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Modeling Inertia and Compliance Mechanisms in Route Choice Behavior Under Real-Time Information

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This research examines route choice, in the presence of real-time information, as a consequence of two underlying behavioral mechanisms: compliance and inertia. The compliance mechanism reflects the propensity of a user to comply with the information supplied by advanced traveler information systems (ATIS). The inertial mechanism represents the tendency of users to continue on their current paths. These two mechanisms in route choice are neither mutually exclusive nor collectively exhaustive. A framework is proposed to model these mechanisms explicitly. The proposed framework decomposes the route choice into two states by exploiting the user's path choice structure (resulting from the current choice prior to the decision of interest) and the information supplied by ATIS. In each state, the mechanisms are incorporated by associating their utilities with those that reflect the specific attributes of the alternative paths. The resulting nested choice structure is implemented using the multinomial probit model. This framework is illustrated using route choice data obtained from dynamic interactive simulator experiments. The empirical results strongly support the simultaneous presence of both the compliance and inertia mechanisms in route choice behavior. The results also indicate that information quality, network loading and day-to-day evolution, level-of-service measures, and trip-makers' prior experience are significant determinants of route choice through the inertial and compliance mechanisms. These findings have important implications in travel behavior forecasting, ATIS design and evaluation, demand management, and network state prediction.

Advanced traveler information systems (ATIS) promise to influence tripmaker behavior favorably (relative to system objectives) by supplying users with real-time information. A considerable body of knowledge on user behavior under ATIS continues to evolve, providing valuable preliminary insights into route choice behavior. Empirical studies indicate the important factors influencing route choice include system performance attributes such as trip time and congestion; experience factors such as schedule delay and familiarity (*1–3*); and the nature, extent, and quality of ATIS information (*4*, *5*). ATIS information also indirectly influences route choice through users' expectations of system performance (anticipated trip times, congestion, etc.) and their perception of experience (feedback on actual performance measures ex post facto and on alternative routes) (*6*, *7*). Most of the studies referenced above, however, fail to distinguish between route switching and choice behavior (*8–11*). With three or more available routes, route switching does not completely determine choice, and switching models are inadequate to predict users' route choices. Another significant shortcoming of existing analyses is that they provide limited insight into behavioral processes operating in route choice decisions under ATIS.

The need to investigate these processes derives from the following considerations: robust behavioral insights into route choice will translate into more accurate and reliable demand forecasts; modeling these processes is critical for the evaluation of transportation demand management measures; and research into this line, when combined with a network microsimulation assignment framework, should result in significantly improved network performance and state prediction models with important applications in traffic management and planning.

This research focuses on developing a framework for modeling behavioral mechanisms in route choice and also illustrates the implementation of this framework. It is proposed that the observed route choices in response to information are a consequence of two principal mechanisms operating in the decision-making process, namely compliance and inertia. These mechanisms reflect the propensities of a user to comply with the ATIS information (best path) and to retain the current path, respectively. (For simplicity, the least trip time path is considered to be the best path.) The two mechanisms are not collectively exhaustive in the sense that other mechanisms may also influence behavior. The mechanisms also are not mutually exclusive and can operate simultaneously.

Modeling the mechanisms of compliance and inertia is difficult because they are latent and hence unobservable. The proposed framework for modeling the two mechanisms exploits the users' current choice (prior to the decision of interest) and ATIS-supplied information to condition the route selection decision into two distinct states: decision situations when the user's current choice coincides with the best path (recommended by ATIS) and when the user's choice and best path are distinct. In each state, the mechanisms are incorporated by associating their utilities with those that reflect specific attributes of alternative paths. The resulting nested choice structures are jointly analyzed using the multinomial probit model. This formulation is illustrated using route choice data from interactive laboratory-like experiments. The empirical results provide strong evidence of the simultaneous presence of both the compliance and inertia mechanisms in route choice behavior.

In addition to the above behavioral and methodological objectives, this research also addresses the following substantive issues: How does the day-to-day variability in network conditions affect choice? What is the nature of influence of system performance measures and their temporal variability, experience factors, and ATIS characteristics on the behavioral mechanisms. In this research, dynamics in route choice behavior are modeled implicitly through the influence of network loads, user's past experience in traffic, and

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time-dependent system performance measures; heterogeneity in behavior, however, is not considered. The issues (stated above) are important for the design and evaluation of congestion alleviation measures as well as for the specification and design of ATIS capabilities and content.

The following section reviews the experimental design and procedures of the interactive simulator experiments. It is followed by an exploratory analysis of path choice as a prelude to developing a modeling framework incorporating the compliance and inertia mechanisms in route choice. The empirical results of the modeling framework are then discussed. Finally, concluding comments and suggestions, including directions for future research, are proposed.

EXPERIMENTAL DESIGN AND PROCEDURES

Laboratory experiments using simulators are a cost-effective and practical approach to investigate driver behavior under ATIS in the absence of adequate real-world deployment (*3*, *12*, *13*). As ATIS usage becomes prevalent, the insights from laboratory experiments need to be validated using other data such as travel diaries and questionnaires.

For this study, laboratory experiments were conducted using the interactive travel behavior simulator developed at the University of Texas at Austin. This simulator is based on an underlying traffic simulation-assignment model. The simulator provides ATIS information consistent with prevailing traffic conditions to users as well as updates the prevailing traffic conditions based on trip-makers' decisions. The simulator's multiuser capabilities allow several subjects to interact simultaneously with each other and the prevailing conditions, as in the real world. Unlike most other simulators, ATIS information and supply conditions are not exogenous to user choices but are in fact a consequence of the collective decisions of all users on the network. Further details on the simulator are available in the literature (*12*).

An experiment was conducted in a simulated commuting corridor with three parallel facilities. The three facilities, Highways 1, 2, and 3, have speed limits of 55 mph (88.55 km/h), 45 mph (72.45 km/h), and 35 mph (56.35 km/h), respectively (Figure 1). Each highway consists of nine 1-mi segments as shown. In addition to the pretrip location, there are four en route crossover locations ($j = 2$ to $j = 5$) where drivers may switch from one facility to another. In this experiment, each user traveled from home to a work location in the central business district for a series of T days. Each user thus faced $5T$ route choice decisions in the experiment. The first day was discarded as a trial day for analysis purposes.

TABLE 1 Loading Levels and Day-to-Day Evolution for Random and Systematic Treatments

Batch	Random Loading Levels	Systematic Loading Levels (4 days/ level)
1	C, A, C, B, B, A	A, B, C
2	B, B, A, B, C, C	B, C, A
3	A, A, C, B, C, C	C, A, B

Note: A,B, and C correspond to 60 veh/min, 75 veh/min, and 90 veh/min loads respectively.

To simulate the morning commute, the work start time was set at 8 a.m. Users selected their departure time (pretrip) and routes (pretrip and en route) with the aid of ATIS information. Among the simulated commuters (background traffic), 25 percent were selected (randomly) to receive real-time traffic information. Additional details on the experimental setup can be found in Srinivasan and Mahmassani (*6*).

Two experimental factors were examined. The first was network load. Three loading levels were simulated in the network by increasing network loads from one level to the next (Table 1). The levels were chosen to ensure significant differences in trip times and concentrations on each of the three facilities over a wide range of departure times. The resulting time-dependent congestion levels experienced by the user depended on their departure time and the behavior of other drivers in the network. With increased loading, the simulated commuters were distributed in the network in a manner consistent with reduced rerouting opportunities.

The second experimental factor related to network state evolution from day to day and consisted of two levels. In the first, referred to as the sequential (or systematic) treatment, a given loading level was applied over 4 consecutive days. Thus each commuter encountered three loading levels in a sequential manner. The order in which these loading levels were administered varied between different batches of participants as shown in Table 1. This sequential level was intended to simulate a gradual change in network states over time. In contrast, the second level was intended to represent the effect of random fluctuation in network states from day to day. This was simulated by providing the three levels of network loads in a random order over 6 days.

The profile of 62 randomly selected commuters recruited to participate in the experiments was as follows. The majority of subjects (84 percent) were between the ages of 20 and 60. The mean travel time (actual) to work was approximately 31 min with a standard deviation of about 19 min. The average work start time in the sample was 8:01 a.m. (standard deviation = 32 min). About 42 percent of the participants reported tolerance to lateness of less than 15 min

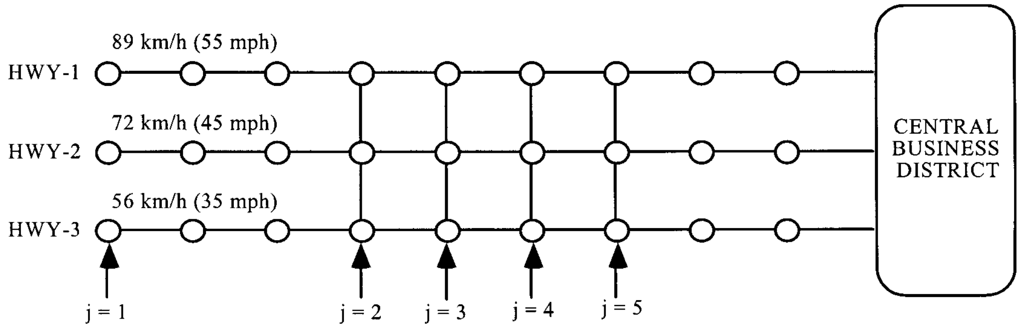

FIGURE 1 Commuting corridor layout, with three parallel facilities.

at the workplace; the average preferred arrival time was 7.56 min before work start time. The profile of participants was comparable to the commuter profile obtained from a 1990 field survey of 638 respondents in the city of Austin, with the following differences (*14*)—the average trip time reported in the 1990 survey was 21 min, compared to the 31 min reported here, and 60 percent of the respondents had no lateness tolerance at the workplace. (It may be noted that Austin has experienced considerable growth in both population and traffic congestion in the intervening years.)

In the experiment, information provided by ATIS to commuters included trip times on the three facilities (at decision locations), congestion indicated by color code (updated in real time), a message alerting the driver when they are stuck in a queue, and posttrip feedback (departure time, arrival time, and trip time on the chosen path). The information was supplied on the basis of prevailing traffic conditions. Prevailing conditions, information supplied, and user responses were then recorded. The following sections discuss the data analyses from these experiments.

EXPLORATORY ANALYSIS

Exploratory analysis results are presented here as a prelude to the development of the model framework in the following section. Given the topology of the corridor network under consideration, it is assumed that users perceive and identify a path in terms of its major highway facility. Thus a path in this analysis consists of a single major facility (to the destination) along with its connecting link. The user therefore effectively considers only three paths at each decision location (node) to follow to the destination.

Aggregate route switching behavior is first examined. For en route choices, the current path (cp) followed by a user is defined in an obvious manner. For pretrip choices, the current path on a given day is defined as the path chosen, pretrip, on the previous day. The path corresponding to the least trip time reported by the ATIS is referred to as the best path (bp). In general, both the current path and the best path can vary over time.

Route choice when the current path coincides with the best path recommended by ATIS (cp = bp), is examined. In this case, it was observed that 85 percent, 13 percent, and 2 percent chose the current path, the faster alternative path, and the slower alternative path, respectively, under the random treatment (day to day). The corresponding proportions were 57 percent, 33 percent, and 10 percent respectively for the systematic treatment. When the two paths (current and best) were distinct, the proportion choosing the current path, best path, and alternative path were respectively 50 percent, 42 percent, and 8 percent in the random treatment, and 43 percent, 44 percent, and 13 percent in the sequential treatment. Chi-squared tests confirmed that the differences in the two cases (cp = bp, cp ≠ bp) were indeed statistically significant ($\chi^2_{\text{random}} = 110.70$, $\chi^2_{\text{sequential}} = 33.69 >> \chi^2_{\text{critical}}(2) = 5.99$). Thus choice behavior varies depending on whether the current path happens to be the best path between the two treatments. Note that whether the current path coincides with the best path is exogenous to a user's decision (at the next decision location), since the best path is a consequence of the choices of all trip makers on the network. Two other interesting observations may be made. The choice of current and best paths together comprised nearly 60 to 90 percent of observed route choices. The likelihood of choosing the current path and best path was nearly equal when the two paths were distinct.

The propensity to choose the current path is due to an inertial effect. This inertial factor may reflect lower cognitive costs of information search and processing, lower switching cost, habit persistence of trip makers with satisfactory choices, and familiarity with alternatives. In spite of this inertial effect being observed experimentally in a substantial body of route choice literature (*2*, *5*, *11*, *14–16*), it has with few exceptions hardly been explicitly captured. This oversight is attributable to the following experimental design and specification limitations. First, a majority of studies model the diversion decision (from a given current path) instead of choice. Consequently the inertia effect is captured through an alternative-specific constant that is generally confounded with the baseline levels of other categorical variables in the models, thus losing behavioral robustness. Furthermore, the cross-sectional nature of many of these studies precludes capturing a time-varying specification of the propensity to retain the current path. A few researchers, however, have noted the presence of behavioral inertia as a counteracting force to switching (*11*). Mahmassani (*8*) proposes indifference band models of route switching that represent trade-offs between habit persistence of users and the factors inducing switching.

Information supplied by ATIS is one such factor. By supplying information regarding more efficient opportunities that could induce switching, ATIS can encourage the user to select the best path instead of continuing on the current path. The propensity to switch to the best path (reported by ATIS) is driven by a compliance mechanism. Compliance with ATIS information (for simplicity perfect information is assumed) may be motivated by awareness of opportunities, trip time savings, congestion avoidance, and schedule delay considerations. Since descriptive information is supplied by ATIS in this set of experiments, a user is said to comply with information if the user follows the least-trip-time path from among those reported by ATIS. Compliance behavior is critical for predicting user response to ATIS and assessing ATIS impacts. User compliance with ATIS is influenced by information attributes such as quality, nature and feedback, traffic conditions, trip-maker characteristics, and prior experience (*5*, *8*).

The inertial effect increases the utility of the current path, whereas the compliance effect increases the utility of the best path. As a preliminary test for the presence of inertia and compliance effects in choice behavior, the following simple trinomial logit model was estimated. The choice alternatives consisted of the three available paths at each decision point. The utility of each alternative consisted of a generic component (including trip times to destination and downstream congestion at the current link) and a route-specific constant for two of the three alternatives. In addition, binary indicator variables were activated: inert (inertia) for the current path and compl (compliance) for the best path. The estimation results, reported in Table 2, suggest that compliance and inertial effects are significant in route choice at the usual 5 percent level (t-critical = 1.96) .

The observed differences noted above, however, may have alternative explanations. One plausible explanation is that trip makers are more likely to choose the best and second-best paths on the basis of information. The observed propensity to choose the current path may be a consequence of the current path coincidentally being the best or second-best path. To test this conjecture, an indicator variable was added to the utility of the second-best path. This factor was only significant in the systematic treatment (at the 10 percent significance level). However, this factor was much less influential than the inertial factor (coefficients of 0.27 to 1.30). Further, the model fit of the best and second-best path specification was inferior to the model incorporating compliance and inertia for both treatments (Table 2). Therefore, a modeling framework is proposed (next section) to incorporate inertia and compliance as mechanisms influencing route choice.

TABLE 2 Calibration Results from Exploratory Route Choice Analysis

Variable Description	Random Coefficient	Random t-stat	Systematic Coefficient	Systematic t-stat
Highway 1 (Alternative Specific Const)	0.17	1.09	-0.23	-1.80
Highway 2 (Alternative Specific Const)	0.41	4.01	0.50	6.25
Trip Time (reported)	-0.06	-3.08	-0.06	-3.31
Congestion (next segment)	-0.68	-6.12	-0.53	-7.14
Inert (=1, if route = cp, else 0)	1.29	14.48	0.96	11.42
Comply (=1, if route = bp, else 0)	0.81	7.50	1.43	20.44
No. of Observations	800		1469	
LL(0)	-878.89		-1613.9	
LL(final)	-550.53		-942.36	

Notes: The log-likelihoods in the random treatment for comply only, inert only, and specification with fastest and second-fastest paths (instead of both inert and comply) are -669.2, -576.02, and -574.34, respectively. The corresponding log-likelihoods in the sequential case are -1194.7, -1004.7, and -985.39.

MODELING COMPLIANCE AND INERTIAL MECHANISMS IN ROUTE CHOICE

Modeling Framework

In the exploratory analysis above, compliance and inertia are treated as exogenous influences on route choice and are modeled through indicator variables. This assumption imposes the unlikely restriction that these effects are constant over time and choice instances. In fact, previous studies by the authors demonstrate that compliance and switching (reflective of inertia) vary dynamically in response to experienced congestion, information supplied, and user characteristics (*6*, *7*). In contrast to the exogenous treatment, these previous studies treated compliance and switching as observed choices. However, treating compliance and inertia as dependent variables results in an inefficient use of choice-related information. Modeling compliance and inertia as actual choices reduces the multinomial choice situation (with at least three alternatives) to respective binary decisions (whether to switch or not, whether to comply or not). The loss of predictive power in resulting models becomes evident when reconstructing the path choice from these inferred decisions. Whereas compliance implies that the best path was chosen, noncompliance merely indicates that it was not chosen. With only two paths, the selected path is trivially determined. However, when several paths are available, the chosen path cannot be determined on the basis of this information alone. Similarly, although nonswitching completely defines the chosen path, switching merely eliminates one path from the choice set. Thus compliance and switching are only partial but interrelated determinants of route choice.

Treating compliance and inertia either as exogenous factors or as observed choices is therefore undesirable for the reasons outlined above. To resolve this dilemma, they are characterized as mechanisms influencing route choice. A mechanism, in this context, is defined as a set of principles or rules that operate, either in isolation or in conjunction, in the decision process to determine the behavioral outcome of interest. The advantage of this notion in modeling route choice is that it allows the treatment of compliance and inertia as functions of other exogenous variables and choice context, without any loss of observed choice information. Although the route choice behavior is likely to be influenced by other possible mechanisms, attention in this research is restricted to compliance and inertia, which are described next.

Inertia is defined as the mechanism underlying a decision maker's tendency to retain the current path. Compliance is the mechanism related to the tendency of a trip maker to comply with the best path (as recommended by ATIS). In some cases, both mechanisms may act collectively to favor a particular alternative (cp = bp), whereas in others, they may favor distinct alternatives (cp ≠ bp). In general, the two mechanisms may operate simultaneously and the observed choice may result from a trade-off between them. Furthermore, a given user may apply different mechanisms to determine choice in different choice instances. The formulation presented next incorporates both mechanisms simultaneously in the choice process.

Each user faces the decision of selecting a route from a set of alternatives (three in the experimental scenario) over repeated choice instances (both within-day and from day to day). In each choice instance, a user is assumed to select the alternative with the highest total utility (consistent with random utility maximization framework). The total utility of alternative p ($\tilde{U}_p$) accounts for the utilities of U_a and U_c, associated with inertial and compliance mechanisms, respectively (if route p is either the current path or best path), in addition to a path-specific utility (U_p) considered in previous specifications. These mechanism-specific utilities are unobserved and can vary across individuals and choice instances. Therefore they are modeled as latent random variables whose means vary systematically with level-of-service measures and trip-maker attributes. They may be expressed as

$$U_a(i,t) = f[Z(i), X_a(i,t), \beta_a] + \epsilon_a(i,t)$$

$$U_c(i,t) = f[Z(i), X_c(i,t), \beta_c] + \epsilon_c(i,t)$$

where

i = user,
t = choice instance,
$Z(i)$ = trip-maker attributes,
$X_a(i, t)$ and $X_c(i, t)$ = vectors of attributes related to the inertia and compliance utilities,
$\epsilon_a(i, t)$, $\epsilon_c(i, t)$ = corresponding error components, and
β_a and β_c = vectors of parameters associated with inertia and compliance.

In view of the exploratory analysis results, route choice is examined separately for the two states (i.e., whether or not current path coincides with best path). The total utility of the path alternatives in each case is constructed from the path-specific components and the mechanism-related utilities in the following two cases of interest [for ease of exposition, the arguments *(i, t)* are dropped and attention is focused on a single choice instance for a given individual]:

Case 1: the current path coincides with the best path. In this situation following the current path is consistent with both compliance and inertia. Hence the utility of the current path consists of U_a and U_c and a path-specific component. An interaction component $U_{a,c}$, given by $U_{a,c} = f(\beta_{a,c}, Z, X_{a,c}) + \epsilon_{a,c}$, is introduced to capture the interaction effect between compliance and inertia. The choice of the remaining alternatives involves noncompliance and noninertia (switching). Without loss of generality, the contribution of the mechanism utilities to their total utilities is taken as zero (base level). Their utilities consist only of path-specific components. As a result of possible shared-error terms associated with noninertia and noncompliance, the error components of these alternatives are assumed to be correlated. This is modeled through the common error component as shown in the nesting structure on the left half of Figure 2.

Case 2: the current path is distinct from the best path. In this case the inertial utility component is associated with the current path and the compliance utility with the best path. The mechanism-related components do not contribute to other alternatives. The error terms of the current path are modeled as correlated to other paths sharing noncompliance. Similarly, the best path is expected to be correlated with other paths because of shared noninertial error terms. The resultant nesting structure is displayed on the right half of Figure 2 and, next, is mathematically formulated.

Model Formulation

The path choice utilities for the three-alternative experimental scenario are presented here. They can be easily generalized to route choice with more than three alternatives. The following notation is introduced for the rest of the analysis. Let $p1$, $p2$, and $p3$ represent the current path and the remaining alternative paths for Case 1, and let $p4$, $p5$, and $p6$ represent the current path, best path, and the remaining alternative in Case 2. The mechanism utilities may be expressed as

$$U_a = V_a + \epsilon_a, U_c = V_c + \epsilon_c, \text{ and } U_{a,c} = V_{a,c} + \epsilon_{a,c}$$

Path-specific utilities can be written as $U_k = V_k + \epsilon_k$, where V stands for deterministic utility and $k = 1, \ldots, 6$.

It is assumed that the error components above are independently normally distributed with mean zero. The components of variance structure introduces the following correlation between the utilities of the route choice alternatives. Alternatives $p2$ and $p3$ share unobservables as a result of noninertia and noncompliance, $p4$ and $p6$ are correlated as a result of noncompliance, whereas $p5$ and $p6$ share unobservables as a result of noninertial elements (Figure 2). The pairwise correlations are represented by the common error terms, η_1, η_2, and η_3, respectively. As is evident from Figure 2, the nonnested alternative pairs $(p1, p2)$, $(p1, p3)$, and $(p4, p5)$ are uncorrelated. Thus the covariance corresponding to these pairs is zero. The total utility is then constructed by aggregating the utility of alternatives as follows:

$$\tilde{U}_k = \hat{W}_k + \nu_k \qquad k = 1, \ldots, 6$$

where

$\hat{W}_1 = V_1 + V_a + V_c + V_{a,c}$,
$\hat{W}_4 = V_4 + V_a$,
$\hat{W}_5 = V_5 + V_c$, and
$\hat{W}_k = V_k$, otherwise.

The ν_k are obtained similarly by aggregating the error components.

It can be shown that the error term assumptions and shared unobservables above across alternatives lead to a correlation structure of the following form (Figure 2):

$$[\nu_1, \nu_2, \nu_3]' \sim \text{MVN } [0, \Sigma_1]$$

$$[\nu_4, \nu_5, \nu_6]' \sim \text{MVN } [0, \Sigma_2]$$

where

$$\Sigma_1 = \begin{pmatrix} \sigma_1^2 & 0 & 0 \\ 0 & \sigma_2^2 & \rho_1\sigma_2\sigma_3 \\ 0 & \rho 1 & \sigma_3^2 \end{pmatrix} \quad \text{and}$$

$$\Sigma_2 = \begin{pmatrix} \sigma_4^2 & 0 & \rho_2\sigma_4\sigma_5 \\ 0 & \sigma_5^2 & \rho_3\sigma_5\sigma_6 \\ \rho_2\sigma_4\sigma_5 & \rho_3\sigma_5\sigma_6 & \sigma_6^2 \end{pmatrix}$$

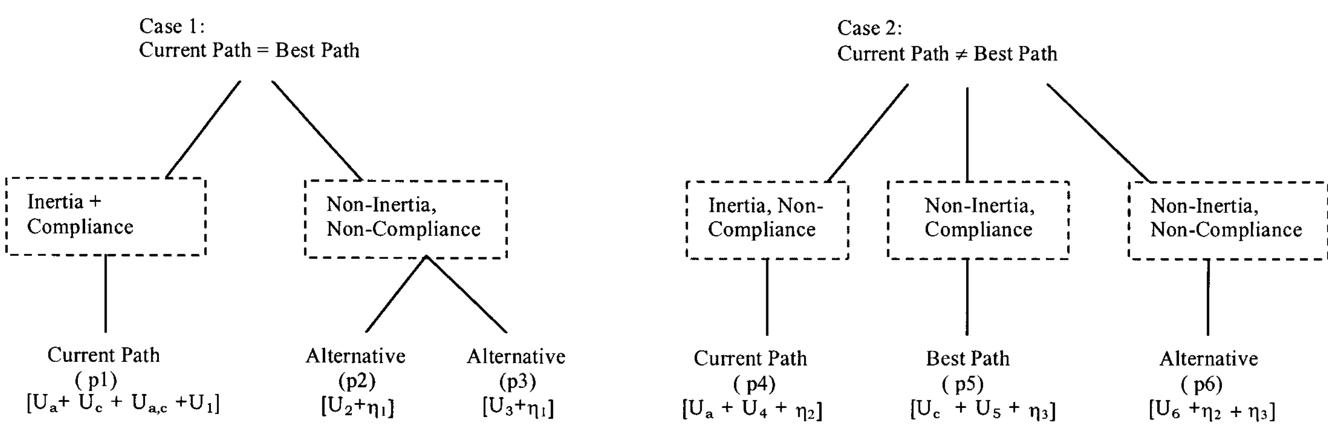

FIGURE 2 Route choice structure incorporating both inertia and compliance.

where σ_k represents the standard deviation of error term associated with path ρ_k and the ρ_k captures the correlation between the alternative paths.

Although the two cases may be calibrated by separate multinomial probit (MNP) models (in view of the nesting structures), such an approach results in an inefficient use of route choice information and loss of inferential power of estimates. Hence the two cases are estimated jointly by an MNP formulation. This joint MNP model is implemented by a binary indicator variable that activates the utilities $\tilde{U}_1$, $\tilde{U}_2$, and $\tilde{U}_3$ for Case 1 (if cp = bp) and utilities $\tilde{U}_4$, $\tilde{U}_5$, and $\tilde{U}_6$ for Case 2 (cp ≠ bp). The joint MNP model is calibrated using MNP software based on Monte Carlo simulation of multivariate normal error terms. Because of identification considerations, equality of variances is assumed among the alternatives in both Σ_1 and Σ_2. For purposes of scaling, these variances are set to unity (i.e., $\sigma_k = 1$, $k = 1, \ldots, 6$). The coefficients of the systematic components and the correlation parameters are estimated for the experimental data and are presented next.

MODELING RESULTS

The route choice models are calibrated based on the formulation with both mechanisms (Table 3) for the random and sequential treatments, respectively. The corresponding log-likelihoods with both mechanisms for the two treatments are –483.96 for the random treatment

TABLE 3 Route Choice Model Including Compliance and Inertia Mechanisms

Variable Definition	Random		Sequential	
	Coefficient	t-stat	Coefficient	t-stat
Inertia				
Constant	1.82	5.86	3.63	9.03
Network Loads and Conditions				
Level 2 (pre-trip)	-	-	-1.17	-2.33
Level 3 (pre-trip)	-0.65	-2.05	-1.17	-2.33
Level 2 and 3 (en route)	-	-	-0.45	-2.53
Relative Trip Time Saving (%)	-	-	-2.35	-1.55
Information Quality				
Overestimation Error	-0.98	-2.52	-0.73	-2.94
Underestimation Error	-0.60	-1.63	-0.17	-2.24
Past Traffic Experience				
Early Schedule Delay (previous day)	-	-	-0.04	-2.93
Cumulative Proportion of Switches to Later Departure Times	0.77	2.30	-1.00	-2.36
Cumulative Proportion of Switches to Earlier Departure Times	-	-	-0.99	-1.89
Compliance				
Constant	-0.46	-0.83	1.50	4.07
Network Loads				
Level 2 and 3 (en route)	0.50	2.54	-	-
Costs and Benefits				
Relative Trip Time Saving (%)	3.65	2.00	1.83	1.48
Switching Cost (miles)	-1.86	-4.10	-1.72	-4.40
Information Quality				
Overestimation Error	-0.94	-2.53	-0.80	-3.16
Past Traffic Experience				
Late Schedule Delay (previous day)	-	-	0.02	3.21
Cumulative Proportion of Switches to Earlier Departure Times	-	-	1.01	2.56
Inertia-Compliance Interaction				
Constant	-1.26	-1.90	-2.11	-3.07
Information Quality				
Overestimation Error	1.09	1.34	1.22	2.34
Underestimation Error	1.68	2.12	-	-
Past Traffic Experience				
Cumulative Proportion of Switches to Later Departure Times	-0.76	-1.33	1.65	1.47
Path Specific Utility				
Trip Time (min)	-0.23	-4.46	-0.05	-3.19
Anticipated Congestion	-0.70	-5.69	-0.61	-7.15
Highway 1 (ASC)	0.52	2.66	0.05	0.31
Highway 2 (ASC)	0.39	3.18	0.42	4.25
Correlations				
ρ1	0.05	2.51	0.02	2.24
ρ2	0.03	1.91	0.09	3.21
ρ3	0.04	2.22	0.07	1.81
Log-Likelihood	-483.96		-883.07	
LL(0)	-841.54		-1613.9	
Number of Observations	766		1469	

(22 parameters) and –883.07 for the sequential treatment (23 parameters). For comparison purposes, the models with only the inertial and compliance mechanisms alone and neither mechanism are also calibrated. The corresponding log-likelihoods for the random treatment were –503.22 (13 parameters), –562.04 (15 parameters), and –695.39 (4 parameters), respectively. The corresponding log-likelihoods for the systematic treatment were –953.45 (16 parameters), –1110.2 (18 parameters), and –1239.3 (4 parameters), respectively. Thus chi-squared tests indicate that both mechanisms operate simultaneously in route choice, whereas inclusion of at least one mechanism still significantly improves the model relative to the model that incorporates neither mechanism.

The calibration results displayed in Table 3 correspond to the random and systematic treatments and are indicated alongside each other for comparison purposes. The explanatory variables are vertically arranged (from top to bottom) in the following order: variables influencing deterministic utility of inertia, variables affecting utility of compliance, variables influencing interaction utility of inertia and compliance ($V_{a,c}$), variables influencing path-specific utilities, and correlation coefficients. The coefficients of these variables are interpreted below based on the relative magnitudes, signs, and statistical significance as in a typical discrete choice model.

Network Loads

The magnitude of network loads influences both the compliance and inertial mechanisms. However, this influence varies considerably between the random and systematic evolution in the network. In the random treatment, there is little effect of network loading on inertia except following the highest loading on the previous day (Level C), when inertia is decreased (i.e., increased switching occurs). In the systematic treatment, increased network loads on both current and previous day (Levels B and C) result in decreased inertial effect. This inertial effect decrease is considerably larger in response to increased loading on the previous day. These findings are consistent with an earlier analysis by the authors investigating the effect of network loads on route switching (*6*). Increased network loading on the current day (Levels B and C), relative to the baseline, results in increased compliance with information under the random treatment. In contrast, increased loading has no effect on compliance in the sequential treatment. This finding suggests that ATIS plays a greater role in influencing user behavior when traffic load fluctuates drastically from day to day (as in the random treatment), especially with a higher magnitude of loads. This suggests that ATIS information could be used by trip makers at least in part to accommodate increased uncertainty associated with random day-to-day evolution in highly congested systems.

Experience

The effects of users' past experience in traffic—specifically the effect of early and late schedule delays, and the cumulative frequency of departure time switches to later and earlier departure times—on inertial and compliance mechanisms are now investigated. Experience variables were found to have a smaller impact when the day-to-day evolution is random. Trip makers with more frequent switches to later departure times (presumably in response to early arrivals) tend to retain their current paths. However, this effect is insignificant when the current path coincides with the best path. The remaining variables did not significantly affect either mechanism in the random treatment.

When the day-to-day evolution of traffic is systematic, an increased compliance tendency is observed following lateness on the preceding day, whereas a decreased inertial effect is found following earliness. With more switches to earlier departure times, decreased inertial tendency and increased compliance are observed. This behavioral response may be explained by the failure to meet aspirations regarding preferred arrival time (as a result of many unacceptably late arrivals). In contrast, with increased switches to earlier arrival times (too many early arrivals), trip makers display a decrease in both inertial and compliance propensities.

The difference in experience effects between random and systematic treatments reveals that when traffic conditions fluctuate drastically from day to day, users are less likely to adjust their behavior based on experience. Results also show that under systematic evolution, where a user can learn about traffic evolution over time, the influence of ATIS is enhanced following unacceptably late arrivals, since compliance increases.

System Performance Measures

The effect of relative trip time savings between the current path and the best path and the cost of switching from the current path to the best path are now investigated. While these factors exert a significant influence on the inertial mechanism in the systematic treatment, they are insignificant in the random treatment. In the systematic treatment, increased relative trip time savings and increased switching cost decrease the propensity to retain the current path. In contrast to the effect of these two factors on the inertial mechanism, their influence on the compliance mechanism appears to be robust across the two treatments. Increased trip time savings leads to increased compliance, whereas increased cost results in lower compliance. The effect of trip time savings and switching cost confirms similar findings by the authors in another study (*7*).

Trip time and anticipated congestion downstream are included as explanatory variables in the path-specific utility of each alternative. Both are significant and negative as expected for both treatments. However, when the network conditions vary randomly, trip makers are more sensitive to trip time than in the systematic treatment.

Information Quality

To represent the effect of information quality, the following measures of information accuracy are incorporated in the utility specification. The underestimation error reflects the discrepancy between the reported time and experience when the reported time is smaller (*17*). Overestimation error represents the discrepancy in the other direction. In both treatments, increased overestimation errors lead to reduced inertia and compliance. However, underestimation error merely reduces the tendency to continue on the current path. When the current path also happens to be the best path, then the negative effect of the information errors on this choice is diminished for overestimation error in both cases and for underestimation error in the random treatment. These findings also corroborate earlier findings about the role of information quality reported by Liu and Mahmassani (*17*).

The framework proposed in this paper incorporates mechanisms in modeling route choice behavior in the presence of ATIS, thus overcoming some of the limitations of conventional route choice models based solely on systematic performance measures and the utility maximization paradigm. Furthermore, this work has significant application in travel demand forecasting under ATIS. Given the departure times of various trip makers, the proposed route choice model can be applied at a disaggregate level to obtain a time-dependent assignment of traffic on various paths on the network. By integrating departure time choice with the route choice framework proposed here, day-to-day variation in demand may also be captured (*18*).

Because of the nature of simulated experiments, network structure used, and associated experimental conditions, the insights here need to be confirmed with other empirical data from actual commuting systems as ATIS usage becomes prevalent. In extending the insights from the laboratory to the real world, data necessary for implementing the proposed framework can be obtained using available Intelligent Transportation Systems technologies. Data sources include GPS and onboard devices (for mean compliance and switching rates), traffic management center data (for system performance measures and historic data), and personal trip diaries and onboard surveys (for data on user's traffic experience).

A possible limitation of this study is the potential underestimation of inertial effects present in real-world systems. This study considers a route choice scenario with only three alternatives. However, this limitation may be relaxed by generalizing the proposed framework to larger path sets by suitably extending the nesting structure with additional alternatives. Attention is restricted here to commuting trips (particularly home-to-work). It is possible that the inertial mechanism that is significant here may play a smaller role in other trip types (noncommuting, recreational trips, etc.). This work also does not consider heterogeneity in route choice behavior. Heterogeneity in behavior may be accommodated by including a user-specific component in the utility.

CONCLUSIONS

In this research it was proposed that observed route choices in the presence of ATIS are a consequence of two underlying behavioral mechanisms: compliance and inertia. The influence of these mechanisms on route choice behavior was modeled by exploiting the path choice structure in relation to a user's current choice and the information supplied by ATIS. These behavioral mechanisms are simple from a cognitive perspective, as they directly relate to the propensity of choosing the current path or the best path. However, the model structure does not preclude the choice of other alternatives. The framework was implemented on route choice data from interactive experiments using a multinomial probit model. The results demonstrate that these mechanisms considerably increase the explanatory power of the route choice model.

Inertial tendency is generally reduced with increasing congestion under both sequential and random day-to-day evolution, although this influence is considerably stronger in sequential evolution. The propensity to retain the current path is also diminished by information quality errors. The experience of users (schedule delay and number of departure time switches) exerts mixed influence on inertia with an increase in random evolution and a decrease in sequential day-to-day variation.

Increased compliance propensity is seen with increased trip time savings and lower switching costs. However, the compliance propensity decreases with inaccurate information (overestimation errors). Past negative experiences relative to preferred arrival time seem to increase the likelihood of compliance in the sequential treatment.

The results indicate that compliance, inertial mechanisms, and path-specific utilities are influenced by supply conditions both within-day and day-to-day. This is evident from the significance of network loads and level-of-service measures such as trip time and anticipated congestion. It is noteworthy that the influence of network loads and users' past experience in traffic have differing impacts depending on whether network conditions change day to day in a random or systematic manner. Random changes are reflective of incident-induced congestion in actual traffic networks.

While this research focused on the mechanisms of compliance and inertia, identifying and operationalizing other mechanisms in commuters' route choice behavior is an interesting area for future work. Further investigation is also necessary to examine trip maker decision processes for other trip types, such as noncommuting, recreational, return-home, and personal business.

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The authors are solely responsible for the work and the opinions presented in the paper.