Published in final edited form as:

Transp Res Rec. 2011 ; 2248: 104–110. doi:10.3141/2248-14.

Predicting Route Choices of Drivers Given Categorical and Numerical Information on Delays Ahead:

Effects of Age, Experience, and Prior Knowledge

Gautam Divekar,

Department of Mechanical and Industrial Engineering, Arbella Insurance Human Performance Laboratory, University of Massachusetts, Amherst, Amherst, MA 01003

Hasmik Mehranian,

Department of Mechanical and Industrial Engineering, Arbella Insurance Human Performance Laboratory, University of Massachusetts, Amherst, Amherst, MA 01003

Matthew R. E. Romoser,

Department of Mechanical and Industrial Engineering, Arbella Insurance Human Performance Laboratory, University of Massachusetts, Amherst, Amherst, MA 01003

Jeffrey W. Muttart,

Department of Mechanical and Industrial Engineering, Arbella Insurance Human Performance Laboratory, University of Massachusetts, Amherst, Amherst, MA 01003

Per Garder,

Department of Civil and Environmental Engineering, University of Maine, Orono, ME 04469

John Collura, and

Department of Civil and Environmental Engineering, University of Massachusetts, Amherst, Amherst, MA 01003

Donald L. Fisher

Department of Mechanical and Industrial Engineering, Arbella Insurance Human Performance Laboratory, University of Massachusetts, Amherst, Amherst, MA 01003

Abstract

In recent years there has been a considerable increase in the systems used to provide real-time traffic information to motorists. Examples of such systems include dynamic message signs and 511 travel information systems. However, such systems can be used to reduce congestion—one of their primary purposes—only if one can predict the route choices of drivers as a function of the information displayed. This simulator study looks at the diversion pattern that occurs when delays are reported ahead on the main route and how these diversion patterns vary as a function of delay times (for numerical delay signs), message content (for categorical delay signs), use of 511, and drivers' familiarity with the alternative route travel times across two different age groups. For numerical delay signs, the study shows that one can reliably predict the diversion frequencies at the different delays and across the different ages; then it is possible for traffic engineers to know ahead of time how likely it is for drivers to take an alternative route. For categorical delay signs, the findings indicate that drivers' knowledge of the alternative route travel time affects the choices of older versus younger or middle-aged adults differently. When the times are not known, the two

Corresponding author: G. Divekar, gautamdivekar2000@gmail.com.

The contents of this paper are the responsibility of the authors and do not necessarily represent the official views of any agency.

The User Information Systems Committee peer-reviewed this paper.

groups behave differently; when the times are known, the groups behave similarly. This finding suggests that traffic engineers should try where possible to present the alternative route travel times as well as the delays on the main route.

With the increasing volume of motorists on the road today, the current highway infrastructure seems inadequate to deal with congestion, especially during peak hours. These delays, whenever they occur, are typically caused by the closure of a single lane, most often because of work zones and other associated construction, but also less commonly because of crashes, debris, or special events (1). A growing concern for business and government is not only the time wasted due to traffic congestion, but also the costs incurred due to wasted fuel and loss of productivity. According to an article in the July 2005 issue of *Public Works Magazine* entitled “U.S. Traffic Delays Skyrocket,” it is estimated that the cost of travel delays and wasted fuel as a result of congestion surpassed \$63 billion (2). In addition, it is also estimated that \$60 billion is lost annually as a result of decreased productivity due to time spent in traffic, making it imperative that something be done.

To deal with these traffic congestion issues, more states are investing in and implementing real-time traveler information systems. Examples of such systems include dynamic message signs (DMSs), pretrip electronic route planning, onboard navigation systems, and 511 travel information systems. These systems are used to provide real-time traffic information, including information relevant to delays caused by crashes and work zones as well as information about alternate routes to destinations. For example, with 511 travel information systems, drivers can access real-time traffic information, typically by dialing 511 on their cell phones and entering their route. The goal of the above real-time traveler information systems is to present current travel information to motorists that would potentially influence a driver’s choice of routes and divert traffic from congested areas to improve mobility. However, without knowing the precise effect of a given message on the diversion frequency, there is no clear-cut way to determine how close to the optimal diversion pattern the response to a given message will be. Potentially, congestion could be worsened.

In recent years there have been attempts to evaluate empirically potential impacts of these systems on driver route choice, including field studies, surveys, and driving simulator studies (3). Recent empirical studies have also attempted to model the diversion frequencies as a function of information that is provided on a DMS (4–7). Most of these models are based on the principles of bounded rationality (8), simple heuristics, and a limited set of choice rules (4, 9). All such models assume that drivers take into consideration information about the travel times and variability in the travel times. However, the above studies and others have identified many additional factors that influence drivers’ choices. Three general factors have emerged over the past 10 to 15 years: decision biases, familiarity with the network features (endogenous or exogenous), and cognitive load.

To begin, consider the work on decision biases. Katsikopoulos and Fisher were among the first to apply the insights gained about decision biases to the understanding of route choice (6, 7). They developed a model that could be used to predict the diversion frequency when the travel times along the main and alternative routes were given as ranges. This model was based on the assumption that a driver’s estimate of the travel time along the main and alternative routes was equal to the midpoint plus some noise. The study had 30 participants with an average age of 23.7 years. The authors found that drivers were risk averse in the domain of gains (i.e., if the average time along the alternate route was less than the average time along the main route, then the fraction diverting decreased as the range of the alternate route travel times increased) and risk seeking in the domain of losses (i.e., if the average time along the alternate route was greater than the average time along the main route, the fraction diverting increased as the range of alternate route travel times increased).

Other researchers have since found that drivers display the same risk-seeking and risk-aversion biases [e.g., Ben-Elia (4)]. Investigators have gone on to consider how additional factors influencing behavioral decision making might affect route choice. For example, it is well known that increasing the variability in the payoff schedule causes choices between alternatives to become increasingly random, a result known as the payoff variability effect (10–12). In the domain-of-route choice, this is consistent with the results of a study reported by Avineri and Prashker (13). It is also known that if individuals have only their own experiences to rely on, then highly variable alternatives become less attractive over time, a result known as the hot stove effect (14, 15). In the domain-of-route choice, the hot stove effect is consistent with the results reported by Abdel-Aty (5, 16).

Next consider the research on familiarity. Recently, factors that come under the general heading of familiarity were evaluated in an experiment reported by Ben-Elia (4). These include the drivers' knowledge, at the start of the experiment, of the variability in the travel times of two different routes to the same destination (an exogenous familiarity factor) and the knowledge over time that drivers develop from their own experiences of the variability in the travel times of two different routes to the same destination (an endogenous familiarity factor). Participants were randomly assigned to two groups. Both groups were told how long each route took, on average, to travel. The initial knowledge of the travel time variability was manipulated by giving one group this information directly; the other group received no such information. The actual travel time was varied randomly on each successive trial. Participants received feedback indicating the length of their trip after having made their choice. The results of the study indicate that knowledge of the variability when the drivers are unfamiliar with the route at the start of the experiment leads the drivers more frequently to choose the route with the shorter average travel time. Furthermore, after repeated feedback on the travel time of the route that a driver did choose, both groups (those who received information on the variability from the start and those who did not) were more likely to choose the route with the shorter travel time.

Finally, consider the effect that engaging in a secondary task has on drivers' choice behavior. Investigators have found that the cognitive load at the time of the decision influences drivers' choice of routes. For example, in a study reported by Katsikopoulos and Fisher (7), drivers' choices were compared on a paper-and-pencil evaluation and on a driving simulator evaluation. Although the model described above (7) captured participants' behavior in both evaluations, the variability in the travel times (range) played much less of a role on the driving simulator than it did on the paper-and-pencil test. This is what one would expect if drivers tried to simplify their decision making under higher cognitive loads. In either case, this study suggests that the use of a driving simulator should be preferred for gathering route choice data because the demands of the driving simulator are arguably closer to those of the real world than are those of a paper-and-pencil test [Kaptein et al. (17)].

These findings suggest that a more thorough understanding of route choice must consider factors known to affect individuals' willingness to take risks (e.g., whether the choice is perceived as being made in the domain of gains or domain of losses) as well as both factors specific to the knowledge that drivers have of their environment, either given to them (e.g., on a DMS) (i.e., exogenous factors) or learned through experience (i.e., endogenous factors), and factors that affect cognitive load at the time of the decision. With this as background, this study investigated route choices of drivers when given information on a DMS that there were delays on the main route (a highway) and that there was an acceptable alternative route. Because decision biases have been shown to influence route choices as a function of whether the choice was in the domain of gains or losses, it was decided to vary the relative length of the delay along the main route. Because familiarity has been shown to influence route choices of drivers, it was decided to vary both the age of the participants (older adults

have more experience with congestion than do younger adults) and participants' knowledge of the length of the alternative route (by using drivers familiar with the local network of roads and drivers not familiar with this local network). Finally, because cognitive load has been found to influence route choice decisions, drivers were either given or not given information (prior knowledge) about the delays ahead before they began their trip (representative of the prior knowledge one can obtain about the delay with 511 travel information systems).

METHOD

Participants drove through two virtual databases that represented an interstate environment while making route choice decisions based on varying levels of direct delay information displayed on a DMS while on their way to their assumed destination. Seven different delay messages were presented: two categorical (i.e., with no information on the length of the expected delay) and five numerical (i.e., with actual information on the duration of the expected delay). All signs were designed in accordance with *Manual on Uniform Traffic Control Devices* standards. Familiarity was varied between subjects both endogenously (age, young or old) and exogenously (knowledge, or lack thereof, of the alternative route travel time). Finally, cognitive load was varied within subjects. Half of the participants received the delay information only via the DMS that was posted halfway through the brief drive to the alternative route exit. The other half of the participants began the drive seeing the delay on the main route and then, halfway through the drive, the participants again received the main route delay information on the DMS. These latter participants were arguably less cognitively loaded since they got their delay information earlier, giving them more time to make their decision based on the delay information provided.

Participants

There were two age groups of participants: (a) younger and middle-aged experienced drivers between the ages of 26 and 55 years and (b) older drivers between the ages of 65 and 85 years. The younger and middle-aged group had a mean age of 39.23 years and a standard deviation of 9.77 years and the older group had a mean age of 76.73 years and a standard deviation of 3.95 years. All the participants were required to have at least 10 years of driving experience in the United States and currently be licensed active drivers. Twelve participants taken from both age groups participated in each of the four conditions, totaling 48 participants in the study.

Driving Simulator

The driving simulator at the Human Performance Laboratory is a full-sized, fixed-based, midrange 1995 Saturn sedan. The visual world is projected on three screens, one in front of the car and two on each side; these three screens together subtend a 135° field of view. The refresh rate of the simulation is set to 60 Hz and the projector image resolution is set to 1,400 × 1,050. A network of four advanced Realtime Technologies, Inc., simulator servers process the images projected to each of the three screens using high-end multimedia video processors, which help the visuals to smoothly change appropriately as the driver turns, brakes, or accelerates through the virtual world. The sound system for the simulator consists of three Logitech Dolby 2.1 Surround Sound speakers, two located on the left and right sides of the car and one, a subwoofer, located in front of the car. The system provides realistic road, vehicle, wind, and other noises with appropriate direction, intensity, and Doppler shift.

Virtual World

The virtual world through which the participants drove was developed as a four-lane freeway with two lanes in each direction. The freeway had exit and entry ramps with a DMS, guide signs, and exit signs (Figure 1).

Since the study had two levels of familiarity and two levels of prior information about travel times, four conditions were used (Table 1). All four conditions had similar environmental characteristics; the only difference among them was the kind and type of information that was provided to the participants based on the condition to which they were assigned. Each participant drove one drive and each drive had seven scenarios (varied levels of delay information). In each of the scenarios the participants came across five signs. The sequence of the five signs that the participant saw in each scenario was as follows: (a) scenario information sign, (b) DMS, (c) guide sign with exit and route number, (d) exit sign, and (e) end-of-scenario sign. The information on the first sign was varied based on the condition (Table 1). The DMS was placed 1 mi before the exit sign and the guide sign was placed ½ mi before the exit sign.

Delay Information

The delay on the main route and an alternate route to the driver's destination were presented on the DMS. There were two categorical delays and five numerical delays that were presented on the DMS (Figure 2). The categorical delay signs did not indicate the length of the delay on the main route nor did it indicate which alternative route to take to the destination. In comparison, the five numerical delay signs indicated the specific length of the delay on the main route and which alternative route to take to the destination. The durations of the expected delays displayed on the DMS were 20, 30, 40, 50, and 70 min. The order in which the delays were displayed to participants was counterbalanced across drives (i.e., conditions). The logic behind selecting the above-mentioned delays was to make sure that the design included delays in which almost no drivers would divert (20-min delay, total time equals 80 min, that is, less than the alternate route travel time of 90 min) as well as delays where almost all drivers would divert (70-min delay, total time equals 130 min, that is, greater than the alternate route travel time of 90 min). Also increments of 10 min in the delay times were chosen to allow the drivers to easily estimate the total times along the main route with the given delay.

Experimental Design

The experimental design had two main conditions that were varied between subjects: familiar and unfamiliar. Under the familiar condition, the participants were instructed to assume that they were driving on a local freeway (the Massachusetts Turnpike), since most participants were from western Massachusetts and were familiar with the Massachusetts Turnpike and they also knew the alternate routes to their destination reasonably well. In this condition, the participants were provided with the main route travel time as well as the alternate route travel time at the beginning of the drive. In the unfamiliar condition, the participants had to assume that they were driving in the state of Ohio (or some similar unfamiliar location) and were unfamiliar with the alternate routes to their destination. In this condition only the main route travel time was provided to the participants.

Within each of these main conditions, the way in which the travel information was presented to the participants was also manipulated as a within-subjects variable. In the first presentation condition, the delay information was displayed only on the DMS. In the second presentation condition, the delay information was provided at the beginning of each scenario (much as drivers would get when using 511 travel information) and then as the participants

drove through the virtual world; travel time information was also provided on the DMS before the exit sign.

Hypotheses

For the numerical delay signs, it was predicted that the longer the delay is, the more likely drivers are to divert—a prediction that is hardly surprising given both intuition and the results from earlier related studies (7). The effects of age are somewhat harder to predict. Although it is well known that in traffic younger adults are more willing to take risks than older adults, at least when these risks include speeding, it is not immediately clear whether it is more or less risky to take an alternative (as opposed to the main) route. If experience has any role to play, then presumably older adults have been caught in long delays one too many times and so may be more willing to divert than younger adults (i.e., the hot stove effect may come into play) (14, 15). The effects of familiarity will depend on the estimation by older and younger adults of the average travel time of the alternative route. This cannot be predicted beforehand, but one can predict that familiarity should have an effect. So, for example, if drivers who are unfamiliar with the alternative route travel time use an estimate that is shorter than the estimate of drivers who are familiar with the alternative route travel time, then there should be an increase in the diversion frequency in the familiar condition. Finally, it is predicted that 511 travel information will have an effect on older adults, but not on younger and middle-aged adults. It is well known that older adults are slower to process information. Thus, receiving this information beforehand should alter the decision of older adults to divert, although the direction of the diversion cannot be predicted.

For the categorical delay signs, the hypothesis that the message content influences the diversion frequency was tested. Additionally, it was predicted that age will have the same effect as it does with the numerical delay signs (e.g., if older adults are more willing to divert in the numerical delay condition, then they should be more willing to divert in the categorical delay condition). Similar predictions follow for familiarity and 511 travel information.

RESULTS

The effects of the five numerical delay information signs and the two categorical delay information signs were analyzed separately. Summary information is presented here. The statistical analyses are presented below.

For the categorical signs, older drivers diverted with a probability of .2139 and younger drivers diverted with a probability of .0795. Drivers given prior information (511 present) diverted with a probability of .1271; drivers not given prior information diverted with a probability of .1663. Finally, drivers familiar with the alternative route travel time diverted with a probability of .1545; drivers not familiar with the alternative route travel time diverted with a probability of .1389.

For the numerical delay signs, older drivers diverted with a probability of .6767 and younger drivers diverted with a probability of .6623. Drivers given prior information (511 present) diverted with a probability of .6592; drivers not given prior information diverted with a probability of .6797. Finally, drivers familiar with the alternative route travel time diverted with a probability of .6873; drivers not familiar with the alternative route travel time diverted with a probability of .6517.

Numerical Delay Signs

For the numerical delay condition, the effect of familiarity (two levels: familiar, unfamiliar), age (two levels: young, old), and 511 travel information (two levels: present, absent) on

diversion patterns was analyzed using a mixed between-within analysis of variance (ANOVA) with the delay as the within-subject variable. The analysis indicated that there is a significant effect of the length of the delay on the diversion pattern of drivers [$F(4,80) = 63.069$, $MSE = 7.584$, $p < .000$], regardless of age, familiarity, and 511 travel information (Figure 3). There was no significant effect of age on diversion patterns across all delays [$F(1,80) = 0.078$, $MSE = 0.021$, $p < .781$], but there is a marginally significant interaction between age and the length of the delay [$F(4,80) = 1.946$, $MSE = 0.234$, $p < .103$].

Categorical Delay Signs

For the categorical delay information signs, again the effect of familiarity (two levels: familiar, unfamiliar), age (two levels: young, old), and 511 travel information (two levels: present, absent) on diversion patterns was analyzed using a mixed ANOVA with the two different categorical signs treated as the within-subject variable. The results of this analysis indicate that there is a significant main effect of age on diversion patterns when the delay information on the main route is not specified [$F(1, 80) = 5.401$, $MSE = 0.718$, $p < .023$]. Also there is a significant interaction between age and familiarity [$F(1, 80) = 6.157$, $MSE = 0.819$, $p < .015$]. The effect of age and the interaction between age and familiarity can be clearly seen in Figure 4.

DISCUSSION OF RESULTS

It is arguably the case that older adults are less willing to take risks than younger and middle-aged adults. Certainly this is the prevailing stereotype. And arguably the alternative route is more risky than the main route. Thus, all other things being equal, it was expected that younger and middle-aged drivers would be more willing to divert than older drivers. However, the opposite was found. The results with numerical delay signs and categorical delay signs need to be considered separately.

Numerical Delay Signs

Consider the findings with numerical delay signs (Figure 3). There was no main effect of age, but there was an interaction between age and delay. At the shorter delays, the older adults were much more likely to divert. At the longer delays, the diversion frequencies of older and younger or middle-aged adults were about the same. The most likely explanation is similar to what one might expect based on the hot stove effect (14, 15). Specifically, it is not unreasonable to assume that older adults better understand the extreme variability that can exist in the reliability of information presented on a delay sign. Thus, they could be facing extremely long delays even when the length of the delay is reported as relatively short. Seeking to avoid being stranded on a heavily congested highway, they decide to divert more often when the delays are relatively short.

To determine whether a very simple model could explain the effect of delay and the interaction between age and delay, the model of Katsikopoulos and Fisher (7) was extended. It was assumed there was variability in drivers' estimates of the reported delay just as there can be variability in drivers' estimates of the alternative route travel times when those times are presented as a range (7). However, now it was assumed that older adults' estimates of delay times are more variable than younger and middle-aged adults' estimates. Specifically, let M be equal to the driver's estimate of the travel time along the main route, A equal to the driver's estimate of the travel time along the alternative route, and D equal to the driver's estimate of the delay. Then, the probability of a driver diverting can be written as

$$P(\text{divert}) = P(A < M + D)$$

Given that the driver is told the travel time along the main route, the expected value of M can be set to 60 min. Similarly, given that the drivers in the familiar condition are told that the alternative route travel time is 90 min, the expected value of A can be set equal to 90. Finally, given that the drivers are told the expected length of the delay (20, 30, 40, 50, or 70 min), the expected value of D can be set to d , where d is the delay reported on the DMS.

It can now be hypothesized that the variability of the delay time varies for older and younger or middle-aged drivers, with older drivers assuming a higher variability in the delay than younger or middle-aged drivers. Let σ_Y and σ_O represent, respectively, the standard deviation of the younger or middle-aged and older drivers' estimates of the delay time. Then the probability of diverting when the delay is d can be written as follows for the younger or middle-aged drivers:

$$P(\text{divert}|\text{young}, d) = P(90 < 60 + D) = P\left(\frac{D-d}{\sigma_Y} > \frac{30-d}{\sigma_Y}\right)$$

Assuming that D is normally distributed with mean d and variance σ_Y , the following can be obtained:

$$P(\text{divert}|\text{young}, d) = P\left(Z > \frac{30-d}{\sigma_Y}\right)$$

The same model can be developed for older adults, substituting σ_O for σ_Y .

It is now a simple matter to fit the above model to the five delays for the older and younger or middle-aged adults. Since familiarity and 511 had no statistically significant effect, one can collapse across both. Doing such, and selecting the values of σ_O for σ_Y that minimize the sum of the squared deviations between the predicted fraction diverting and observed fraction diverting, one finds that the model predicts well the diversion patterns as a function of age and the length of the delay, though slightly less well for older adults than for younger and middle-aged adults (Figure 5). Even though the model has been shown to predict the diversion patterns as a function of the length of delay, it should be noted that the model has been fit only to alternate route travel times of 90 min and main route travel times of 60 min. However, the same model could be potentially applied to alternative and main route travel times of any length. This remains an open experimental question and more experiments are needed to test the fit of the model to predict diversion patterns for varying length of delays.

It is of some interest to ask whether there is any reason to expect that older drivers might actually be less likely to divert as the length of the delay increased from 40 to 50 min and then again to 70 min. One possibility that makes sense in this context is that an older driver's estimate of the variability in the delay time is not a constant, but is instead a function of the mean. Thus, as the mean increases, so does the variability. If that were the case, then older drivers could find that a larger fraction of their estimates of the true delay, when 70 min was the reported delay, led to alternative route travel times that were less than the main route travel time. Obviously, more experiments are needed to determine whether the results for the older adults are simply noise or represent a more fundamental change in some aspect of their underlying route choice model.

Categorical Delay Signs

The diversion frequency of both age groups is almost the same when the travel time on the alternate route is known, but the diversion patterns are significantly different when the travel

time on the alternate route is not known. Arguably, this is because older and younger or middle-aged drivers have different experiences with delays, resulting in older drivers estimating much more variable delays than younger or middle-aged drivers. Since both groups have been given the same estimate of the alternative route travel time, this difference in experience would account for the observed interaction.

511 Travel Information (Prior Knowledge)

There was not even a hint of an effect of 511 travel information on drivers' decisions, perhaps because of the design of the experiment. The traffic was relatively light in the driver's direction and so the cognitive load, above and beyond deciding at the DMS which route to take, would have been relatively light. Perhaps had the traffic been more dense, older drivers would have made different decisions when given information at the beginning of a trip (when there was no load whatsoever) than they did when given information in the middle of the trip (when they were driving and trying to read the DMS at the same time).

Familiarity

Familiarity does not have a main effect nor does it interact even marginally with any of the other factors when drivers are given numerical delay information. However, there is a significant interaction when the drivers are given categorical delay information. The failure to find an interaction in the numerical delay condition may be because the authors did not look for an interaction at each delay. For example, consider a delay of 20 min, the shortest delay in the numerical delay condition. The probability that older adults divert in the unfamiliar condition is .28, whereas the probability that they divert in the familiar condition is .20. By contrast, the probability that older adults divert at the longest delay presented (70 min) when the alternative route travel time is unfamiliar is .78. whereas the probability that they divert in the familiar condition is .90. This is exactly what one would expect. And these interactions could be washed out in the larger analyses. The power is too small to do finer-grained analyses.

Age

The effect of age has largely been discussed, especially its interaction with delay in the numerical delay condition and its interaction with familiarity in the categorical delay condition. The authors hesitate to claim that the older adults would not have trouble reading the DMSs on the open road, even though this is what the results would seem to imply. That is, given that 511 travel information did not influence older drivers' decisions, they were able to get all of the information that they needed from the sign itself as they passed by it. While this is true in the driving simulator, because one cannot replicate exactly the visual characteristics of signs in the real world on the driving simulator, there may be issues with reading signs in the real world that do not appear when reading signs on the driving simulator (though, as an aside, signs are typically more difficult to read on the driving simulator than in the real world because the resolution is still not as good in the simulated world as it is in the real world). Other reasons why 511 travel information may not have influenced the route choices of older adults are discussed below.

CONCLUSIONS

The above results extend the knowledge of drivers' decision making when confronted with numerical and categorical delay signs as a function of age, familiarity with the alternative route travel time, and use of 511 travel information systems. The results have clear implications for practice. First, it is possible to predict the diversion frequency when numerical delay signs are used and one could fine tune this prediction if one had knowledge of the distribution of the ages of the drivers using a particular highway where delay

information was presented. This can be used by traffic engineers to determine whether the presentation of delay information will actually minimize congestion. Second, and somewhat surprisingly, 511 travel information does not influence drivers' route choices, at least as it was presented here. This is especially surprising concerning the older adults, where it would be expected to find an effect of load. Thus, there is no reason to market 511 travel information to any particular cohort of drivers as defined by age. Obviously, 511 travel information is useful for many other reasons and so this is not a comment on its general utility. Finally, the differences in the diversion frequencies of younger or middle-aged and older adults when categorical delay signs are presented are large if no information is given on the length of the alternative route—younger or middle-aged drivers never diverting and older drivers diverting 28% of the time. This could make prediction difficult. However, when information on the length of the alternative route travel time was given, there was no significant difference in the diversion frequencies. Obviously, prediction is much easier in this case and, it is assumed, a model could be developed for categorical delay signs that would predict the diversion frequency as a function of the alternative route travel time.

Acknowledgments

This research has been supported in part by a grant from the New England University Transportation Center to Per Garder, John Collura, and Donald Fisher; by a grant from Massachusetts Department of Transportation to Donald Fisher and John Collura; and by a grant to Donald Fisher from the National Institutes of Health.

References

1. Kwon, J.; Mauch, M.; Varaiya, P. Transportation Research Record: Journal of the Transportation Research Board. Transportation Research Board of the National Academies; Washington, D.C: 2006. Components of Congestion: Delay from Incidents, Special Events, Lane Closures, Weather, Potential Ramp Metering Gain, and Excess Demand; p. 84-91.
2. U.S. Traffic Delays Skyrocket. [Accessed July 25, 2010] Public Works Magazine. Jul 1. 2005 <http://www.pwmag.com/industrynews.asp?sectionID=%20770&articleID=271500>
3. Bonsall, P.; Parry, T. Transportation Research Record. Vol. 1306. TRB, National Research Council; Washington, D.C: 1991. Using an Interactive Route-Choice Simulator to Investigate Drivers' Compliance with Route Guidance Advice; p. 59-68.
4. Ben-Elia EE. The Combined Effect of Information and Experience on Drivers' Route-Choice Behavior. Transportation. 2008; 35(2):165-177.
5. Abdel-Aty MA. Modeling Drivers' Diversion from Normal Routes Under ATIS Using Generalized Estimating Equations and Binomial Probit Link Function. Transportation. 2004; 31(3):327-348.
6. Katsikopoulos KV, Fisher DL. Risk Attitude Reversals in Drivers' Route Choice When Range of Travel Time Information Is Provided. Human Factors. 2002; 44(3):466-473. [PubMed: 12502163]
7. Katsikopoulos KV, Fisher DL. The Framing of Drivers' Route Choices When Travel Time Information Is Provided Under Varying Degrees of Cognitive Load. Human Factors. 2000; 42(3): 470-481. [PubMed: 11132808]
8. Simon, HA. Models of Man. John Wiley & Sons, Inc; New York: 1957.
9. Ben-Akiva MK. Simulation Laboratory for Evaluating Dynamic Traffic Management Systems. ASCE Journal of Transportation Engineering. 1997; 123(4):283-289.
10. Myers JL, Sadler E. Effects of Range of Payoffs as a Variable in Risk Taking. Journal of Experimental Psychology. 1960; 60(5):306-309. [PubMed: 13727221]
11. Busemeyer JR, Townsend JT. Decision Field Theory: A Dynamic Cognitive Approach to Decision Making. Psychological Review. 1993; 100(3):432-459. [PubMed: 8356185]
12. Erev I, Barron G. On Adaptation, Maximization, and Reinforcement Learning Among Cognitive Strategies. Psychological Review. 2005; 112(4):912-931. [PubMed: 16262473]
13. Avineri, E.; Prashker, JN. Transportation Research Record: Journal of the Transportation Research Board. Transportation Research Board of the National Academies; Washington, D.C: 2003. Sensitivity to Uncertainty: Need for a Paradigm Shift; p. 90-98.

14. Denrell J, March JG. Adaptation as Information Restriction: The Hot Stove Effect. *Organizational Science*. 2001; 12(5):523–538.
15. Denrell J. Adaptive Learning and Risk Taking. *Psychological Review*. 2007; 114(1):177–187. [PubMed: 17227186]
16. Abdel-Aty MA. Using Stated Preferences Data for Studying the Effect of Advanced Traffic Information on Drivers' Route Choice. *Transportation Research Part C*. 1997; 5(1):39–50.
17. Kaptein, NA.; Theeuwes, J.; van der Horst, R. *Transportation Research Record*. Vol. 1550. TRB, National Research Council; Washington, DC: 1996. Driving Simulator Validity: Some Considerations; p. 30-36.

\$watermark-text

\$watermark-text

\$watermark-text

FIGURE 1.
Virtual world through which participants drove (guide sign displayed on right with exit and route number).

FIGURE 2.

Traffic signs: [a and b] categorical delay signs and (c) numerical delay sign.

FIGURE 3.
Proportion of drivers diverting as function of delay in minutes on main route.

FIGURE 4.
Proportion of young and old drivers diverting as function of knowledge of alternative route.

FIGURE 5. Probability of diverting (a) younger and middle-aged drivers and (b) older drivers [-■- = observations; -▲- = predictions].

TABLE 1

Information Provided to Participants Based on Allotted Condition

Condition	Information
Familiar	Main route travel time, alternate route travel time
Familiar+ 511 information	Main route travel time, amount of delay on main route and alternate route travel time
Unfamiliar	Main route travel time, alternate route information (no travel time for alternate route was provided)
Unfamiliar + 511 information	Main route travel time and amount of delay on main route, alternate route information (no travel time for alternate route was provided)