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ABSTRACT

An experiment to collect sequential route choice data under the influence of an Advanced Traveller Information System (ATIS) was performed using a PC-based simulation. The experiment collected information on drivers' pre-trip route choice behavior at three levels of information accuracy, 60 percent, 75 percent 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 with mixed results. It was assumed that drivers update their knowledge of the system based on their previous experiences and 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 being provided and that they adjust their behavior accordingly. There is also evidence which indicates an accuracy threshold level does exist 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 which was 79 percent accurate but also indicated that previous experiences had little effect on current route choices. This may be the result of a mis-specified updating function indicating further research is required to identify these learning relationships.

INTRODUCTION

Current research being performed at the University of California at Davis is investigating the impact of Advanced Transportation Information Systems, or ATIS, on travel demand. The goal of the project is to understand how people will adopt ATIS, learn its use, devise rules for travel planning and how all these relate to travel demand. A part of this larger project is the research efforts described in this paper and in a companion paper (Yang et al. 1992). This paper

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describes the experimental analysis techniques and modelling efforts applied to sequential pre-trip route choice behavior data. This effort is the first step in a process to develop a basic understanding of the factors which influence route choice and how ATIS will affect drivers' route choice behavior over time.

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 (Abdel-Aty et al. 1992), therefore, it was decided to analyze route choice behavior in the most simplistic, controlled environment possible. It was felt that this level of control would allow us to adequately restrict and analyze the effects of various factors on route choice behavior. The factor of utmost importance to any analysis of driver behavior influenced by ATIS is a measure of the information accuracy. 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 by Bonsall et al. (1991) has indicated the importance of system accuracy on compliance with advice. If a system consistently provides bad information drivers will soon begin to ignore the advice and route choice patterns will remain unchanged. If highly accurate information is consistently provided, drivers will likely perceive a benefit from following the advice and adapt their behavior to the advice. How do drivers perceive the accuracy of provided information? Is there an accuracy threshold below which drivers perceive no benefit from following advice? If such thresholds do 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 in order to maximize the potential of ATIS.

The analysis suggests that initially drivers are predisposed to following 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 eight of thirty-two 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, while 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 pre-trip route choice behavior under ATIS was performed using an interactive route choice simulation experiment carried out on a PC. 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" which will provide them with traffic information prior to their route selection. 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 become 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.

When the subjects are ready to begin the simulation, they are presented with a screen indicating that it is trial day number one and instructed to position their hands on the computer key-board and to press the space bar when they are ready to receive advice. Upon 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 below:

When the subject selects a route, a red blinking curser (depicted above by the 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 the figure above, the double line link represents the freeway and the single line link represents the side road. Upon completion of each trial subjects were asked to rate their choice satisfaction (i.e. Correct, Probably Correct, Don't Know, Probably Incorrect, Incorrect), and to provide an estimate of their travel time on their chosen route (i.e. Fastest Possible, Reasonably fast, Moderate, Fairly slow, Incredibly slow).

The simulation was developed such that various treatments could be applied and then data could be collected under these different conditions. The treatments which 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%. 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 the equal to the accuracy level of the experiment. For example condition 1 of experiment 1 used an accuracy level of **60%,** thus on any given trial day i, **$P_i=0.6$** 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 (again, subjects were not aware of the level of accuracy assigned).

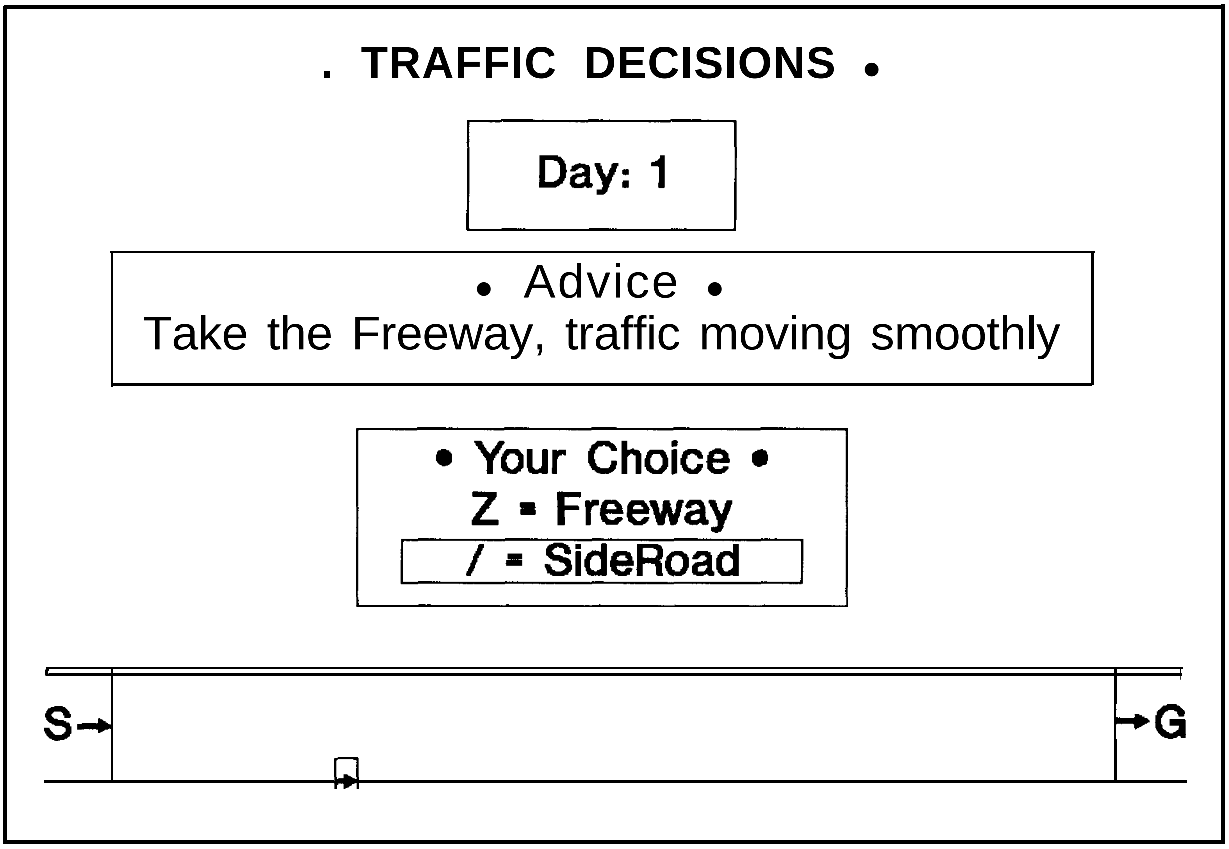

Figure 1: Typical Screen Display of Simulator

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 above 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 percent, 75 percent 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 report provides an initial analysis of the data collected in the first and third experiments utilizing four of the sixteen 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 to routes with slower travel times but with a greater amount of certainty (similar to surface street routes). Upon 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 to the information device.

Table 1: Experimental Treatments

Experiment	Condition	Treatment Number						Number of Subjects
		1	2	3	4	5	6	
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

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. The variables recorded by the program are defined below:

1. ADVROUTE: The advised route given by the simulated information system taking on values of 1 for the side road and 2 for the freeway. The advised route is based on the delay assignments and accuracy level, in general for correct advice the minimum delay route (1 or 2) is advised while for incorrect advice, the maximum delay route is advised. The number of freeway and side road **advices** were balance across the 32 trials.

2. RELDELAY: The relative delay between the routes based on the advised route.

   For advised route = 1, 2

   1 = Delay on advised route is two units of delay less than on the other route.

   2 = Delay on advised route is one unit of delay less than on the other route.

   3 = Delay on advised route is one unit of delay greater than on the other route.

   4 = Delay on advised route is two unit of delay greater than on the other route.

3. DFREE: Delay on the freeway, 1 to 5 units of delay.

4. DSROAD: Delay on the side road, 2 to 6 units of delay.

5. CHOICE: Route chosen by the subject for an individual trial, taking on a values of 1 for the side road and 2 for the freeway.

6. SAT: An individual's level of satisfaction with the choice made.

   1 = Correct Choice
   2 = Probably Correct
   3 = Don't know
   4 = Probably incorrect
   5 = Incorrect

7. EST: An individual's estimate of their perceived speed on their chosen route.

1 = Fastest possible
2 = Reasonably fast
3 = Moderate
4 = Fairly slow
5 = Incredibly slow

8. DTIME: The decision time of the individual (i.e. the time, in seconds, to choose a route after information is received.

9. SEX: Individual's gender; 1 = Female, 2 = Male.

10. AGE: Individual's age category.

1 = less than 21
2 = 21 -24
3 = 25 - 35
4 = greater than 35

11. DFREQ: Driving frequency or level of experience.

1 = Currently commute
2 = Do not now but formerly commuted
3 = Never commuted but drive frequently
4 = Drive infrequently
5 = Do not drive

12. USAGE: Potential information system usage.

1 = Extremely likely to buy
2 = Very likely
3 = Likely
4 = Undecided
5 = Unlikely
6 = Very unlikely
7 = Would not buy

13. ACC: An individuals perceived accuracy of the information system.

1 = Perfectly accurate
2 = Extremely accurate
3 = Reasonably accurate
4 = Moderately accurate
5 = Inaccurate
6 = Extremely inaccurate
7 = worse than nothing

14. ABL: Personal ability, an individuals rating of their own ability selecting routes as compared to the information system.

1 = Much, much better
2 = Much better
3 = Somewhat better
4 = About the same
5 = Not as well
6 = Not nearly as well
7 = Much, much worse

15. PAADV: Percent accuracy level of the advice given; 60 % , 75 % , & 90 % .

16. TRIAL#: The sequential trial number; 1 through 32.

The following variables were created from the original data set:

17. TBLOCK: Trial block;

1 = Trial 1 through 8
2 = Trial 9 through 16
3 = Trial 17 through 24
4 = Trial 25 through 32

18. AGR: Agreement (i.e. follow) with advice; 1 = agree, 0 = disagree.

19. ACCRATE: Average acceptance rate of advice for an individual at the time each choice is made.

20. ADV_N-1: The accuracy of the advice given on the previous (n-l) trial; 1 = advice on previous trial was correct, 0 = Advice on previous trial was incorrect, -1 = no previous trial (n = 1).

21. NDFREQ Modified driving frequency variable;

1 = High, if DFREQ = 1 OR 2
2 = Medium, if DFREQ = 3
3 = Low, if DFREQ = 4 OR 5

INVESTIGATION OF BEHAVIORAL RELATIONSHIPS USING ANOVA

Analysis of variance 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 it is applied here, is that it does not require making assumptions about the nature of the statistical relation, nor does it require that the independent variables be quantitative (Neter, Wasserman & Kutner, 1990).

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 drivers' 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 different 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 "driver's willingness to accept the route choice advice". 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 one if the subject chose the advised route and a value of zero otherwise. This variable was analyzed in two different formulations, the first being the average acceptance rate of the advice given and secondly as 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:

$$\mathbf{ACCRATE_j = (\Sigma_{\mathit{l}=1..j}\ AGR_{\mathit{l}})\ /j}$$

where,

$\mathbf{AGR}_l$ = agreement on day l (l=agree, O=disagree).

The second dependent variable included in the analysis is the subject's decision time, measured in seconds, to select a route. The third variable analyzed was a subject's rating of how likely they would be to buy such an information system.

The next step in the analysis was to simply plot these dependent variables against several grouping variables and block by information accuracy to quickly determine what types of general relationships exist. Figure 2 shows the expected trend that acceptance of advice increases with increasing information accuracy and also indicates that freeway advice is accepted more readily than side road advice. Figure 3 reveals gender differences with males accepting advice at a higher rate than females at all three levels of accuracy. Figure 4 shows that average decision times were greatest at the 75% accuracy level and that subjects accept freeway advice much quicker than for the side road. Figure 5 shows that at 60% and 75 % accuracy levels, males have faster decision times than do females, but at 90% accuracy there is a reversal and male decision times are slower indicating that some interaction effects are present between gender and system accuracy. Figure 6 also suggests a gender/accuracy interaction with females being more likely to purchase an information system at 60% and 75 % accuracy levels but males being more likely at 90% accuracy.

The data set used for the ANOVA consists of the 2464 individual choices made by the 77 subjects from experiment number 1 (conditions 1 through 3) as shown in Table 1 above. A software package was utilized (BMDP 2V) to perform an analysis of variance and covariance on fixed effects factorial designs with two grouping factors (two-way ANOVA). For two-way analysis of variance, 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 described in Neter, Wasserman and Kutner (1990). It was decided to use a two-way factor study and include covariate terms as opposed to performing a full multi-factor study which was not feasible due to the relatively small sample size. The formal model can be written as:

$$y_{ijk} = \mu + \alpha_i + \beta_j + (\alpha\beta)_{ij} + \epsilon_{ijk}$$

where:

y_{ijk} = dependent variable of interest.
μ = a constant.
α_i = a constant vector subject to the restriction $\Sigma\alpha_i = 0$.
β_j = a constant vector subject to the restriction $\Sigma\beta_j = 0$.
$(\alpha\beta)_{ij}$ = a constant vector subject to the restrictions:
$\Sigma_i(\alpha\beta)_{ij} = 0$ for $j = 1,..,b$
$\Sigma_j(\alpha\beta)_{ij} = 0$ for $i = 1,..,a$
ϵ_{ijk} are independent $N(0,\sigma^2)$
$i = 1,.., a;\ j = 1,.., b;\ k = 1,.., n$

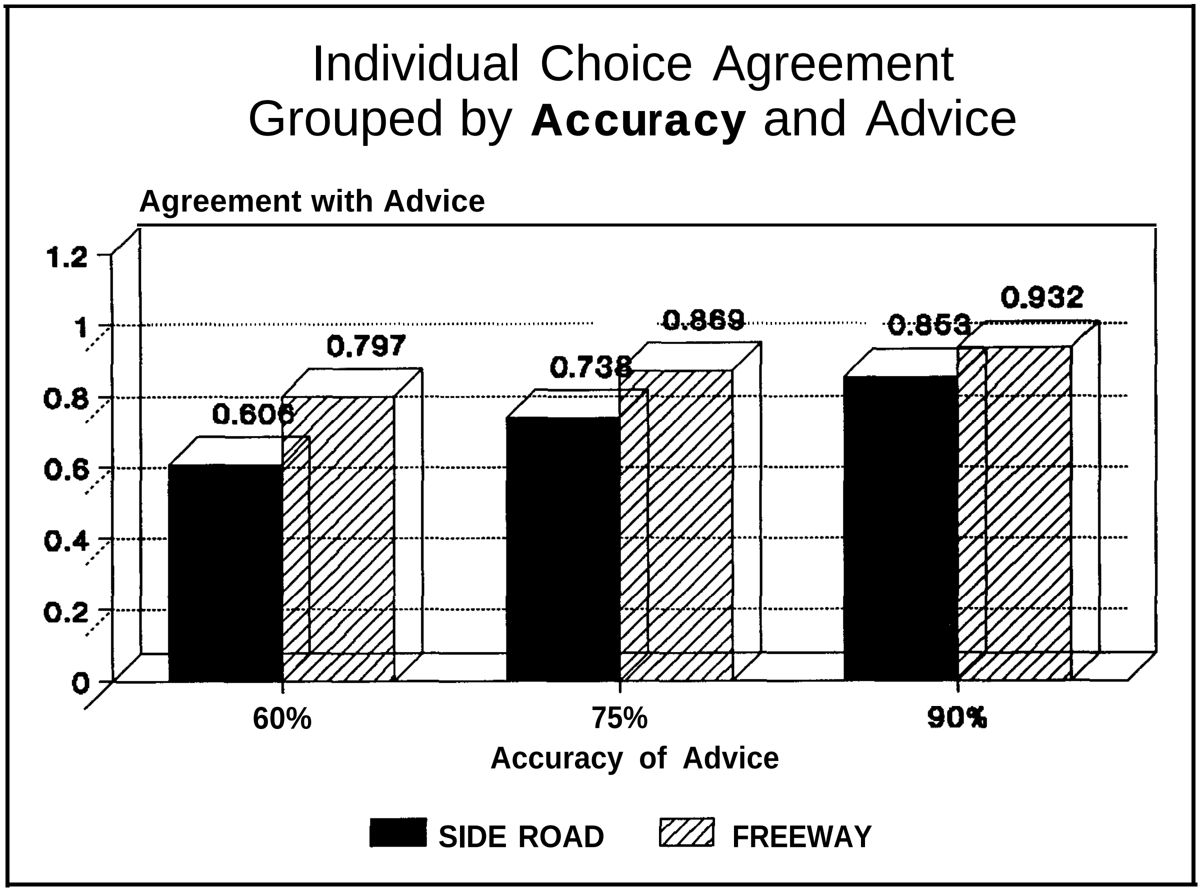

Figure 2: Agreement by Accuracy and Advice

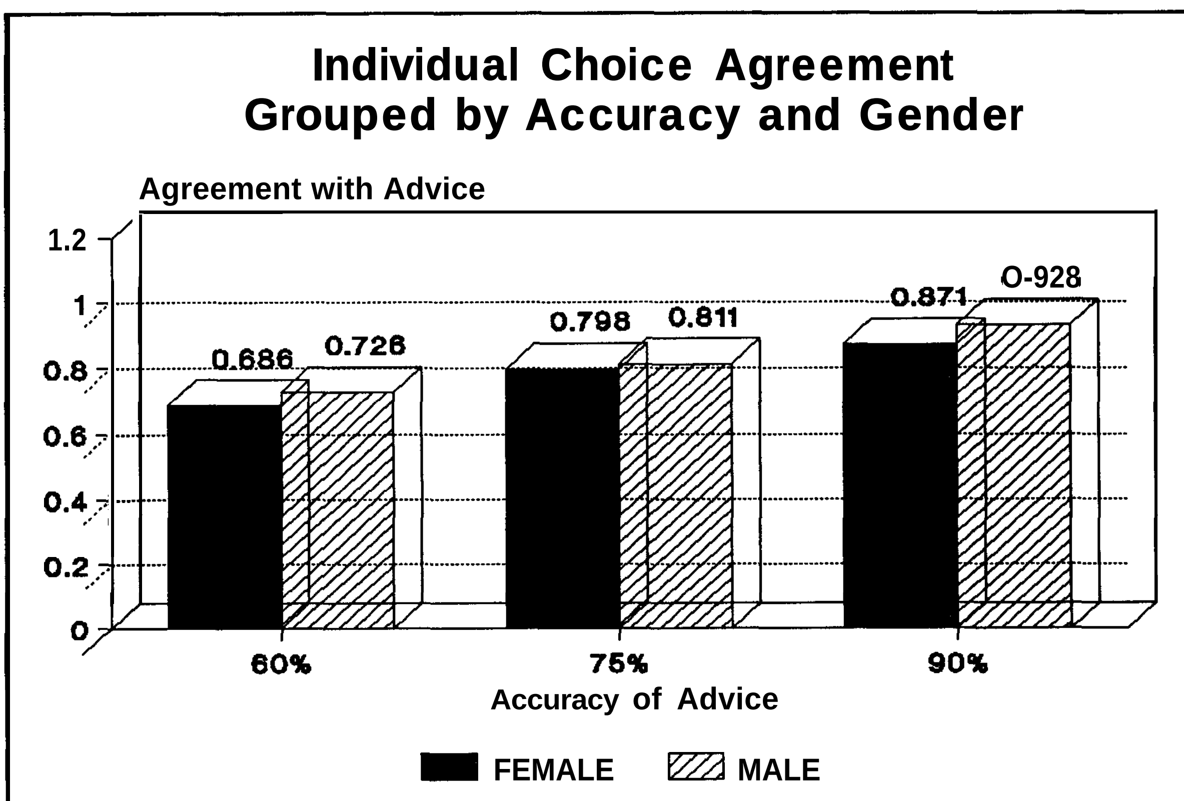

Figure 3: Agreement by Accuracy and Gender

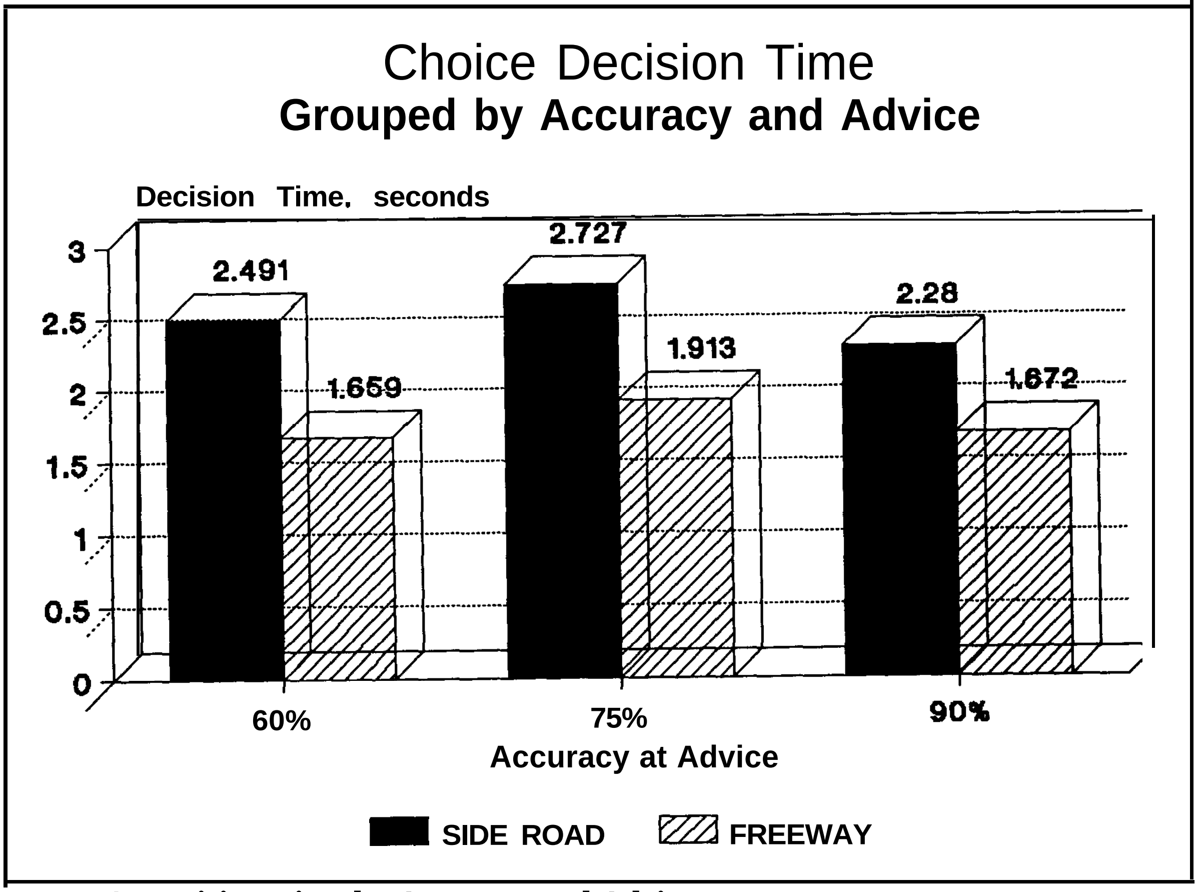

Figure 4: Decision Time by Accuracy and Advice

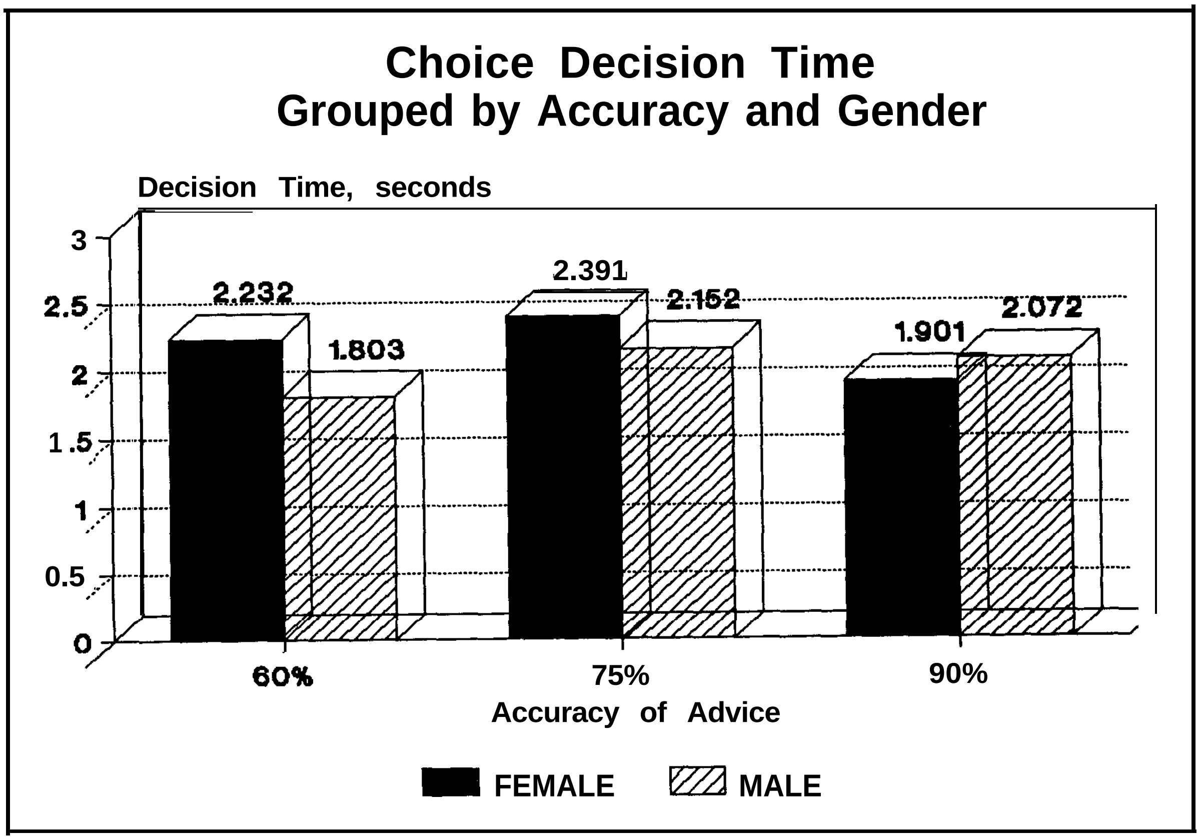

Figure 5: Decision Time by Accuracy and Gender

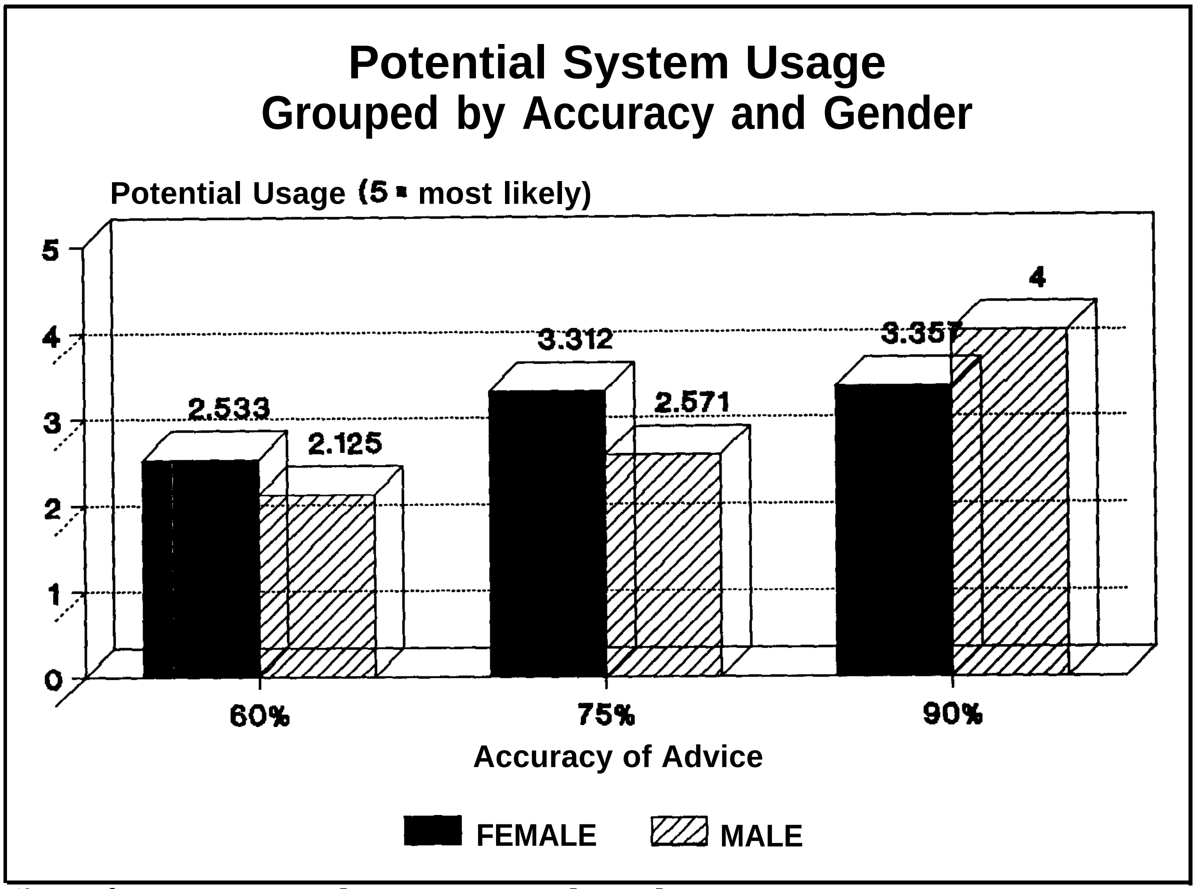

Figure 6: System Usage by Accuracy and Gender

The constants α_i represent the main effects of the first factor (say factor A) at the **ith** level of the factor and likewise, β_j represents the main effects of the second factor **(B)** at the jth level. The interaction effect when factor A is at the ith level and factor B is at the jth level is represented by the constant $(\alpha\beta)_{ij}$. This model then states that a particular case, k, of the dependent variable, y, which falls in the factor group defined by the cell ij, is equal to the sum of: a constant (the grand mean of y), a constant to adjust for the effect of factor A on y, a constant to adjust for the effect of factor B on y, a constant to adjust for the combined effects of factors A and B on y, and an error correction term.

When covariate analysis is performed the model has the form:

$$y_{ijk} = \mu + \alpha_i + \beta_j + (\alpha\beta)_{ij} + \tau_1 x_{1ijk} + \tau_2 x_{2ijk} + , \ldots , + \tau_m x_{mijk} + \epsilon_{ijk}$$

where:

x_{mijk} = the m^{th} covariate included in the model, and
τ_m = the regression coefficient for the m^{th} covariate

Table 2 presents the results of the **ANOVA.** The percent accuracy of advice given (PAADV) was used as the factor A grouping variable for all of the analyses performed. The other four grouping variables were used individually as the B factor for the analyses of the dependent variables; average acceptance rate (ACCRATE) , agreement (AGR) , and decision time @TIME). For the dependent variable, potential system usage (USAGE), the factor A grouping variable was again PAADV, but only one analysis was performed for this dependent variable using SEX as the factor B grouping variable.

For this **ANOVA** model we test the following hypotheses:

$\alpha_i = 0$, for i = l,..,a
$\beta_j = 0$, forj = 1,..,b
$(\alpha\beta)_{ij} = 0$, for i = l,.., aandj = l,.., b
$\tau_s = 0$, for s = l,..,m

Table 2 is organized in the order of the dependent variables analyzed. Blocks 1 through 4 show results for the dependent variable, average acceptance rate of advice (ACCRATE), blocks 5 through 8 are for the individual agreement (AGR), blocks 9 through 12 are for the decision time @TIME), and block 13 is for the potential system usage (USAGE). Within each block the results are listed for the two independent or grouping variables first. The third term is the interaction term of the two grouping variables and is represented by the **first** letter of each of the grouping variables. The interaction term is followed by the covariate terms.

In blocks 1 through 4 of Table 2, we can test the above hypotheses for the dependent variable average acceptance rate of advice **(ACCRATE).** There is strong evidence to reject the hypothesis that the percent accuracy of advice has no effect on the average acceptance rate of the advice. The alternative hypothesis, that the accuracy of the information has an effect on the average acceptance rate of advice, is one which we would expect and helps support the validity of the experimental design. The learning effects over time, which are gauged by where in the sequence of trials the choice was made **(TBLOCK),** are shown to not have a significant effect on the average acceptance rate of advice ($F < 2.6$, df = 3, $\alpha = .05$). The interaction effects of PAADV and TBLOCK, however, are shown to be significantly different from zero. The second B factor grouping variable NDFREQ has a significant effect on the average acceptance rate of advice and so does the interaction effect of PAADV and NDFREQ. The third B factor grouping variable ADVROUTE is shown to not have a significant effect ($F < 3.84$, df = 1, $\alpha = .05$) and the interaction effects of PAADV and ADVROUTE are also shown to be insignificant ($F < 3.0$, df = 2, $\alpha = .05$). The fmal B factor grouping variable, SEX is shown to be highly significant and the interaction effects of SEX with PAADV are also significant. When used as covariates, the variables SEX and driving frequency (NDFREQ) are both significant individually, and have positive regression coefficients. The regression coefficients indicate that males have a higher acceptance rate of advice compared to females, and that inexperienced drivers or those who drive less frequently will more readily accept advice. The other three variables used as covariates, trial number **(TRIAL#),** accuracy on previous trial **(ADV_N-1),** and advised route (ADVROUTE) are shown to be individually insignificant.

Table 2. ANOVA Results

BLOCK I
ANALYSIS OF VARIANCE FOR I-ST DEPENDENT VARIABLE - ACCRATE

SOURCE	SW OF SQUARES	D.F.	MEAN SQUARE	F	TAIL PROB.	REGRESSION COEFFICIENTS
PAADV (grouping)	3.59955	2	1.79977	87.10	0.0000	
TBLOCK (grouping)	0.13125	3	0.04375	2.12	0.0957	
PT (interaction)	2.03843	6	0.33974	16.44	0.0000	
SEX (covariate)	2.89007	1	2.89007	139.86	0.0000	0.0762
NDFREQ (covariate)	0.26886	1	0.26886	13.01	0.0003	0.0135
ALL COVARIATES	3.13389	2	1.56694	75.83	0.0000	
I ERROR	45.33790	2194	0.02066			

BLOCK 2
ANALYSIS OF VARIANCE FOR I-ST DEPENDENT VARIABLE - ACCRATE

SOURCE	SW OF SQUARES	D.F.	MEAN SQUARE	F	TAIL PROB.	REGRESSION COEFFICIENTS
PAADV	3.45819	2	1.72910	84.10	0.0000	
NDFREP	I.10384	2	0.55192	26.84	0.0000	
PN	I.53756	4	0.38439	18.70	0.0000	
SEX	I.67888	1	1.67888	81.66	0.0000	0.0639
TRIAL#	0.02033	1	0.02033	0.99	0.3201	-0.0003
ALL COVARIATES	I.69921	2	0.84960	41.32	0.0000	
I ERROR	45.16961	2197	0.02056			

BLOCK 3
ANALYSIS OF VARIANCE FOR I-ST DEPENDENT VARIABLE - ACCRATE

SOURCE	SW OF SQUARES	D.F.	MEAN SQUARE	F	TAIL PROB.	REGRESSION COEFFICIENTS
PAADV	3.42608	2	I.71304	92.17	0.0000	
ADVROUTE	0.00222	I	0.00222	0.12	0.7297	
PA	0.00730	2	0.00365	0.20	0.8216	
SEX	2.86993	I	2.86993	154.42	0.0000	0.0771
NDFREQ	0.30130	I	0.30130	16.21	0.0001	0.0145
ADV_N-1	0.00747	I	0.00747	0.40	0.5262	0.0046
ALL COVARIATES	3.15176	3	I. 05059	56.53	0.0000	
I ERROR	39.58538	2130	0.01858			

BLOCK 4
ANALYSIS OF VARIANCE FOR I-ST DEPENDENT VARIABLE - ACCRATE

SOURCE	SUM OF SQUARES	D.F.	MEAN SQUARE	F	TAIL PROB.	REGRESSION COEFFICIENTS
PAADV	3.25344	2	I.62672	87.88	0.0000	
SEX	2.79828	1	2.79828	151.18	0.0000	
PS	0.16699	2	0.08350	4.51	0.0111	
ADVRWTE	0.00236	1	0.00236	0.13	0.7213	0.0021
NDFREP	0.22009	1	0.22009	ii.89	0.0006	0.0133
ADV N-I	0.00652	1	0.00652	0.35	0.5530	0.0043
ALL-COVARIATES	0.22935	3	0.07645	4.13	0.0062	
I ERROR	39.42569	2130	0.01851			

BLOCK 5
ANALYSIS OF VARIANCE FOR Z-ND DEPENDENT VARIABLE - AGR

SOURCE	SW OF SQUARES	D.F.	MEAN SQUARE	F	TAIL PROB.	REGRESSION COEFFICIENTS
PAADV	12.44757	2	6.22378	40.83	0.0000	
TBLOCK	0.29121	3	0.09707	0.64	0.5912	
PT	3.12319	6	0.52053	3.41	0.0023	
SEX	0.73047	1	0.73047	4.79	0.0286	0.0383
NDFREP	0.59214	1	0.59214	3.88	0.0487	0.0200
ALL COVARIATES	1.30370	2	0.65185	4.28	0.0140	
I ERROR	334.42999	2194	0.15243			

Table 2. ANOVA Results

BLOCK 6
ANALYSIS OF VARIANCE FOR 2-ND DEPENDENT VARIABLE - AGR

SOURCE	SUM OF SQUARES	D.F.	MEAN SQUARE	F	TAIL PROB.	REGRESSION COEFFICIENTS
PAADV	11.49206	2	5.74603	37.58	0.0000	
NDFREQ	1.21244	2	0.60622	3.96	0.0191	
PN	0.94549	4	0.23637	1.55	0.1858	
SEX	0.34943	1	0.34943	2.29	0.1306	0.0292
TRIAL#	0.16363	1	0.16363	1.07	0.3009	0.0009
ALL COVARIATES	0.51306	2	0.25653	1.68	0.1870	
1 ERROR	335.92183	2197	0.15290			

BLOCK 7
ANALYSIS OF VARIANCE FOR 2-ND DEPENDENT VARIABLE - AGR

SOURCE	SUM OF SQUARES	D.F.	MEAN SQUARE	F	TAIL PROB.	REGRESSION COEFFICIENTS
PAADV	11.00634	2	5.50317	36.76	0.0000	
ADVROUTE	9.38943	1	9.38943	62.72	0.0000	
PA	1.10630	2	0.55315	3.70	0.0250	
SEX	0.71519	1	0.71519	4.78	0.0288	0.0385
NDFREQ	0.61788	1	0.61788	4.13	0.0422	0.0208
ADV_N-1	0.08829	1	0.08829	0.59	0.4425	0.0157
ALL COVARIATES	1.40085	3	0.46695	3.12	0.0249	
1 ERROR	318.86050	2130	0.14970			

BLOCK 8
ANALYSIS OF VARIANCE FOR 2-ND DEPENDENT VARIABLE - AGR

SOURCE	SUM OF SQUARES	D.F.	MEAN SQUARE	F	TAIL PROB.	REGRESSION COEFFICIENTS
PAADV	9.95338	2	4.97669	33.14	0.0000	
SEX	0.69687	1	0.69687	4.64	0.0312	
PS	0.09412	2	0.04706	0.31	0.7310	
ADVROUTE	9.39641	1	9.39641	62.57	0.0000	0.1326
NDFREQ	0.53862	1	0.53862	3.59	0.0582	0.0208
ADV_N-1	0.11602	1	0.11602	0.77	0.3794	0.0180
ALL COVARIATES	10.07398	3	3.35799	22.36	0.0000	
1 ERROR	319.87267	2130	0.15017			

BLOCK 9
ANALYSIS OF VARIANCE FOR 1-ST DEPENDENT VARIABLE - DTIME

SOURCE	SUM OF SQUARES	D.F.	MEAN SQUARE	F	TAIL PROB.	REGRESSION COEFFICIENTS
PAADV	31.22748	2	15.61374	6.93	0.0010	
SEX	12.63576	1	12.63576	5.61	0.0179	
PS	10.93754	2	5.46877	2.43	0.0886	
ADVROUTE	306.51274	1	306.51274	135.99	0.0000	-0.7573
NDFREQ	28.14571	1	28.14571	12.49	0.0004	0.1501
ADV_N-1	3.56268	1	3.56268	1.58	0.2087	-0.0996
TRIAL#	624.98431	1	624.98431	277.28	0.0000	-0.0604
ALL COVARIATES	958.16138	4	239.54035	106.28	0.0000	
1 ERROR	4798.65269	2129	2.25395			

BLOCK 10
ANALYSIS OF VARIANCE FOR 1-ST DEPENDENT VARIABLE - DTIME

SOURCE	SUM OF SQUARES	D.F.	MEAN SQUARE	F	TAIL PROB.	REGRESSION COEFFICIENTS
PAADV	37.78034	2	18.89017	8.37	0.0002	
ADVROUTE	306.99564	1	306.99564	136.06	0.0000	
PA	5.83468	2	2.91734	1.29	0.2747	
SEX	11.85118	1	11.85118	5.25	0.0219	-0.1567
NDFREQ	47.96123	1	47.96123	21.26	0.0000	0.1829
ADV_N-1	3.61380	1	3.61380	1.60	0.2057	-0.1004
TRIAL#	625.61532	1	625.61532	277.27	0.0000	-0.0605
ALL COVARIATES	689.11226	4	172.27807	76.35	0.0000	
1 ERROR	4803.75555	2129	2.25634			

Table 2. ANOVA Results

BLOCK II
ANALYSIS OF VARIANCE FOR 1-ST DEPENDENT VARIABLE - DTIME

SOURCE	SW OF SQUARES	D.F.	MEAN SQUARE	F	TAIL PROB.	REGRESSIDU COEFFICIENTS
PAADV	78.30064	2	39.15032	18.37	0.0000	
NDFREQ	267.34288	2	133.67144	62.71	0.0000	
PN	65.37765	4	16.34441	7.67	0.0000	
SEX	10.03290	1	10.03290	4.71	0.0300	-0.1587
ADVRDUTE	315.05319	1	315.05319	147.80	0.0000	-0.7679
ADV_N-1	3.93242		3.93242	I.84	0.1744	-0.1046
TRIAL#	625.04572	I	625.04572	293.22	0.0000	-0.0604
ALL COVARIATES	949.90990	4	237.47747	111.40	0.0000	
I ERROR	4531.91749	2126	2.13166			

BLOCK I2
ANALYSIS OF VARIANCE FOR I-ST DEPENDENT VARIABLE - DTIHE

SWRCE	SW OF SQUARES	D.F.	MEAN SQUARE	F	TAIL PROB.	REGRESSION COEFFICIENTS
		2				
PAADV	58.33455	3	29.16728	9.62	0.0001	
TBLDCK	1148.27596		382.75865	126.22	0.0000	
PT	50.20202	6	8.36700	2.76	0.0113	
SEX	IO.34497	I	IO.34497	3.41	0.0647	-0.1441
NDFREP	52.17221	1	52.17221	17.21	0.0000	0.1878
ALL COVARIATES	63.20817	2	31.60408	IO.42	0.0000	
I ERROR	6653.02489	2194	3.03237			

BLOCK I3
ANALYSIS OF VARIANCE FOR I-ST DEPENDENT VARIABLE - USAGE

SOURCE	SUM OF SQUARES	D.F.	MEAN SQUARE	F	TAIL PROB.	REGRESSION COEFFICIENTS
PAADV	642.16208	2	321.08104	290.48	0.0000	
SEX	15.33543	1	15.33543	13.87	0.0002	
PS	205.34009	2	102.67005	92.88	0.0000	
NDFREQ	30.29485		30.29485	27.41	0.0000	0.1532
I ERROR	2432.88610	220:	1.10535			

In blocks 5 through 8 of Table 2, we can test the above hypotheses for the dependent variable AGR, the agreement with the individual day's advice. The A factor grouping variable, percent accuracy of advice (PAADV), is significant again indicating that the level of accuracy of advice provided has a significant effect on a person's willingness to accept the advice. The first B factor grouping variable, trial block (TBLOCK), does not have a significant effect on a subject's agreement with advice ($F < 2.60$, df = 3, $\alpha = .05$), but the interaction effects of TBLOCK and PAADV are significant. The second B factor grouping variable, driving frequency (NDFREQ), is shown to have a significant effect on agreement (AGR) but the interaction effects of NDFREQ and PAADV are insignificant ($F < 2.37$, df = 4, $\alpha = .05$). The third B factor grouping variable, advised route (ADVROUTE), is shown to be highly significant and the interaction effects of ADVROUTE with PAADV are also significant. The final B grouping variable SEX is shown to have a significant effect but the interaction effects of SEX with PAADV are shown to be insignificant. When used as covariates the variables SEX and driving frequency (NDFREQ) both have individually significant effects on agreement (AGR) and both have positive regression coefficients, again indicating that males agree with the advice more readily than females, and that inexperienced or less frequent drivers accept advice more readily than experienced or frequent drivers. The covariate advised route (ADVROUTE) is highly significant and has a positive regression coefficient. This indicates a route bias towards the freeway with subjects accepting advice to take the freeway link more readily than the advice to take the side road. The remaining covariates, trial number **(TRIAL#)** and accuracy on previous trial **(ADV_N-1),** are shown to be individually insignificant.

In blocks 9 through 12 of Table 2, we can test the above hypotheses for the dependent variable **DTIME,** the decision time to select a route. The A factor grouping variable, percent accuracy of advice PAADV, is significant indicating that the level of accuracy of advice provided has a significant effect on a person's decision time. All of the B factor grouping variables, TBLOCK, SEX, ADVROUTE, and NDFREQ, are shown to be significant while only the interaction effects of PAADV and NDFREQ are significant. When used as covariates, the variables SEX, ADVROUTE, NDFREQ, and **TRIAL#** are shown to be individually significant. The regression coefficients on the covariates SEX, ADVROUTE, and **TRIAL#** are negative indicating that males respond quicker than females, subjects accept freeway advice quicker than side road, and that the decision time decreases with the number of trials made. The covariate **ADV_N-1** is shown to be insignificant but its regression coefficient does have the expected sign indicating that for a given trial, decision time is quicker if the subject was given accurate advice on their previous trial.

Block 13 of Table 2 presents the **ANOVA** results for the dependent variable potential usage (USAGE). Both the A factor grouping variable, PAADV, and the B factor grouping variable, SEX, are shown to have a significant effect on the subject's potential usage of a traffic information device. The interaction effects of PAADV and SEX are also shown to have a significant effect. The covariate NDFREQ is shown to be individually significant and its regression coefficient indicates that more frequent or more experienced drivers would be more willing to purchase such a device than less frequent or less experienced drivers.

These 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 which route is being advised. The effects of learning, gauged by the number of trials, was shown to have little effect on 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 usage of an information system was shown to be influenced by the accuracy of advice, gender and 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 which is equivalent to the **ANOVA** model. The factor effects model has the form:

$$y_{ijk} = \mu + \alpha_i + \beta_j + (\alpha\beta)_{ij} + \tau_1 x_{1ijk} + \tau_2 x_{2ijk} + ,\ldots, + \tau_m x_{mijk} + \epsilon_{ijk}$$

and can be represented in the matrix form, Y $= \beta X + \tau x + \epsilon$. There are a levels within the A factor, and b levels within the B factor resulting in $a*b$ interactions. Since $\Sigma\alpha_i = \Sigma\beta_j = 0$, we need only (a-l) α_i parameters and (b-l) β_j parameters in the regression model, and since

$$\Sigma_i(\alpha\beta)_{ij} = 0 \text{ for } j = l,..,b$$

$$\Sigma_j(\alpha\beta)_{ij} = 0 \text{ for } i = l,..,a$$

we need only (a-l)*@-1) interaction terms in the regression model. The independent dummy variables of the regression model are defined as follows:

$$X_1 = \begin{cases} 1 & \text{if case from level 1 of factor A} \\ -1 & \text{if case from level a of factor A} \\ 0 & \text{otherwise} \end{cases}$$

$$X_2 = \begin{cases} 1 & \text{if case from level 2 of factor A} \\ -1 & \text{if case from level a of factor A} \\ 0 & \text{otherwise} \end{cases}$$

.

$$X_{(a-1)} = \begin{cases} 1 & \text{if case from level (a-l) of factor A} \\ -1 & \text{if case from level a of factor A} \\ 0 & \text{otherwise} \end{cases}$$

$$X_a = \begin{cases} 1 & \text{if case from level 1 of factor B} \\ -1 & \text{if case from level b of factor B} \\ 0 & \text{otherwise} \end{cases}$$

$$X_{(a+1)} = \begin{cases} 1 & \text{if case from level 2 of factor B} \\ -1 & \text{if case from level b of factor B} \\ 0 & \text{otherwise} \end{cases}$$

.

$$X_{(a-1)+(b-1)} = \begin{cases} 1 & \text{if case from level (b-l) of factor B} \\ -1 & \text{if case from level b of factor B} \\ 0 & \text{otherwise} \end{cases}$$

and the general regression equation has the form:

$$y_{ijk} = \mu + \alpha_1 X_{ijk1} + \alpha_2 X_{ijk2} + \ldots + \alpha_{(a-1)} X_{ijk(a-1)} + \beta_1 X_{ijka} + \beta_2 X_{ijk(a+1)} + \ldots$$

$$+ \beta_{(b-1)}X_{ijk(a-1)+(b-1)} + \Sigma_l(\alpha\beta)_{1l}X_{ijk1}X_{ijk(a-1l)} + \Sigma_l(\alpha\beta)_{2l}X_{ijk2}X_{ijk(a-1+l)} + \cdots$$

$$+ \Sigma_l(\alpha\beta)_{(a-1)l}X_{ijk(a-1)}X_{ijk(a-1+l)} + \tau_1 X_{1ijk} + \tau_2 X_{2ijk} + , \cdots , + \tau_m X_{mijk} + \epsilon_{ijk}$$

for, $i=1,..,(a-l)$, $j=1,..,(b-l)$, $k=1,..,n$, $l=1,..,(b-1)$.

From the analysis of variance, the factors and covariates which 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 3. The fitted regression equations for the four models are:

$$\text{ACCRATE} = .7887 - .043X_1 - .0125X_2 - .0375X_3 - .0064X_{13} + .0164X_{23} + .0115(\text{NDFREQ})$$

where, X_1 represents 60 percent accurate advice, X_2 represents 75 percent accurate advice and X_3 represents females.

$$\text{AGR} = .715 - .0926X_1 + .0033X_2 - .0685X_3 - .0282X_{13} + .002X_{23} + .0382(\text{SEX}) + .0195(\text{NDFREQ})$$

where, X_1 represents 60 percent accurate advice, X_2 represents 75 percent accurate advice and X_3 represents side road advice.

$$\text{DTIME} = 3.3665 - .0787X_1 + .2239X_2 + .4029X_3 - .003X_{13} + .0944X_{23} - .1431(\text{SEX}) + .1905(\text{NDFREQ}) - .0768(\text{TRIAL\#})$$

where, X_1 represents 60 percent accurate advice, X_2 represents 75 percent accurate advice and X_3 represents side road advice.

$$\text{USAGE} = 2.7493 + .6629X_1 + .0447X_2 - .0879X_3 - .1642X_{13} - .3059X_{23} + .1532(\text{NDFREQ})$$

where, X_1 represents 60 percent accurate advice, X_2 represents 75 percent accurate advice and X_3 represents females.

Table 3. 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 (l=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	-0.043	-9.25	-0.0926	-7.99	-0.0787	-1.53	0.6629	19.58
X2	-0.0125	-2.65	0.0033	0.29	0.2239	4.36	0.0447	1.30
x3	-0.0375	-11.42	-0.0685	-8.36	0.4029	11.11	-0.0879	-3.67
x13	-0.0064	-1.34	-0.0282	-2.43	-0.003	-0.06	-0.1642	-4.70
X23	0.0164	3.44	0.002	0.17	0.0944	1.84	-0.3059	-8.83

For the average acceptance of advice, the coefficients all have the appropriate sign. The first two coefficients show that as the accuracy of the advice increases, the average acceptance rate increases. The third coefficient indicates that males have a higher acceptance rate than females. The last two coefficients represent the interaction effects of the two factors and the effects of the interaction of 75 percent accurate advice with female gender are the most significant. The coefficient on the covariate term indicates that acceptance of advice increases with decreasing driving experience.

For the agreement with individual route advice, the coefficients again have the appropriate sign. The first two coefficients indicate that individual agreement with advice increases as the accuracy of advice increases. The third coefficient indicates that a "freeway bias" exists resulting in increased acceptance for freeway advice over side road advice. The last two coefficients represent the interaction effects with the interaction effects of 60 percent accurate advice and side road advice being the most significant. The coefficients on the two covariates again show that males and less experienced drivers more readily accept advice.

The first two coefficients of the decision time model show an interesting effect of information accuracy. Subjects tend to make their route choices the quickest at the highest level of accuracy (90 percent), and at the lowest level (60 percent) but have a significantly increased decision time at a more moderate level of information accuracy (75 percent). This finding would indicate that drivers can quickly realize and adapt to good information or bad information but at accuracy levels where they are experiencing only a marginal gain in utility, they take longer to adapt to the advice. The third coefficient is another indicator of the "freeway bias", indicating that subjects have longer decision times when advised to take the side road as opposed to the freeway. The last two coefficients represent the interaction effects of accuracy of advice and advised route and are shown to be insignificant ($t < 1.96$). The coefficients on the covariate terms indicate that males and more experienced drivers have faster decision times than females and less experienced drivers, and that the decision times of all subjects decreases with increasing system experience (trials).

The first two coefficients of the potential usage model indicate that the more accurate the advice, the more likely subjects would be to purchase such an information device. The third coefficient indicates that females would be more willing to purchase such a system than males. The last two coefficients represent the interaction effects of advice accuracy and gender on potential usage, and both are shown to be significant. The coefficient on the covariate term indicates that more experienced, frequent drivers would be more willing to purchase an information device than less frequent, inexperienced drivers.

The ANOVA results have given an indication of which variables have significant effects on subjects' willingness to follow route advice, their decision time and their potential usage of an information system. The ANOVA regression technique has 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.
3. Experienced drivers are not as willing to accept advice as less experienced drivers, and also make their decisions faster.
4. A "freeway bias" exists with subjects more willing to accept freeway advice.
5. While males are more willing to accept advice, they are also less likely to purchase an information system.
6. While 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. There are currently two modeling approaches being investigated 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 in a companion paper (Yang et al. 1992). 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, while the actual utility may be greater or less than the perceived utility, it is an individual's perception of reality that ultimately drives their 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 due to a repetitive choice effect. Simply stated, the more times one chooses an alternative the greater the perceived utility becomes for that alternative due to some habitual nature of the individual. This general framework is 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 then in turn influences the next choice. Just how much this past experience affects the current choice and how rapidly individuals modify their behavior based on 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:

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

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-l. Thus defmed, $x_{ij}(k)$ becomes an endogenous variable. At this early stage of the modeling effort we have ignored the issue of endogeneity. The variable $u_{ij}(k-1)$ is the actual value of the attribute as experienced by individual i on the previous trial k-l. 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 his/her perception or expectation on the current trial.

For an individual who has not performed any trials, no previous experiences exist, and therefore a perception of the attribute cannot be developed from previous experiences. Individuals may, however, make assumptions regarding the initial conditions of certain attributes, in which case initial conditions must be established within the model framework 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 modelled using the following binary logit formulation:

$$P_{i1}(k) = e^{Vi1(k)}/(e^{Vi1(k)} + e^{Vi2(k)})$$

$$P_{i2}(k) = 1 - P_{i1}(k)$$

where $P_{i1}(k)$ is the probability that person i will choose route 1 (side road) on day k and $P_{i2}(k)$ is the probability route 2 (freeway) is chosen by i on day k. V&k) is the random utility function and is the perceived utility of person i, for route j, on the k^{th} day. The utility function is defined as follows:

$$V_{ij}(k) = \beta_0 + \Sigma_{l=1,5}\beta_l X_{ijl}(k) + \epsilon_{ij}(k)$$

where,

$X_{ij1}(k)$ = a dummy variable indicating which route is the advised route, and takes on a value of 1 when the advised route is alternative j for day k and is zero 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 which takes on a value of one if the subject **is male for the** advised route.

$X_{ij5}(k)$ = a dummy variable which takes on a value of one 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 $\epsilon_{ij}(k)$. 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 then their perceived utility for that route increases, thus increasing the probability **of choosing that** route. Based on the **ANOVA** results which 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 representing 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 based **on previous** experiences. This variable is updated using the updating function previously described. 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 which 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 for 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 towards 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 1376 individual choices made by 43 subjects (23 from experiment 1, condition 2 and 20 from experiment 3, condition 7) all or 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 4.

RESULTS

Of the six models estimated and presented in Table 4, the model with the greatest log-likelihood value is the model for which τ was set equal to 0.8. Of the models which incorporate some amount of utility based on 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 zero ($t < 1.96$ @ $\alpha = 0.05$), indicating caution in the interpretation of this variable. The second variable, which is an updated perception of the delay on the alternative routes, has a coefficient value of -.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 zero. 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 zero. The last two coefficients, which are indicators of the subject’s sex and driving experience level, both have positive values and have t-statistics indicating individual significance as was expected based on the ANOVA results. The freeway alternative specific coefficient has the expected sign and is individually significant, again reiterating the “freeway bias” of subjects. It should be noted that this coefficient and its associated t-statistic remained relatively constant across all estimated models.

Table 4. Logit Model Coefficients

	$\tau = 0$		$\tau = 0.2$		$\tau = 0.4$	
	ß	t	ß	t	ß	t
$X_{ij1}(k)$ Advised route dummy entering the advised route	1.199	7.15	1.136	6.06	0.998	4.61
$X_{ij2}(k)$ perceived delay entering alternative 1 and 2	0.059	1.67	0.065	1.49	0.065	1.18
$X_{ij3}(k)$ perceived accuracy of advice entering advised route	-0.094	-0.58	-0.009	-0.05	0.174	0.71
$X_{ij4}(k)$ male gender dummy entering advised route	0.294	2.00	0.293	2.00	0.292	1.99
$X_{ij5}(k)$ inexperienced driver dummy entering advised route	0.331	2.41	0.328	2.39	0.326	2.38
$ß_0$ freeway alternative specific coefficient	0.514	7.21	0.514	7.21	0.514	7.20
L(ß) log-likelihood at convergence	-670.03		-670.40		-670.46	
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					

Table 4. Logit Model Coefficients (continued)

	τ = 0.6		τ = 0.8		τ = 1.0	
	ß	t	ß	t	ß	t
$X_{ij1}(k)$ Advised route dummy entering the advised route	0.741	2.75	0.409	1.01	1.135	9.90
$X_{ij2}(k)$ perceived delay entering alternative 1 and 2	0.047	0.62	-0.039	-0.33	-	
$X_{ij3}(k)$ perceived accuracy of advice entering advised route	0.511	1.59	0.922	1.86	-	
X,(k) male gender dummy entering advised route	0.294	2.00	0.296	2.02	0.290	1.98
$X_{ij5}(k)$ inexperienced driver dummy entering advised route	0.327	2.38	0.334	2.43	0.325	2.37
$ß_0$ freeway alternative specific coefficient	0.513	7.17	0.503	6.87	0.510	7.17
L(ß) log-likelihood at convergence	-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					

The overall fit of this model is not significantly different from the fit of any of the other models 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 into 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 zero ($\beta_2 = \beta_3 = 0$) and is identified as $L(\beta_c)$ then the value $-2[L(\beta_c) - L(\beta)]$ has a **chi-square** distribution with 2 degrees of freedom and can be used to test the collective null hypothesis. From the values in Table 4, 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, α = 0.05).

These results indicate two distinct possibilities. The first being 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 1376 choices accurately predicted. The prediction rates for this model are presented below in Table 5.

Table 5. 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%**

These results would seem to 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. While excluding experience effects seems 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 then this simple model of route choice may be adequate for use in a traffic assignment model. It should be noted that only one possible updating function was utilized in this analysis which may be why there were no significant effects due to updated perceptions. Continued modelling efforts will be undertaken using different updating schemes to determine the significance of drivers' learning experiences.

SUMMARY AND CONCLUSIONS

Previous research by the authors (Abdel-Aty et al.) has shown that a basic understanding of drivers' route choice behavior is necessary in order to develop predictive models of drivers' en-route diversion choice. In order to study the basic underlying factors which contribute to diversion behavior, an interactive computer simulation experiment was developed in an attempt to capture drivers' sequential learning processes. Analysis of this 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 usage of such an ATIS device, females were more likely to purchase an information device when accuracies were at 60 percent and 75 percent, but at 90 percent accuracies, males were more likely to purchase a device. This indicates that while 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 fmding related to driving experience also exists. While 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 due to their limited driving. Conversely, more experienced and more frequent drivers perceive a net gain and responded 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 rapid drop in the decision times over the first 8 of 32 trials and that then 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, seem to 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 accurate. 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 which incorporates the learning processes of drivers had mixed results. A model was developed which included drivers' updated perceptions of route delay and information accuracy, but the model was not significantly different from a model which excluded these perceived attributes. The model includes the advised route as a variable, and since subjects followed the advice so readily, the model may simply be predicting that subjects will select the advised route and therefore predicts 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 modelling effort to a more realistic transportation network environment.

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