Impact of Objective Route Attributes on the Choice of Primary Morning Commute Route

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ABSTRACT

This paper examines the impact of objective route attributes on morning commuters' choice of primary commute route in the Atlanta metro area based on repeated choice observations. Data used in this paper were taken from the in-vehicle travel behavior data set collected using Global Positioning Systems (GPS) technologies from 182 commuters during a ten-day period. This paper identifies objective level route attributes that differentiate a commuter's primary commute route and the other alternative routes that the same driver occasionally uses. Research results of this study indicate that, compared to the alternative commute routes, the primary route usually has shorter travel time and distance, faster average speed, fewer number of idle stops and traffic signals, and higher freeway percentage. The research also indicates that GPS-based technology is a viable tool for route choice data collection though challenges exist on data mining and data processing of the large volume of high resolution data.

INTRODUCTION

The underlying route choice models of conventional traffic assignment procedures are normally based on the assumption that travelers minimize their travel time or travel distance and typically use a single measure of travel impedance such as travel time, travel distance, or generalized travel cost that consists of travel time, distance and other factors. Empirical research on route choice behavior indicates that drivers use numerous criteria in formulating a route: travel time, number of intersections, traffic safety and other factors (Table 1). Yet, most of the previous research findings are based on survey methods, including stated preference survey and revealed preference survey, and laboratory simulation.

Objective route choice data are difficult to obtain because of the inherent complexity of gathering and subsequently analyzing observations of the phenomena of interest. Collecting objective link-level route choice data involves tedious and time-consuming processes. Hence, route choice data are not included in traditional travel diary data collection. In fact, very little empirical work is based on real world observations. Recent advances in GPS and GIS technologies make the collection and analysis of link-level route choice data a reality. The research by Jan, et al. (1) and Wolf, et al. (2) concluded that GPS is a viable tool to study travelers' route choice patterns. GPS-based data can reveal important travel behavior information that was impossible to discern with earlier conventional survey methods.

A better understanding of route choice is important in improving the traffic assignment methods; a major transportation planning modeling step. As the focus of today's transportation planning increasingly moves away from transportation investments that meet unrestricted demand, to applications of new technologies that manage travel demand and achieve more efficient use of the systems, better understanding of route choice behavior is central to the modeling of travel behavior and the assessment of policy impacts.

This paper uses multi-day travel behavior data collected using GPS technology to identify objective route attributes that differentiate a certain commuter's primary commute route and other alternative routes of the same driver that have been occasionally used. Statistic models were developed to identify the factors that appear to influence morning commuters' choice of primary route. The remainder of this paper is organized as follows: section 2 presents the literature review, section 3 presents data collection methods, and describes data source and sample statistics, section 4 presents empirical results of data analysis and the final section provides a summary of the research findings, and identifies possible extensions of the research.

LITERATURE REVIEW

Although the shortest-path routine has been adopted over the years because of its simplicity and linkage with algorithms for generating equilibrium in static traffic assignment models, in real life, drivers' routes are likely to significantly deviate from the fastest path (3). Empirical research on the route choice behavior shows that drivers use numerous criteria in formulating a route. Drivers' experiences, habits, cognitive limits and other behavioral considerations may also produce variations in route selection.

Antonisse, et al. (4) summarized previous research findings on specific route attributes to which drivers are attracted, which includes travel time, distance, number of traffic signals, scenery, time or distance on limited-access highways, safety, commercial development, congestion, road quality, and road signing.

Jackson and Jucker (5) investigated the impact of a specific measure of reliability, the variability of travel time, on the route-to-work choice through the use of a survey instrument posing hypothetical commute alternatives. The authors suggested that including travel time variability in the impedance function along with travel time might improve the traffic assignment process for two reasons. First, the reliability of transportation systems is considered of prime importance to the traveler. Second, a number of criteria not included in traditional impedance functions, such as the number of stop lights on a route and the safety of that route, may be positively correlated with the variability of travel time measure.

Stern, et al. found driving efforts measured with a psychological scale have considerable influence in the individual's route choice process (6). In their study, driving efforts are measured by the number of turns along an alternative route, and the effect of the number of turns is much stronger for short-time routes compared to long-time routes.

Jan, et al. (1) classified potential factors that influence drivers' route choice behavior into four groups, as shown in Table 1.

Table 1: Route Choice Factors

Traveler	Age, gender, life cycle, income level, education, household structure, race, profession, length of residence, number of drivers in family, number of cars in family, etc.	
Route	Road	Travel time, travel cost, speed limits, waiting time. Type of road, width, length, number of lanes, angularity, intersections, bridges, slopes, etc.
	Traffic	Traffic density, congestion, number of turns, stop signs, and traffic lights, travel speed, probability of accident, reliability and variability in travel time, etc.
	Environment	Aesthetics, land use along route, scenery, easy pick-up/drop-off, safety, parking, etc.
Trip	Trip purpose, time budget, time of the trip, mode use, number of travelers	
Circumstances	Weather conditions, day/night, accident en route, route and traffic information, etc.	

DATA COLLECTION

Vehicle Activity Data

The objective route choice data used in this paper come from an ongoing in-vehicle activity data collection effort known as Commute Atlanta project in Atlanta, GA. This project, funded by FHWA and GDOT, is being implemented by the Georgia Institute of Technology. The project deployed instrumentation in approximately 487 vehicles from 268 representative households in the 13-county Atlanta metro area. To date, the project has collected second-by-second speed and position data for more than one million vehicle trips. The passive in-vehicle GPS-based data collection unit designed for the project provides accurate second-by-second time, speed and location information (providing accurate trip itineraries). The data collection unit turns on and off automatically with the vehicle ignition. Hence, no human input is required. Recorded data are downloaded automatically over a cellular connection every week. These features make the unit a practical option to monitor travel behavior 24 hours a day during multi-day period. The GPS receiver used in the study has a position accuracy of 10 meters and is capable to acquire satellite signal within 8 seconds under hot engine start situation and 45 seconds under cold engine start situation, per GPS manufacturer specifications. The actual data accuracy may vary depending on the real world situation such as weather, satellites configuration, and urban canyon. The data are sufficiently accurate for the research purpose of this study under most situations.

The majority of the Commute Atlanta data collection started in August, 2003. The data set used in this paper was created in December, 2003. Total duration of the data used in the sample is around 3 months and avoided the summer season and the holiday season. Observation time frame for each commuter may vary due to the fact that not all the data collection instruments were installed at the same time.

Identify Morning Commute Journey

The in-vehicle data collection unit monitors a vehicle's activity 24 hours a day and the recorded vehicle activities consist of a series of files defined by engine-on and engine-off activities. Because this paper is focused on morning commute activities, the first step of the data cleaning is to differentiate morning commutes from other types of activities.

A morning commute journey is defined as a series of trips with the first trip starting at home, the last trip ending at the work place, and all trips intermediate that take place during the morning commute time-period on a given day Monday through Friday. Vehicle activities that occurred on public holidays were excluded from the dataset.

The household travel survey provides the home address of each household and the work address of each worker in the household geo-coded in latitude and longitude format. However, the geo-coded household survey address data are incomplete and inaccurate at the time the analysis was performed. To get accurate location information for each home and work location, the authors developed a script to identify the vehicle's home and work locations based on the vehicle's activity pattern from GPS data set itself. Based on the fact that the first trip of a day usually starts at home, starting positions of the first trips during a day are candidates of the driver's home location. A location that occurs most often is determined as the home location of that driver. Similarly, ending positions of all the trips during the commute time period are candidates for the driver's work location. A location that occurs most often is determined as the work location of that driver if he/she is part-time or full-time worker. Two locations are assumed to be identical if the distance between them is less than 1000 ft (to account for the fact that the driver may park at different locations on a parking lot). The authors examined the commute activities of the vehicles that were identified by both the script and the geo-coding method. The result shows that the home and work locations generated by the scripts correspond to those generated by the geo-coding address method, except one commuter who works in a hospital and commutes work-to-home during the morning period. That commuter was excluded from the sample.

To capture as many commute behavior during representative time periods, the authors decided to use ten-day as the study duration. Based on this criterion, commute trips for 182 drivers from 138 households were identified. Since the data used in this paper were collected at the beginning of the project, and the data collecting equipments were installed in batches, if the study period is too long, fewer drivers meet the duration requirement. If the study period is too short, the data set may not be adequate to represent general commute behavior of that driver. Due to the fact that a certain driver may not necessarily work all five weekdays and the driver may use travel mode other than drive alone in his/her primary car occasionally, the 10-day period does not necessarily represent 2 continuous work weeks (Monday through Friday).

The 182 drivers included in this study have known gender information, work full time or part time at a fixed working location, and commute from home to work during the morning commute period. Significantly fewer commuters in the lower income households meet all of these conditions. Hence, conclusions regarding behavior with demographics need to be restricted to each sample strata where sufficient data are available (Table 2).

Table 2: Sample Socio-demographic Characteristics Summary

Average household size	2.86
Commuters' residence type	
Single house	162 (89.01%)
Apartment, condo or townhouse	11 (6.04%)
Unknown	9 (4.95%)
Commuters' tenure at residence	
Less than one year	4 (2.20%)
One to three years	27 (14.84%)
More than three years	142 (78.02%)
Unknown	9 (4.95%)
Percent of male / Percent of female	49.45 / 50.55
Average number of vehicles in household	2.37
Number of households with children younger than 16	52
Number of households with children younger than 6	20
Average number of fulltime workers per household	1.45
Commuters with education of	
College graduate and above	100 (54.95%)
Not college graduate	63 (34.62%)
Unknown	19 (10.44%)
Commuters from household income group	
Less than $10,000	0 (0%)
$10,000 – 19,999	1 (0.55%)
$20,000 – 29,999	4 (2.20%)
$30,000 – 39,999	7 (3.85%)
$40,000 – 49,999	12 (6.59%)
$50,000 – 59,999	18 (9.89%)
$60,000 – 74,999	18 (9.89%)
$75,000 – 99,999	40 (21.98%)
$100,000 and above	78 (42.68%)
Unknown	4 (2.20%)
Commuters from age group (cut-off points are based on the census age groups)	
Under 25	14 (7.69%)

25 – 34	33 (18.13%)
35 – 44	37 (20.33%)
45 – 54	54 (29.67%)
55 – 64	38 (20.88%)
64 +	3 (1.65%)
Unknown	3 (1.65%)

Identification of Different Routes Chosen by Each Driver

Placing the GPS data directly onto a GIS-based road network may produce results in which the GPS points and the GIS road links are not congruent, because both the GPS location data and the GIS road network are not one hundred percent accurate. Due to the fact that vehicles almost always travel on the road network, a methodology called map-matching translates the GPS measured position onto the digital road network. The algorithm needs to reconcile two types of error, the inaccurate GPS position and the inaccurate digital road network, and associate the position of a traveler in the real world with a position on a digital road link. Through map-matching algorithms, a route in the format of a sequence of links between trip origin and destination can be generated from a sequence of GPS positions.

The GIS road network data used in this paper is based on Georgia DOT digital line graph files. This dataset provides a 1:2,000,000-scale road layer with full topological structuring. A map-matching procedure written in Arcinfo^{TM} and Perl was developed to translate the participant's location onto the GIS digital road network and hence extract the route traveled. Details of the map-matching are in Li, H. (7). The generated route for each trip is in the format of a sequence of road network links.

Routes were compared against each other. If the network links of two routes share greater than 90 percent of the total length, they are assumed to be the same route; otherwise they are different. As drivers' route choice behaviors do vary a lot, the route choice patterns are extremely complex. The authors performed a manual double-check of the automatic route choice pattern detection result on the commute routes identified. Minor deviations around the neighborhood streets close to trip ends or deviations to avoid a certain intersection at a network node are not counted as a route change.

Identification of Intermediate Trip-Chaining Stops

Because drivers may or may not turn off the engine when they stop, stops made during the morning commute have been divided into two types. Engine-off stops take place when the driver turns off the engine during the stop; such trips are captured automatically in the data stream. Engine-on stops take place when the driver does not turn off the engine during the stop. Engine-on stops are detected by a script that examines the travel trace in detail. Based on experiment results, an engine-on stop is detected using the criteria that the vehicle's position falls outside of the 100-foot buffer of the road network, and the vehicle speed is less than 5 mph for duration longer than one minute can identify majority of the engine-on stops. Among the 1820 commute journeys from 182 commuters during 10-day period analyzed in this paper a total of 722 vehicle-stops were detected in the sample. Among them, 460 were engine-off stops and 262 were engine-on stops.

Identification of Objective Route Attributes

Objective road characteristics used in the paper are based on the Georgia Department of Transportation (GDOT) Road Characteristics (RC) database for the year 2000. This database contains road features collected by subcontractors of GDOT. The original database is in ACCESS format and each record is identified by a unique key composed of a RC link number and a mile-point number. To generate the road network for the study area that includes the RC information, the authors combined the RC database with the GIS road network using linear referencing method.

Road characteristics, including road functional classifications and traffic controls are analyzed in this paper. Based on functional classifications, roads are grouped into freeways and non-freeways (surface streets). Traffic control devices are grouped into traffic signals and signs. No clear-cut accuracy measures of the RC database are available because the database is undergoing continuous updates and no accuracy information at a specific time is maintained. The authors performed random accuracy check of the functional classification and traffic control device of the RC data. Based on the random check results, road functional classifications were mostly accurate. Around 90% of the traffic signal information is accurate. On the other hand, stop sign information is missing for some intersection locations. Due to the low accuracy of the stop sign information, the authors did not include stop sign in further model development.

Travel time (exclude stop duration when the driver leaves the road network) and travel distance for each commute trip were calculated based on the GPS data. Number of signals, and percent of freeway sections are calculated based on the road characteristics database information joined to the route during the map-matching process that generate the traveled routes. Two additional variables were calculated based on the GPS vehicle activity data. The number of idle stops is defined as the number of periods during the commute journey when the vehicle is traveling at speed less than 5 mph for as least one minute duration, a value designed to catch the traffic volatility and driving experience on a certain route. A route with more traffic signals, stop signs and other traffic control devices, or a route is more congested may have larger number of idle stops. We define the most frequently used route during the study period as a commuter’s primary route. The travel time reliability of the primary route can be expected to play an important role in the traveler’s decision of whether using a secondary route. Travel time standard deviation was proposed to investigate the effect of travel time variability on the primary route.

DATA ANALYSIS

Descriptive Statistics of the Number of Commute Routes

A total of 1528 out of 1820 (84 %) of the morning commute journeys were along the commuters’ primary routes (the most frequently used route for each commuter during the study period). The remaining 292 (16 %) commutes were on alternative routes. In the sample, around 40 percent of the commuters had only one route for commutes during the 10-day period studied (see Table 3). The remaining 60 percent of the commuters used at least two routes for their commute. If we define the routes that appear at least twice during the study period as routine routes, around two thirds of the commuters have one routine route and one third of the commuters have two routine routes (see Table 3). Very few commuters have more than two routine routes. This result is higher than the research result of Abdel-Aty et al. (8), in which only 15.5 percent of the respondents said they use more than one route to work. The difference may result from the fact that commuters may consider several similar routes as a single one in a travel survey.

Table 3: Number of Commute Routes Distribution

Number of Routes	Number of Commuters	Number of Routine Routes	Number of Commuters
1	72 (39.6%)	1	122 (67.0%)
2	55 (30.2%)	2	54 (29.7%)
3	35 (19.2%)	3	6 (3.3%)
4	16 (8.8%)	4	0 (0.0%)
5	4 (2.2%)	5	0 (0.0%)
Total	182 (100.0%)	**Total**	182 (100.0%)

Comparison of Multiple Route Commutes and Single Route Commutes

This section intends to capture the impact of the primary route's objective attributes, traffic condition and driving experience on commuters' decision of using single or multiple commute routes. T-tests were performed at the aggregate level for the average values of travel time and distance, number of idle stops, percent of freeways, number of traffic signal, travel time variation, and number of trip chaining stops.

Table 4 shows the t-test results. Commuters who use single route generally have a primary route with shorter travel time and distance, less number of idle stops and trip chaining stops, and less travel time variation compare to commuters who use multiple routes. The differences in number of signals and freeway percentage between these two groups are not statistically significant at the 0.05 significance level. An analysis at the disaggregate level (9) indicates that work schedule flexibility and trip-chaining have stronger explanation power compare to the objective primary route attributes.

Table 4: Two Sample T-test Assuming Equal Variances of Primary Route Attributes

	Mean Multiple Route	Mean Single Route	Mean Difference (Multiple – Single)	t	df	Significance (2-tail)/(1-tail)
Average Travel Time (minutes)	32.78	24.99	7.79	3.368	180	0.001/0.000
Average Distance (mile)	16.88	12.91	3.98	2.445	180	0.015/0.008

Average Number of Idle Stops	2.37	1.70	0.67	3.161	180	0.002/0.001
Average Number of Signals	7.16	6.30	0.86	1.65	161[1]	0.262/0.131
Average Percent of Freeways (between 0 and 1)	0.29	0.25	0.04	0.847	161[1]	0.398/0.199
Average Travel Time Standard Deviation	6.18	4.38	1.80	2.755	180	0.006/0.003
Average Number of Trip Chaining Stops	0.45	0.20	0.25	3.860	180	0.000/0.000

Aggregate Level Comparison of Primary and Alternative Route Attributes

For those 110 commuters who have at least two commute routes, paired sample t-tests were performed to compare differences in average route characteristics values between the primary routes and the alternative routes for each driver (Table 5).

All the one-tail t-statistics (because of known direction of change) are significant at the 95% confidence level. The results indicate that a certain commuter's primary routes have shorter travel time, shorter distance, less number of idle stops, fewer traffic signals, and higher percentage of freeway sections comparing to the alternative routes of that same commuter. Travel time variability was not compared due to the limited number of observations on the alternative routes.

Table 5: Paired Sample T-Tests of Primary and Alternative Route Attributes

	Mean Primary Route	Mean Alternative Route	Mean Difference (Primary - Alternative)	t	df	Significance (2-tail)/(1-tail)
Average Travel Time (minutes)	32.80	39.10	-6.30	-5.43	109	<0.0001
Average Distance (mile)	17.12	18.96	-1.84	-4.12	109	<0.0001
Average Number of Idle Stops	2.43	3.27	-0.83	-4.72	109	<0.0001
Average Number of Signals	7.16	9.14	-1.98	-3.56	100	<0.0001
Average Percent of Freeways (between 0 and 1)	0.29	0.25	0.04	2.34	100	0.021/0.011

The paired t-test results indicate that alternative routes employ a lower freeway percentage compared to primary routes. The majority of commute journeys, 960 of the 1820 (53 %), traveled on freeway segments. For commutes on primary route, about 54 percent involve freeway travel. For commutes on alternative routes, about 33 percent involve freeway travel. The result is comparable to Abdel-Aty's study result (10). In his study, about 50 percent of the

[1] Due to signal delay in cold-engine start situation, some of the trips cannot be matched to route 100 percent.

respondents that had at least one freeway segment in their primary routes, and 38 percent had at least one freeway segment in their secondary routes. Abdel-Aty also mentioned that secondary routes tend to have more surface streets than primary routes, possibly as alternatives used to avoid congestion on freeways. Even in Atlanta, a city that is generally considered saturated with freeways, 47 percent of the primary routes involve no freeway at all.

Fixed-Effects Logit Analysis

The decision of route choice is qualitative (or discrete) in nature. A route is chosen to the exclusion of one or more possible alternatives. Discrete choice models can be used to analyze and predict the choice of decision makers of one alternative from a finite set of mutually-exclusive and collectively-exhaustive alternatives based on certain decision rules. This section analyzes route choice at the discrete level based on the objectively measured route attributes.

In general logit models, the error terms are assumed to be identically and independently distributed (iid) across alternatives and individuals. Since the data set used in this paper contains multiple observations from the same individual, the estimation of a general logit model based on repeated observations from each object causes an obvious correlation of the disturbance term and violates the model assumption of the general logit models.

Because there is a natural grouping of the observations in the data set, one can think of the observations for a given individual as a group. This kind of data set is often referred to as a panel data set. In some case, the number of observations per unit will be allowed to be different across observations, so it is referred to as an unbalanced panel (11). The correlation within a group is often modeled by allowing for a group-effect which has the interpretation as an unobserved group-specific explanatory variable. As the observation period of this study is within two weeks for a certain driver, it is possible to argue that the values of most exogenous variables remain constant over time which means the group-effects stay constant over time. α_i was added to the general utility function to account for the individual specific effects for individual i. α_i is a time-invariant and individual specific effect. If we assume that α_i is distributed conditional on x_i, then the model is a random effects model. Otherwise, if we make no distribution assumptions on the distribution of α_i, but treat α_i as parameters to be estimated, the model is a fixed-effects model. Since the main goal of this paper is to judge the relative importance of a number of variables, or to statistically test whether certain variables are needed, a fixed-effects approach is preferable because it is less sensitive to distributional assumptions. Please refer to (11) for a detailed discussion of fixed and random effects models. The fixed-effects model is specified as follows:

$$y_{it} = \begin{cases} 1 & \text{if } X_{it}\beta + \alpha_i + \varepsilon_{it} >= 0 \quad (1) \\ 0 & \text{Otherwise.} \end{cases}$$

In which, y_{it}=1, if individual i choose a certain alternative at time t, y_{it}=0, otherwise
$X_{it}\beta$ is the systematic (observable) portion of utility for individual i at time t
α_i is the individual specific effects for individual i
ε_{it} is the random portion of utility for individual i at time t

The panel data version of the logit model assumes random errors ε_{it} are independent and identically distributed (i.i.d.) Gumbel. In the fixed-effects logit models, a sufficient statistic, S_i, for α_i is defined to be a function of the data such that the distribution of y_i, conditional on (S_i, X_i, α_i), does not depend on α_i. If one has a sufficient statistic, which has the property that the distribution of y_i conditional on (S_i, X_i, α_i) depends on β, then one can estimate β by maximum likelihood using the conditional distribution of the data, given the sufficient statistic.

The conditional distribution of y_i given ($Si=\sum_{t=1}^{T} y_{it}$, X, α_i) is:

$$P(y_{i1,},...,y_{iTi} \mid \sum_{t=1}^{Ti} y_{it}, x_{i,}\alpha_i) = \frac{\exp(\beta \sum_{t=1}^{Ti} x_{it} y_{it})}{\sum_{d\in Bi} \exp(\beta \sum_{t=1}^{Ti} x_{it} d_t)} \qquad (4)$$

Where B_i consists of all sequences of length T_i with elements that are all 0 or 1.

Because the probability function does not depend on α_i, the conditional maximum-likelihood estimator of β can be obtained by using standard maximum-likelihood logit programs, and it is consistent under mild conditions (12).

Fixed-effects logit models are set up using the methodology presented above. The commuters' primary route and alternative routes are defined as chosen and un-chosen route, respectively. Trip-chaining is modeled as one independent impact variable.

Univariable models were first fit for all the independent variables analyzed under the paired sample t-test. All the independent variables have the expected signs and are statistically significant at the 95% level. Based on the pseudo R-square values, travel time has the strongest explanatory power, followed by travel distance. Travel time and travel distance are highly correlated (Table 6). This multi-colinearity makes it impossible to evaluate the relative importance of each predictor. To work around this problem, separate models were built based on either travel time or travel distance. The final model specifications and parameter estimation results are presented in Table 7. Most of the predictors in these models are significant at the 95% level. For the alternative-specific variables, the odds ratios are the multiplicative effect of a unit change in a given independent variable on the odds of any give outcome. For example, based on the information in model 1 of Table 7, increasing the travel time by one minute for a given route decreases the odds of that route being chosen as the primary route by a factor of 0.9538 (4.62%), holding the values for the other alternatives constant.

Table 6: Correlation Table of the Independent Variables

	distance	Travel time	Number of idle stops	Percent of freeway	Number of traffic signals	Number of trip-chaining stops
Distance	1					
Travel time	0.8179	1				

Number of idle stops	0.3794	0.7477	1			
Percent of freeway	0.5624	0.2867	-0.0466	1		
Number of traffic signals	0.2995	0.3555	0.3517	0.1003	1	
Number of trip-chaining stops	0.3202	0.4305	0.4713	0.0812	0.2076	1

Table 7: Fixed-Effects Logit Model Estimations

Variable	Model 1		Model 2	
	Coef. (Odds)	*t (p)*	*Coef. (Odds)*	*t (p)*
Travel time	-0.0473 (0.9538)	**-4.43 (0.000)**		
Distance			-0.2004 (0.8259)	**-4.24 (0.000)**
Number of idle stops			-0.1616 (0.8125)	**-2.58 (0.010)**
Percent of freeway	0.0182 (1.0184)	**2.14 (0.033)**	0.0239 (1.0262)	**2.69 (0.007)**
Number of traffic signals	-0.0796 (0.9235)	**-2.92 (0.003)**	-0.0594 (0.9433)	**-2.11 (0.035)**
Number of trip-chaining stops	-0.2896 (0.7486)	**-2.16 (0.031)**	-0.1012 (0.8962)	-0.70 (0.485)
Model Summary Statistics				
Log Likelihood at Zero	-368.73		-368.72	
Log likelihood at convergence	-330.47		-326.34	
Prob>Chi2	0.0000		0.0000	
Pseudo R-square	0.1254		0.1363	
Number of observations	948		948	

CONCLUSIONS

This paper studied the route choice impact factors based on objective real-world observations of travel behavior during a multi-day period. The findings of this study confirm that minimizing travel time, although very important, is not the only factor that differentiates morning commuters' choice of primary route. Several other factors have been identified to impact commuters' route choice. Those factors include traveling distance and route factors, such as number of idle stops, traffic signals on the way, road functional classification, and percentage freeway distance.

Although GPS data provide very accurate record of travel behavior, GPS data by themselves do not provide information about the underlying reasons why traveler choose a certain route over others. To some degree, the drivers' knowledge of attribute values will be a distorted image of the actual values. The travelers' perception of relevant alternatives and their attributes is somewhat incomplete and inaccurate. Subjective perceptions and attitudes about objective route attributes on different alternatives drive them to a certain choice. Different usage of route attributes, different perceptions of route attributes, different interpretation of the traffic network situation can result in different behavior even in the same situation. Travelers' decision-making process, their perceptions and knowledge about these routes are unknown in this study. Investigating how much information drivers have about their routes, their awareness of alternate routes, their usage of different traffic information either before or during the trip would be helpful. Undertaking surveys to identify "normal travel patterns," day-to-day scheduling (work schedule, route choice, and response to recurring congestion), pre-trip and en-route response to unexpected congestion information, delay tolerance thresholds, and willingness to change driving patterns would also be helpful in further studies on route choice behavior.

A study that combines both the field observation and survey methods such as follow-up household interviews can provide more insightful discovery on travelers' route choice behavior and it is now a viable method due to the use of GPS–based travel study tools such as the one used in this study. An example of this comprehensive approach can be found in the ongoing study of Doherty et al. (13), which combines GPS and GIS technologies with a recently developed computerized activity scheduling survey. Such research has the potential to simultaneously observe detailed spatial-temporal activity-travel patterns and underlying decision processes of individuals within a household over long periods of time, while at the same time minimizing respondent burden.

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