors of explanatory variables whose elements may be either cross sectional (gender) or time dependent (traffic information on day $t$), or both (perception variables). $\boldsymbol{\beta}$ is a $k \times 1$ parameter vector that is assumed to be the same for all $i$. Kmenta (*8*) presents a framework for estimating models with cross-sectional, time-series data. The assumptions of the Kmenta model allow for cross-sectional heteroskedasticity and assume cross-sectional independence and first-order autocorrelation AR(1). Estimation of this model can be performed by using feasible generalized least squares (FGLS) and maximum likelihood methods (*8,9*).

TABLE 1 ANOVA Table

| Dependent → | Agreement[a] | Decision Time[b] | Purchase[c] |
|---|---|---|---|
| Independent ↓ | F-stat[d] | F-stat[d] | F-stat[d] |
| Feedback | 31.01 | 17.63 | 596.09 |
| Rationale | 13.19 | 22.53 | 147.89 |
| Freeway | 1.07 | 0.22 | 12.62 |
| Stops | 1.76 | 41.00 | 87.90 |
| Stops/Rationale interaction | 13.11 | 47.10 | 448.22 |

[a]Agree (1=yes,0=no)
[b]Decision time is time in seconds
[c]Purchase (1=extremely likely to buy, to 7=would not buy)
[d]F critical = 3.84 ($\alpha$=0.05,1,$\infty$)

The factor effects model with ANOVA regression was estimated with a pooled, cross-sectional, time-series model by the FGLS method with an econometrics computer package (*9*) for the dependent variables agreement and decision time. Tests for heteroskedasticity were performed on the pooled model for these dependent variables, and significant violation of the homoskedastic assumption was indicated. The pooled, cross-sectional, time-series model corrects for cross-sectional heteroskedasticity, and log likelihood ratio tests indicated significant improvement in log likelihood values for the pooled, cross-sectional, time-series models. The dependent variable purchase is purely cross-sectional, and this model was estimated by OLS procedures. In addition to the main and interaction effects of the ANOVA models, the covariates included in the models were the trial number, a dummy variable indicating side road advice, a male dummy variable, a driving experience variable, and a perception variable. The results of the model estimation are presented in Table 2.

The first two models presented in Table 2 are static models of behavior; observed behavior at time *t* is only dependent on contributing factors also observed at time *t*. The assumption underlying this model is that behavior (**Y**) changes immediately in response to a change in contributing factors (**X**) and that behavior does not depend on past history. The second two models presented an attempt to capture the behavioral dynamics by including a time-

TABLE 2 ANOVA Regression Models

| Dependent → | Agreement[a] | Decision time[a] | Agreement[b] | Decision time[b] | Purchase[c] |
|---|---|---|---|---|---|
| Independent ↓ | Coeff.(t) | Coeff.(t) | Coeff.(t) | Coeff.(t) | Coeff.(t) |
| Intercept | .7446(50.23) | 3.8124(55.94) | -.0991(-1.04) | 4.3959(62.08) | 4.0524(100.1) |
| Trial number | .0031(6.39) | -.0741(-34.01) | - | - | - |
| Side road advice | -.0607(-10.07) | .3119(19.51) | -.0624(-10.27) | .3172(19.64) | - |
| Sex(M=1,F=0) | -.0394(-4.10) | -.2907(-6.53) | -.0399(-4.18) | -.2805(-6.61) | -.1131(-3.61) |
| Driving experience | .0043(0.72) | .0464(1.75) | .0069(1.18) | .0484(1.90) | .0198(1.00) |
| Feedback | .0217(4.45) | .0420(1.82) | .0223(4.58) | .0488(2.22) | -.3922(-24.67) |
| Rationale | .0243(3.53) | .1536(5.01) | .0274(3.98) | .1229(4.17) | -.2785(-12.14) |
| Freeway | -.0060(-0.87) | .0074(0.25) | -.0091(-1.32) | .0373(1.33) | .0838(3.67) |
| Stops | -.0108(-2.20) | -.1305(-5.63) | -.0087(-1.78) | -.1337(-5.95) | -.1514(-9.47) |
| Stops/Rationale interaction | .0188(3.58) | -.1691(-6.90) | .0213(4.08) | -.1838(-7.72) | -.3660(-21.41) |
| Perceived accuracy of information | - | - | 1.3034(9.52) $\lambda$=.97,ic=.65 | -3.4078(-41.27) $\lambda$=.89,ic=0 | - |
| Log likelihood | -4100.98 | -13436.40 | -4081.31 | -13303.80 | -14839.0 |
| [d]Buse $R^2$ | .777 | .674 | .780 | .698 | - |
| $R^2$-adj | - | - | - | - | .144 |

[a]Static, pooled cross-sectional, time-series model (FGLS)
[b]Adaptive expectations, pooled cross-sectional, time-series model (instrumented FGLS)
[c]Static, cross-sectional model (OLS)
[d]See reference (*10*)

varying covariate that is formulated as the subjects' perceived (or expected) accuracy of information. This formulation leads to a model known as the *adaptive expectations model* (*8*).

The first model of subjects' agreement with advice indicates that having feedback and providing a rationale for the advice significantly increases the level of agreement with advice. The effects of having one route labeled freeway and having stops on the side road result in a decreased level of agreement. This result is due to subjects being less willing to accept side road advice when one route is labeled a freeway or when the side road route has stops. The interaction of stops on the side road and rationale significantly increases the level of agreement. This result is due to subjects' overcoming the aversion to the side road route with stops when given some rationale as to why they should take that route (e.g., there is a problem on the freeway route today). The covariate terms indicate that less experienced drivers are more likely to follow advice, whereas male subjects are less likely to follow advice, and side road advice results in a reduction in the level of agreement. These results are supported by similar findings from a previous analysis (*3*), previous survey efforts (*5,6*), and other sources (*7*).

The inclusion of a time train variable (the trial number) is an attempt to capture the dynamics of learning in a static framework. The coefficient on this variable gives an indication of the effect of time on the behavior. The coefficient indicates that subjects are increasing their level of advice compliance over time, presumably because they are learning that the information provided is accurate enough to improve their performance in route selection.

To introduce a dynamic relationship into the model it is assumed that the behavior is history dependent; that is, behavior at time $t$ is assumed to be a function of contributing variables measured at time $t - s$ through time $t$. This model may be formulated as

$$\mathbf{Y} = \mathbf{X}\boldsymbol{\beta} + \mathbf{Z}^1\tau + \ldots + \mathbf{Z}^m\mu + \epsilon \tag{2}$$

where

- $\mathbf{Y}$ = a cross-sectional, time-dependent, $NT \times 1$ vector of observed behavior with elements $Y_i(t)$, which is the observation for individual $i$ at time period $t$, $i$ equals 1 to $N$ and $t$ equals 1 to $T$, where $N$ is the number of subjects and $T$ is the number of sequential, equally spaced observations on each subject;
- $\epsilon$ = an cross-sectional, time-dependent vector of errors, with elements $\epsilon_i(t)$;
- $\mathbf{X}$ = an $NT \times k$ matrix of $k$, $NT \times 1$ vectors $(\mathbf{x}_1, \mathbf{x}_2, \ldots, \mathbf{x}_k)$ of explanatory variables with elements $x_{ji}(t)$, where $j$ = 1 to $k_j$;
- $\boldsymbol{\beta}$ = $k \times 1$ parameter vector that is assumed to be the same for all $i_j$;
- $\mathbf{Z}^m$ = NT $\times$ $l$ matrices of $l$, $NT \times 1$ vectors $(z_1, \mathbf{z}_2, \ldots, \mathbf{z}_l)$ of explanatory variables with elements $z_{ji}(t - m)$, where $j = 1$ to $l$, $m = 1$ to $s_j$, and
- $\tau$ and $\mu$ = $l \times 1$ parameter vectors that are assumed to be the same for all $i$.

In this formulation, each $\mathbf{Z}^m$ matrix is a subset of the exogenous variables in $\boldsymbol{X}$, lagged one time period from $t - 1$ to $t - s$, where $t = s + 1, \ldots, T$. $\mathbf{Z}^m$ could also include all exogenous variables in $\boldsymbol{X}$, in which case, $l$ is equal to $k$.

Frequently, some restrictions are placed on the regression coefficients so that the number of the regression parameters is reduced (*8*). The most common is the restriction that the parameters be declining in a geometric progression resulting in a geometric lag distribution and what is known as the *adaptive expectations model*. Suppose that the dependent variable is modeled not as a linear function of some explanatory variable in the same time period but as a function of the expected or perceived value of the variable. Most travel decisions exemplify this relation because the decisions are dependent on the expected characteristics of the travel environment whose true value is not revealed until after the decision has been made. In the model estimated here it is assumed that a subject has some expectation or perception as to whether the information that they receive is accurate and is a function of past experiences.

This model can be formulated as

$$Y_i(t) = \alpha + \beta X_i^*(t + 1) + \epsilon_i(t) \tag{3}$$

where

$$X_i^*(t + 1) = (1 - \lambda)X_i(t) + \lambda X_i^*(t) \tag{4}$$

and $0 \leq \lambda < 1$. This formulation assumes that the expected or perceived value of $X$ at time $t + 1$ is a weighted average of the current value of $X$ and the expected value of $X$ in the current time period. This formulation is based on the idea that the current expectations are derived by modifying previous expectations in light of the new information from the current experience (i.e., dynamic updating) (*8*). This weighted average updating function was also used to update perception variables in earlier work (*3,11*).

Equation 4 can also be expressed as

$$X_i^*(t + 1) = (1 - \lambda)[X_i(t) + \lambda X_i(t - 1) + \lambda^2 X_i(t - 1) + \ldots.] \tag{5}$$

which results in the following geometric lag distribution when substituted into Equation 3:

$$Y_i(t) = \alpha + \beta(1 - \lambda)[X_i(t) + \lambda X_i(t - 1) + \lambda^2 X_i(t - 1) + \ldots.] + \epsilon_i(t) \tag{6}$$

In this form the effect of $X$ on $Y$ extends indefinitely into the past, but the coefficients are declining geometrically such that the distant values of $X$ become negligible. The magnitude of the parameter $\lambda$ then becomes a relative measure of an individual's learning. A large value of $\lambda$ indicates strong memory effects, with experiences in the past significantly contributing to the current expectation, whereas small values indicate that the effects of past experiences have very little or no effect on current expectations.

This model can be estimated by assuming values for $\lambda$ and the initial conditions for $X_i^*(t)$ and then using Equation 4 as an instrumented variable in Equation 3. This instrumented variable method was used in a pooled cross-sectional, time-series model to estimate iteratively across values for $\lambda$ and the initial conditions. The convergence criteria used for the iteration was to maximize the log likelihood value of the estimate. The third and fourth models presented in Table 2 are adaptive expectations models where the perceived accuracy of the information variable has been substituted into the previous models for the time train variable.

In the second model of subject agreement in Table 2, all of the static variables maintain their previous interpretations, which is desired. The perceived accuracy of information is shown to strongly

influence the level of agreement with advice and indicates that as the perception of the accuracy increases, so does the level of agreement. The log likelihood value in this model shows significant improvement over the static model. The value of $\lambda$ was found to be 0.97, indicating very strong memory effects in updating the perception of accuracy. Iida et al. (*12*), who conducted similar simulation experiments, have also found strong memory effects in the updating of subjects' expected travel time on a route.

The static model of subjects' decision times indicates that feedback and rationale significantly increase the amount of time that subjects spend making a decision, whereas stops on the side road and the stops-rationale interactions decrease the time spent making a decision. The covariates in this model indicate that more experienced drivers and male subjects make their decisions faster, whereas advice to take the side road increases the decision time. The time train covariate indicates the improvement in decision making that occurs over time, with subjects spending less time making a decision over time. In the dynamic model of subjects' decision time, there is a significant improvement in the log likelihood value over that in the static model. The perceived accuracy of information is shown to be strongly significant and indicates that an increase in the perception of accuracy leads to reduced decision time. The value of $\lambda$ again suggests the significance of past experiences in current choice behavior.

The last model in Table 2 is a static cross-sectional model of subjects' stated willingness to purchase an information system. In this model all of the treatment main effects and the stops-rationale interaction are shown to be significant. Feedback, rationale, stops, and the interaction term all increase the likelihood of purchasing a system, whereas the freeway treatment leads to lowering the likelihood of a purchase. This indicates that increasing the level of information available in the system increases subjects' willingness to purchase a system. The negative effect of the freeway treatment may be due to the strong freeway bias that is exhibited. If subjects have a strong bias for freeway use and it is in their choice set of route alternatives, then the attractiveness of a system that will be advising them away from their preferred route may be lessened. The covariates in this model indicate that more experienced drivers and male subjects were less likely to purchase an information system, which supports previous results (*3*).

## DYNAMIC MODEL OF ADVICE COMPLIANCE

### Modeling Relative Frequencies

In this section the estimation of a binary choice model that uses choice frequency data that contain a nonnegligible number of limit cases is presented. The model presented here has a binary choice probability formulation that uses a logistic function. Relative frequencies for advice compliance are ratios of the number of agreements with advice over the total number of trips made. Modeling of relative frequencies has been performed by using linear or linearized models (models that by simple mathematical manipulations can be converted into a linear form), nonlinear methods, and limited dependent variable methods (*13*).

When an individual decision maker faces two or more alternatives and a single observation is available for each instance of a set of explanatory variables, a probabilistic model of the choice of alternative can be formulated on the basis of random utility theory. This formulation leads to the classical utility maximization form of the logit or multinomial logit model when the disturbances are assumed to be independent and identically distributed random variables with Weibull distributions. When an individual faces two alternatives and repeated observations are available for each instance of a set of explanatory variables, then sample proportions can be used as estimates of the probabilities of choosing either alternative. A linear probability model of relative choice frequencies, transformed to approximate a logit model, allows for efficient parameter estimation by generalized least-squares methods (*14*). The first use of this method is generally attributed to Berkson (*15*).

### Linear and Linearized Models

Assume that an individual choice maker $i$ makes $n_i$ choices between two alternatives and let $y_i$ be the number of times that alternative 1 is chosen and let $y_i - n_i$ be the number of times that alternative 2 is chosen. A linear probability model of the sample proportions, $p_i = y_i/n_i$, can be formulated as a linear combination of explanatory variables as

$$\mathbf{p} = \mathbf{X}\boldsymbol{\beta} + \mathbf{e} \tag{7}$$

Unbiased, consistent estimates of the model parameters can be obtained by generalized least-squares procedures. A significant problem with the linear model is that the predicted proportions do not necessarily lie between zero and 1.

The true proportions $P_i$ are related to the sample proportions $p_i$ by $p_i = P_i + e_i$. The logit transformation is obtained by assuming that the true proportions are related to the set of explanatory variables by a logistic function, giving

$$P_i = 1/[1 + \exp(-X_i'\beta)] \tag{8}$$

It can be shown that the odds ratio $P_i/(1 - P_i)$ is simply $\exp(X_i'\mathrm{B})$, and Equation 8 can be written as the logarithm of the odds ratio (log-odds):

$$\ln[P_i/(1 - P_i)] = X_i'\beta \tag{9}$$

This equation can be rewritten in terms of the empirical probability (*14*) as

$$\ln[p_i/(1 - p_i)] = X_i'\beta + u_i \tag{10}$$

where $u_i$ is equal to $e_i/[P_i(1 - P_i)]$. Note that the empirical log-odds, $\ln[p_i/(1 - p_i)]$, can be expressed as $\ln[y_i/m_i]$, where $m_i = n_i - y_i$ (*13*). This is called the *logit*.

The error term $u_i$ in Equation 10 can be shown to have $E[u_i]$ equal to 0, and its variance can be approximated as (*14*).

$$\mathrm{Var}(u_i) = 1/[n_i p_i(1 - p_i)] \tag{11}$$

These equations can be used to estimate the parameter vector in the logit. Note that the variance of $u_i$ is heteroskedastic and may be serially correlated as well, depending on the nature of probability $P_i$.

One problem arises when the observed frequencies, $y_i$ or $m_i$, are equal to zero. In this case the log-odds, and thus the empirical probabilities, are undefined (*13*). Haldane (*16*) devised a method to circumvent this problem in which the value ½ is added to all the

frequencies. The dependent variable for this type of methods can be written as

$$Y_i = \ln[(y_i + \delta)/(m_i + \delta)] = X_i'\beta + u_i \quad (12)$$

where $\delta$ is a positive constant ($\delta = 1/2$ by Haldane's method). The logit, $Y_i$, is now defined for all cases and can be used as the dependent variable in the estimation.

## Results

A model of advice compliance was estimated by using the linearized modeling framework and Haldane's method discussed in the previous section and is presented in Table 3. For each individual, the 32 trials were broken into four blocks of 8 trials each. The empirical probability for individual $i$ in trial block $j$ therefore is $P_{ij} = k_{ij}/t_{ij}$, where $i$ is equal to 1 to 266, $j$ is equal to 1 to 4, and $t_{ij}$ is equal to 8 because all subjects made the same number of choices in all blocks. The dependent variable in the model is the logit of advice compliance and is defined as $\ln[(k_{ij} + 1/2)/(m_{ij} + 1/2)]$, where $k_{ij}$ is the number of agreements with advice in trial block $j$, and $m_{ij}$ is the number of disagreements with advice. By grouping the trails into blocks, the dependent variable becomes a cross-sectional, time-dependent vector of observations, and Kmenta's method (*8*) of estimating models with cross-sectional, time-series data accounting for first-order autocorrelation and heteroskedasticity is the method used to estimate this model.

The cross-sectional independent variables in the model included a male gender dummy, and the significant main and interaction effects of the experimental treatments that were identified in the ANOVA model, including feedback, rationale, freeway, stops, and stops-rationale interactions. The time-dependent independent variables include three trial block dummies, the number of times that correct information was provided in the current block, the number of times that incorrect information was provided in the previous block, and the number of times that a correct choice was made in the previous block.

The effects of the experimental treatments in this model are very similar to those discussed earlier for the ANOVA models. Providing feedback and an indication that one of the routes was a freeway significantly increases the probability that subjects will follow the system's advice, whereas having stops on the side road significantly reduces the probability that the subjects will comply. The effect of providing a decision rationale to the subjects has the opposite sign in this model compared with that in the ANOVA model,

**TABLE 3 Linearized Probability Model of Advice Compliance[a]**

| Dependent → | In (Ratio)[b] | |
|---|---|---|
| **Independent ↓** | **Coeff.(t)** | |
| Feedback provided[c] | .2238(16.71) | |
| Decision Rationale provided[c] | -.0222(-1.04) | |
| Freeway route indicated[c] | .1817(8.55) | |
| Stops required on side road[c] | -.2376(-16.92) | |
| Stops & Rationale interaction[c] | .1031(7.67) | |
| Trial block number two[d] | .4228(5.94) | |
| Trial block number three[d] | .5015(6.63) | |
| Trial block number four[d] | .6222(7.92) | |
| Number of correct advice in current block | .0436(5.02) | |
| Number of bad advice in previous block | -.0901(-8.52) | |
| Male gender[d] | -.0733(-3.34) | |
| Number of correct choices in the previous block | -.0367(-3.49) | |
| Constant | .7218(11.60) | |
| Log likelihood | -1009.9 | |
| Buse $R^2$ | .967 | |
| Prediction Rate | 75.1% | |
| **Agree with Advice** | **0** | **1** |
| Actual | 2110 | 6402 |
| Correctly Predicted | 9 | 6381 |
| Market Share | 2217.8 | 6294.2 |

[a]Dynamic, pooled cross-sectional, time-series model (FGLS)
[b]$\text{Ratio}_t$ = (number of agreements in block t)+½ / (number of disagreements)+½
[c]1/-1 dummy variable
[d]1/0 dummy variable

but interpretation of this coefficient is not reliable here because of the low significance level. The interaction effects of stops and rationale significantly increase the probability of compliance, which also agrees with the ANOVA results. The coefficient on the gender variable again indicates that males are less likely to comply with advice.

The dynamic variables in the model give some indication of how subjects are learning and modifying their behaviors over time. The trial block dummy variables are all strongly significant and indicate that as subjects progress through the trials their compliance behaviors change. The greatest change in probability of compliance occurs between the first and second trial blocks, with the probability of compliance continuing to increase from the second through the fourth trial block. This finding supports earlier results indicating that subjects could quickly identify the level of accuracy of the information. Here a significant increase in advice compliance from the first to second trial block can be seen, indicating that subjects have learned that the accuracy of the information provided is at such a level that compliance with advice improves their travel choices. The coefficient on the number of times that correct advice was provided in the current block indicates that even within a block subjects could recognize improved accuracy, and as accuracy improves compliance improves.

As was shown in the ANOVA regression model, the agreement behavior is dependent on the accumulation of past experiences. These effects are captured in this model through the use of lagged variables. The effect of increased levels of bad advice in the previous trial block negatively affects compliance in the current block. The coefficient on the correct number of choices in the previous block is also significant and has a negative effect, which is not intuitive. One would think that as the number of correct choices in the past increases compliance would increase. One must also realize that a correct choice as defined here includes choosing the correct route regardless of advice. If a subject chooses the correct path on a day that it is not the advised path, this could have a negative impact on advice compliance.

## CONCLUSION

Analysis of the experimental treatments used in the simulation found that providing subjects with feedback significantly increased the level of agreement with system advice and that subjects were much more willing to purchase systems that provided feedback. Providing subjects with descriptive information in the form of rationale with the route advice also significantly increased agreement level and willingness to purchase a system. A negative bias toward routes with stops is indicated, with subjects less likely to comply with advice to take a route with stops. This finding is interesting in that even with the stops on the side road, over all 32 trials there is no advantage of the freeway over the side road because the mean travel times for both routes across the trials were equal. This indicates the different values that subjects place on congestion delay versus stopped delay. The significance of the interaction between stops and rationale indicates that the provision of the descriptive information had the effect of reducing the negative bias toward routes with stops and increasing the probability that subjects would accept advice to take routes with stops.

The findings of the effects of gender clarify previous results and agree with real-world results from travel surveys (*3,5–7*). It was found that males were less likely to comply with pretrip route advice. These types of comparisons with real-world studies will help to validate the results of simulations.

The dynamic nature of the decision process was modeled by using an adaptive expectations model and a linearized probability model of discrete choice. The adaptive expectations model was used to model the effects of subjects' perception of the accuracy of information. This framework assumes that for each trial the subject has some perception or expectation of accuracy of the information provided and that this perception is updated over time on the basis of experiences. The results indicate the significance of this perception variable and also indicate that subjects have a strong memory effect, such that current perceptions rely more heavily on the accumulation of past experience as opposed to just recent past experience. A dynamic probabilistic model of advice compliance accounting for heteroskedasticity and autocorrelation was estimated by using a linearized relative frequencies model. The model provided similar results for effects of the experimental treatments and also indicates the significance of dynamic effects in complying with the system's advice.

The use of computer simulation has been found to provide a useful tool for the collection of sequential route choice data in the presence of ATISs. The simulation is simple and structured around a binary choice set (freeway versus side road), yet the results obtained indicate the significance of the behavioral dynamics involved in the decision process. Recognition of the simplicity involved in the simulation as well as the limited choice set and information available has lead to the development of a more complex PC-based simulator. This new simulator operates with a more complex traffic network and incorporates interconnected freeway and arterial and surface street link types to create a large choice set of alternatives from the origin to the destination. The type and level of information that can be provided to subjects have also been expanded to include pretrip route guidance, en route guidance, incident information, and congestion levels. A new set of simulation experiments that uses this expanded simulation software has recently been completed. In those experiments 100 regular commuters from the Sacramento, California, area were recruited, and each commuter completed 20 sequential trials with the simulator. This new set of experiments has provided a rich data source that is under analysis (*17*).

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