Driving Simulator Based Study of Compliance Behavior with Dynamic Message Sign Route Guidance

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ABSTRACT

This study uses a hybrid approach that incorporates a driving simulator in conjunction with a stated preference (SP) survey to analyze driver response behavior under real-time route guidance through dynamic message signs (DMSs). It seeks to better understand factors affecting the route choice decisions by bridging some of the key gaps that limit the applicability of SP approaches. A 400 square kilometer network southwest of the Baltimore metro area is used for the driving simulator based analysis with over 100 participants. The results illustrate that past exposure to DMS, travel time savings, DMS information reliability, and learning from past experience are important determinants of driver response behavior in the real-world. Also, in addition to travel time, inertia and anchoring effects can significantly influence choice decisions. The study also illustrates that the decisions revealed in the simulator experiments at the individual level can diverge significantly from those stated in the SP questionnaire, highlighting the need to go beyond stated intent to analyze the effectiveness of information-based guidance strategies.

Keywords: Dynamic message sign, Compliance behavior, Driving simulator.

1. BACKGROUND

Advanced traveler information systems (ATIS) play a significant operative role in travelers' pre-trip route choice and en-route diversion. With the assistance of real-time traffic prediction information, ATIS guide drivers to make more informed route decisions. Dynamic message sign (DMS) is a successful and widely utilized dissemination mechanism of ATIS that can present generic information on routing and travel time to effectively manage highway congestion. Several studies evaluated the potential of DMS on route guidance and diversion and found it to be an effective and safe traffic management device to convey real-time traffic information to drivers [1, 2, 3]. The effectiveness of DMS depends on the degree of driver response to the information displayed. This is a key research issue as there is heterogeneity in the drivers' compliance with DMS route guidance.

Despite the extensive literature on route choice analysis in the presence of information [4-10], the ability to obtain appropriate data has been a major challenge to the transferability of disaggregate route choice models. Travelers' attitudes have been traditionally elicited through stated preference (SP) surveys, which do not necessarily coincide with the choices being made in reality. Such inherent inconsistency between the stated response and the actual decisions is due to the virtual nature of SP context. Field experiments, a more precise but costly option, are typically not feasible and safe to test various traffic information scenarios and environmental conditions.

Studies that used SP approach to evaluate DMS effectiveness and drivers' compliance with travel information [9, 11, 12] have often suggested that DMS had a capability to induce route diversion, which was strongly correlated with the message content and the quantity of information provided [13]. However, in a guidance compliance study with graphic DMS scene simulation using questionnaire, respondents did not properly judge their route choice style among fixed choice, choice based on experience, and based on DMS guidance styles [14]. A more realistic perspective toward DMS effectiveness was achieved by supplementing SP-based analysis with field data, where the actual diversion rate was 80 percent less than what was stated in the SP questionnaire [15]. To explain such inconsistency, it is asserted that factors such as time period and traffic conditions at off-ramps and downstream of the road are not distinguishable in typical SP-based driver behavior analyses [16]. Therefore, the visible presence of queue and traffic congestion has a significant effect on triggering drivers to divert.

In the real world, many drivers may not be able to read DMS due to the cognitive burden of driving in congested environments. A DMS-based study [17] suggested that there is no significant effect of travel time information on route choice behavior. While many drivers found DMS information useful in a pre-SP survey, only one-third actually read the message [15]. Besides drivers' characteristics, perception of information, DMS content, road familiarity, and drivers' mood were ascertained to determine compliance behavior with DMS guidance [14]. It is suggested that a realistic route choice model in the presence of information should include both strategic and non-strategic behaviors as functions of past route experiences [18]. Drivers have also been grouped into habitual and adaptive travelers emulating pre-trip and en-route choices [19]. Unlike other choice problems in travel demand analysis (such as destination, departure time, and mode choice), travelers make route decisions under the high cognitive loads associated with multitasking (driving and decision-making). While SP method fails to properly address the route choice process under the real-world complexity, a driving simulator (DS) provides a more realistic environment to investigate the latent factors of route choice behavior and the human factors associated with multi-tasking. DS technique has been used to investigate drivers' route choice behavior under various controlled conditions [4, 6, 20, 21]. This approach can also assist in building a behavior-consistent traffic routing model [22-24] based on real-time traffic information.

The aggregate approach in route choice analysis typically assumes homogenous driver behavior with similar reaction to traffic information. Recent studies argue this to be a restricting assumption and promote disaggregate route choice analysis. Although DMS aggregate response is crucial to DMS design, disaggregate analysis provides more insights into individuals' behaviors and attitudes towards DMS information. In a DS-based route choice study, disaggregate modeling approach outperformed the corresponding aggregate approach [21]. One of the principal questions that can be examined at the disaggregate level is drivers' compliance probability with DMS guidance. Drivers are generally presumed to choose the faster route among the alternatives displayed on DMS. The path with the shortest travel time is considered as the recommended path and a route choice compatible with it is assumed as a compliant case. Thus, individuals' compliance can be studied as a probabilistic parameter.

This study aims to analyze driver compliance behavior with DMS travel time information to provide more realistic insights on the effectiveness of DMS as a traffic management tool. Current DS-based route choice studies in the presence of information lack in one or more key features: relatively small transportation network [20, 21], grid-type virtual network [6, 7], lack of environmental features [4, 5, 8], and limited number of study participants [4, 6]. Moreover, some findings such as no evidence of the effect of travel information and familiarity on route diversion seem counterintuitive [17] and necessitate a broader study. To reveal compliance behavior with DMS guidance in the real world, this study addresses the existing gaps in the realism of route choice data. By recruiting more than 100 participants, the study uses a large real network in an interactive high-fidelity DS with traffic information displayed on the DMS. To ensure that travel time and distance represent actual driving experience, a 20X20 km^2 network, including real time traffic and relevant roadside objects such as ramps, bridges, signs, vegetation, and buildings, southwest of the Baltimore (Maryland) metro area are replicated in the DS. This study presents a relatively more realistic environment than other past studies to elicit their DMS guidance response. Obtaining the revealed choices from the DS experiments, the study also assesses the validity of SP responses to the same scenarios.

2. METHODOLOGY

2.1. Study Network Characteristics

The study network consists of a fixed origin—MD-100, 3.45 miles (5,550 m) west of I-95—toward downtown Baltimore. A DMS mounted on an overhead structure was embedded in the network located 1.39 miles (2.24 km) from the start point (on MD-100). The DMS provided drivers with travel time information to the destination through two major alternatives, I-95 and MD-295, among three. The third option (Washington Blvd.) is a local arterial with several traffic signals. Travel distance was chosen long enough to incentivize the subjects to optimize their route choice based on the displayed travel time. Figure 1 shows the study network, origin, destination, three alternatives, DMS position, and DMS view for the first research scenario in the DS environment. Table 1 compares the main features of the two major alternatives, indicating I-95 as a wider, shorter, and faster route under normal traffic conditions, which makes it more appealing to drivers. The study utilizes a high fidelity driving simulator, UC-win/Road by FORUM8 [25], to generate the route choice data.

FIGURE 1 Study area, origin, destination, alternate routes, DMS location, and appearance.

TABLE 1 Specifications of Two Major Alternatives

Route	Number of lanes	Speed limit (mph)	Distance (miles)	Travel time (min) *	Truck percentage **
I-95	4	65	13.9	16	10.0
MD-295	2-3	55	16.2	22	4.2

* In normal traffic conditions
** Source: Maryland State Highway Administration, Traffic Monitoring System 2012.

2.2. Scenario Design and Sequence

Five scenarios were developed in this study to address various traffic regimes and travel time information. Table 2 describes the DMS content displayed in each scenario. Travel time difference (▵TT) and relative travel time difference for each scenario are computed. The former measure shows the travel time savings when the alternate option (MD-295) is chosen over the reference option (I-95). Since the change in the ▵TT was due to the change to both routes' travel times, the relative travel time difference (attributed to I-95) can be an informative indicator.

TABLE 2 Description of Five DMS Scenarios

Scenario	Message	▵TT ($TT_{95} - TT_{295}$)	$▵TT/TT_{95}$	Traffic Condition
1	95: 15 MIN 295:20 MIN	–5	–0.33	both off-peak
2	95: 30 MIN 295:20 MIN	10	0.33	95 peak
3	95: 30 MIN 295:30 MIN	0	0	both peak
4	95: 25 MIN 295:20 MIN	5	0.20	5 min hypothetical delay for 95 only
5	95: 35 MIN 295:20 MIN	15	0.43	15 min hypothetical delay for 95 only

All participants started their driving experiments with the first scenario, while the remaining four scenarios were not presented in a predefined sequence; in turn, scenarios were assigned based on subject's revealed choices in preceding scenarios. This procedure is elaborated as follows. Drive frequency varied from 1 to 12 times per participant with an average of 5.7 times and 22 minutes mean travel time. Considering 15 minutes practice prior to the initial experiment and a 5-minute break between the tests, participants could execute up to 4 scenarios in a 2-hour session. The scenario sequence in response to the posterior route choices for the first four drives was planned not only to randomly generate a fairly equal number of all scenarios, but also to counterbalance the order effects. This arrangement, shown in Figure 2, was designed to capture the participants' travel time sensitivity and inertia relative to their favorable route. Setting a scenario more than once revealed the effect of learning from past experience.

Accurate travel time information provision to drivers is an essential task in ATIS. However, the traffic conditions and subsequent travel time predictions are inherently subject to uncertainties, specifically when drivers receive informative messages and react accordingly. In addition, generating traffic volume higher than 6,000 vph at any given time could impact the visual quality of the simulator. This could precludes the ability to increase travel time by adding traffic volume. Thus, a combination of volume increase and capacity restriction (through lane closure) was deployed to produce desired congestion levels for the study scenarios, in particular scenario-*4* and scenario-*5*.

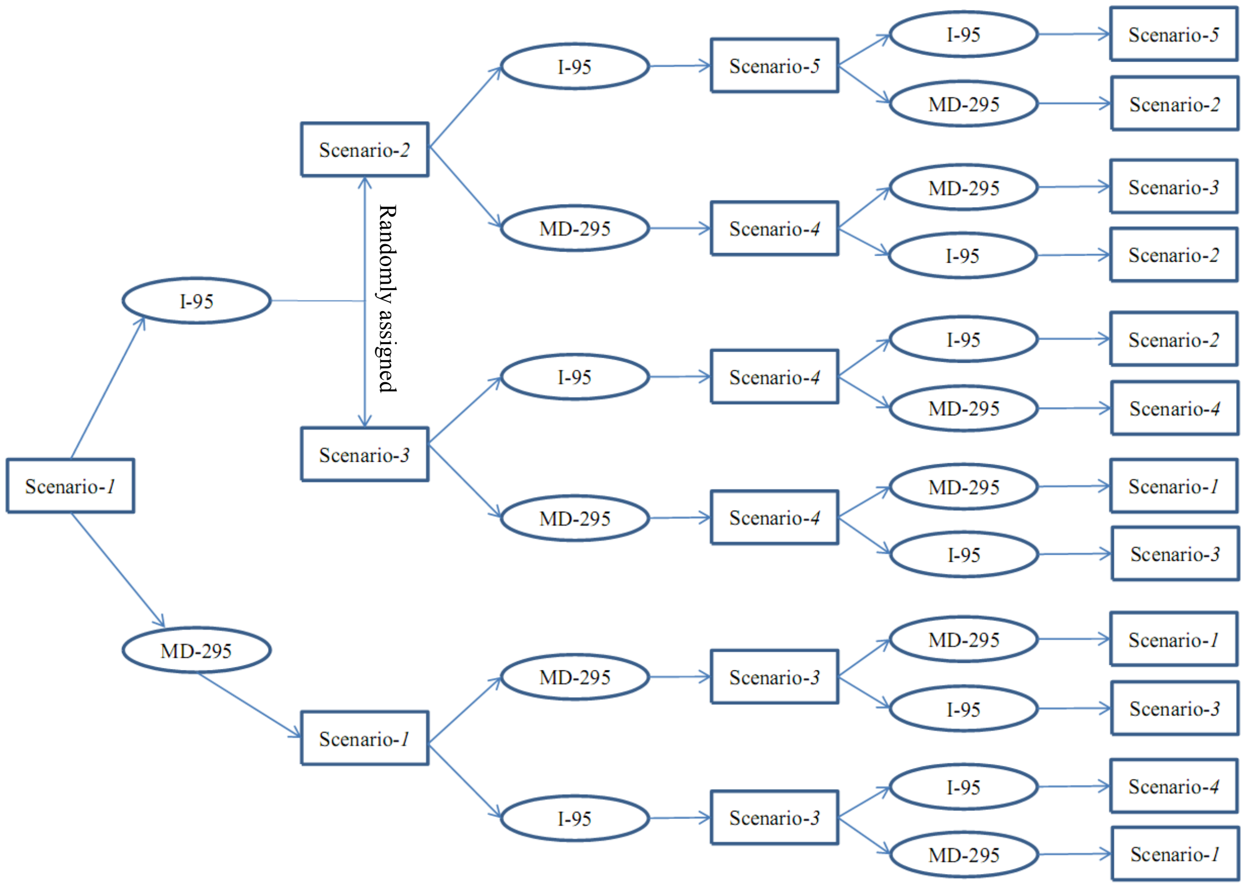

FIGURE 2 Scenario sequence for the first four drives, responsive to posterior choice.

2.3. Study Data

The recruitment of the study participants was conducted through flier distribution across the Morgan State University campus and Baltimore metro area. Reimbursement of participants for their efforts enabled us to collect a fairly unbiased sample in terms of demographics. In an extensive data collection, 102 people completed surveys and accomplished at least one test, for a total of 577 experiments. Table 3 presents the descriptive statistics of the participants' socio-economic characteristics. General attitudes towards DMS and travel information were solicited in the first survey and the preliminary results are presented in Table 4.

TABLE 3 Descriptive Statistics of Socioeconomic Data (Size: 102)

Characteristics	Options	Percentages
Gender	Female	36
	Male	64
Age	< 18	3
	18-25	37
	26-35	18
	36-45	20
	46-55	9
	> 55	13
Education level	High school or less	31
	College degree	32
	Post graduate	37
Job status	Unemployed	28
	Work part-time	30
	Work full-time	42
Income level	< $20K	23
	$20K- $30K	18
	$30K- $50K	13
	$50K- $75K	16
	$75K- $100K	13
	> $100K	17
Household size	1	20
	2	30
	3	17
	≥ 4	33
Car ownership	0	9
	1	39
	2	30
	≥ 3	22
Annual mileage driven	≤ 8,000	29
	8,001 - 15,000	35
	15,001 - 30,000	25
	≥ 30,000	11

TABLE 4 DMS and Travel-Related Attributes

Attributes	Options	Percentages
DMS exposure	None	1
	Occasionally	24
	Everyday	75
DMS attention	Pay no attention	2
	Not able to read	8
	Read it in special occasions (accident, etc.)	30
	Always read	60
Navigation systems usage (GPS, smart phone, etc.)	Never	18
	Sometimes	72
	Always	10
DMS helpful belief	Not a helpful device	3
	Potentially helpful	39
	Absolutely helpful	58
Route familiarity	Unfamiliar	25
	Somewhat familiar	43
	Familiar	32

Presenting a map similar to the study area, subjects' familiarity with the network, rank-based priority of the two alternatives (I-95 and MD-295), and willingness to choose I-95 for the five DMS scenarios (measured on a 5-point Likert scale) were obtained in the second pre-experiment survey to assess the consistency between SP responses and DS choices. The five DMS scenarios in SP were identical to DS, as displayed in Table 2. Participants were inquired to measure the reliability of DMS information on a scale from 1 to 5 (completely accurate) in a post-experiment survey.

3. RESULTS AND DISCUSSION

3.1. Attitude Analysis

Figure 3 evaluates the DMS attention level for two groups of people with low and high exposures to DMS (left chart), and also for two groups who "potentially" and who "absolutely" believed in DMS usefulness (right chart). It is understood from the left chart that people with a higher DMS exposure are relatively more likely to pay attention and read DMS information than those with less exposure. Therefore, more exposure to a DMS leads to more attention. The right chart illustrates that travelers with a stronger belief in DMS's performance are more likely to read and consider the message.

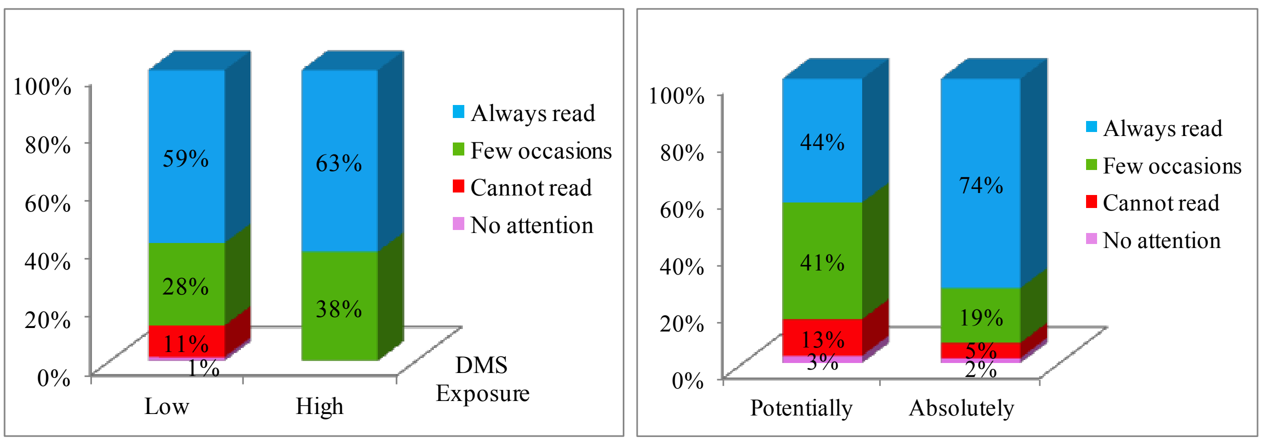

FIGURE 3 DMS attention level based on drivers' exposure (left) and attitude (right) to DMS.

3.2. Aggregate Route Choice Results

In a rank-based SP question to investigate participants' route priorities, 64 percent ranked I-95, 22 percent ranked MD-295, and 14 percent ranked the third local alternative as their first option. However, the selection arrangement for DS scenario-*1* was 80 percent I-95, 18 percent MD-295, and 2 percent Washington Blvd. DS scenario-*1* represented off-peak traffic conditions with normal travel time displayed on DMS (I-95 being 5 minutes faster). This scenario was introduced to all subjects in their first experiment neutralizing the effect of DS past experience. Substantial differences between the choice configurations of SP and DS indicate that travelers' stated route preferences are not necessarily consistent with their revealed choices.

Figure 4 compares DS and SP in terms of the aggregate probability of choosing I-95 as a function of absolute and relative $\vartriangle$TT. There are five options of $\vartriangle$TT from –5 to +15, while the former indicates that I-95 is 5 minutes faster and the latter indicates that MD-295 is 15 minutes faster. Although both curves are descending, a subtle difference between SP and DS is identifiable. While the SP curve presents a smooth systematic decline of I-95 choice probability as $\vartriangle$TT and $\vartriangle TT/TT_{I\text{-}95}$ increase, DS curve shows a noticeable turning point from $\vartriangle$TT=0 to 5 minutes and a sharper downturn from $\vartriangle TT/TT_{I\text{-}95}=0$ to 0.2. In the DS context, while the probability of choosing I-95 decreased by only 3 percent (which was found to be statistically insignificant at α=0.05) from $\vartriangle$TT=–5 to $\vartriangle$TT=0, the choice probability decreased by 30 percent when MD-295 became 5 minutes faster than I-95 ($\vartriangle$TT=5) and the shift was statistically significant (t=3.94 and *p-value* < 0.001). The insignificant shift in route choice from $\vartriangle$TT=–5 to 0 followed by strongly significant shift from $\vartriangle$TT=0 to 5 demonstrated inherent inertia among drivers to maintain the dominant choice. This fact may not be readily identifiable from the SP results, nor from a typical field-base study that does not track individual drivers over time.

The overall decreasing trends suggest that drivers were quite responsive to DMS travel time information. The aggregate compliance rate with DMS information appeared to be consistently higher in the DS than in the SP for all scenarios. That is, for the four scenarios with travel time advantage, the DS resulted in higher choice probability for the shorter route.

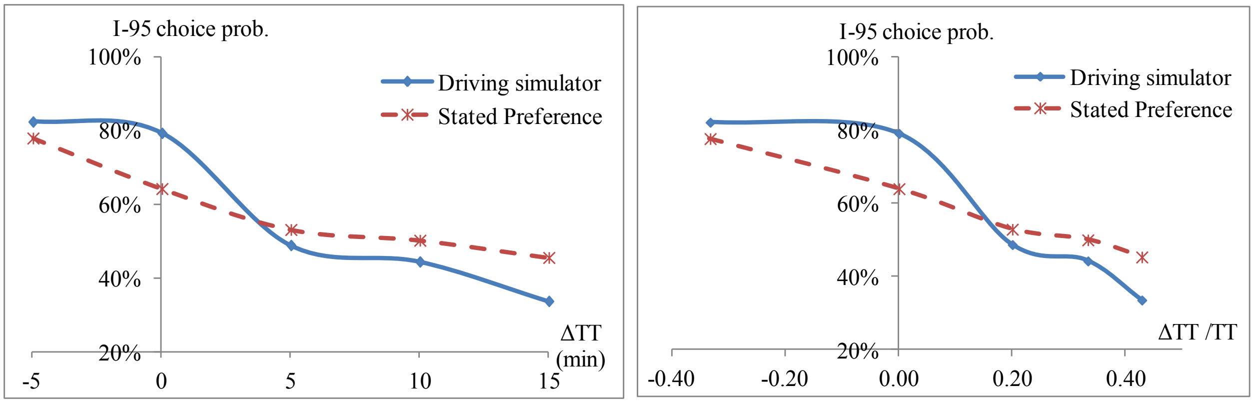

FIGURE 4 I-95 choice probability based on absolute (left graph) and relative (right graph) △TT.

To deduce the effect of DMS on route choice behavior, other potential factors are also taken into consideration. It is postulated that network familiarity and past experiences direct drivers toward more efficient choices. Compared to non-informed drivers, informed participants had faster learning rates and higher sensitivity to travel time variability [26]. The five hypothetic linear trends in Figure 5 illustrate increase in compliance with DMS guidance as subjects acquired more driving experience. This qualitative finding is underpinned by statistical tests in Table 5. Since the size of experiments in many scenario-drive number combinations (that is, 5 scenarios under 12 drive frequencies) were essentially small for statistical tests, drive frequencies were labeled into two groups of starting drives (first to fourth drives) and latter drives (fifth drive or higher), to generate large enough samples for comparative analysis.

When I-95 is 5 minutes faster (the top dotted line in Figure 5), the choice probability ranges upward from 75 percent for the first drive to nearly 100 percent for the twelfth drive, with the growth being statistically significant. When the travel time is equal in both alternatives and when MD-295 is 5 minutes faster (second and third lines from the top in Figure 5), moderate ascending lines exhibit the change in choice probability with driving experience. However, none of the trends are statistically significant. Although the pattern in ▵TT=5 scenario is insignificant, this curve indicates likely effect of perceptive knowledge on route choice behavior that even five minutes travel time savings may not cause a switch from the preferred route. For the last two scenarios (I-95 being 10 and 15 minutes slower than MD-295), I-95 choice probability decreased significantly as the drive frequency increased. Since these two lower lines reached a similar end probability, it can be concluded that drivers who could potentially learn from experience had already chosen the shorter path from the starting drives in ▵TT=15 scenario. The overall results confirm past findings, where no evidence for risk-averse or risk-seeking behavior was discovered when the average travel time of the alternative route displayed on a simulated DMS was less than that of the major route [6].

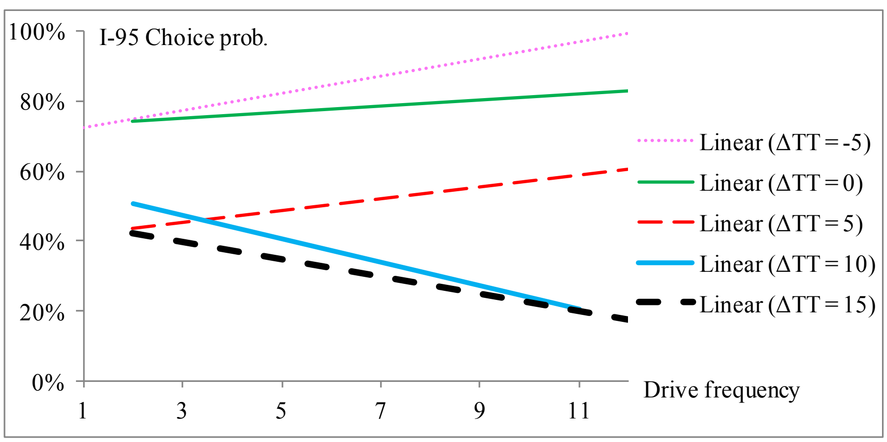

FIGURE 5 Choice probability of I-95 with drive frequency for five DMS scenarios.

TABLE 5 Statistical Test Results of the Effect of Drive Frequency on Route Choice

△TT	I-95 choice prob. (drives 1-4)			I-95 choice prob. (drives 5-12)			t	p-value (one-tailed)
	Mean	Variance	Obs.*	Mean	Variance	Obs.*		
–5	0.78	0.17	124	0.92	0.07	52	2.67	0.004
0	0.78	0.18	36	0.80	0.16	51	0.29	insignificant
5	0.45	0.25	38	0.52	0.25	54	0.67	insignificant
10	0.51	0.25	79	0.34	0.23	47	1.84	0.034
15	0.48	0.26	25	0.29	0.21	56	1.64	0.055

* Number of Observations

3.3. Disaggregate Route Choice Analysis

The scenario-based DMS compliance rates for the DS and the SP are calculated and shown in Table 6. Since there is no travel time distinction between the two routes and compliance does not materialize, scenario-*3* is excluded. According to Table 6, the overall compliance rate with DMS in the DS experiments was 65 percent; higher than 59 percent in the SP (in response to similar scenarios). When I-95 is 5 minutes faster, the I-95 selection rate is 81 percent in the DS as compared to the 69 percent in the SP. Travel time perception and the capacity to connect to the displayed message in the DS experiments rather the SP settings enabled drivers to optimize their route choices more effectively. Thus, the higher likelihood of I-95 selection in the DS better matches the reality.

TABLE 6 DMS Compliance Rate Analysis for SP and DS Approaches

Scenario	Faster route	$\lvert\triangle TT\rvert^*$	DS	SP
1	I-95	5	81%	69%
4	MD-295	5	50%	47%
2	MD-295	10	54%	57%
5	MD-295	15	65%	62%
Overall	-	-	65%	59%

* The absolute value of travel time difference displayed on DMS

The DMS compliance rate with faster route (MD-295) in scenario-*4* was significantly lower than that of scenario-*1* (I-95 being the faster route), though both scenarios displayed similar $\triangle TT$ value. The compliance rate when I-95 is 5 minutes faster is higher than when MD-295 is even 15 minutes faster (81 percent versus 65 percent). This finding demonstrates the anchoring effect in route choice behavior as drivers were prone to persist with their prevailing option. Inertia to continue on the existing route is reciprocal to compliance behavior, and both mechanisms operate simultaneously in route choice [27]. Latent variables concept reflecting the sensation seeking domain is also demonstrated to improve the understanding of route choice behavior [28]. Hence, many unobservable and latent variables can influence the compliance model outcomes.

A disaggregate comparison between choices in SP and DS approaches was also conducted to better evaluate the consistency in subjects' responses to the corresponding circumstances. Considering three possible routes, the overall consistency rate between SP and DS responses was calculated to be 60 percent, which is the summation of the diagonal cells divided by the total number of cases in Table 7. Among the 47 subjects whose preference was I-

95 in SP, 39 drivers selected I-95, 6 chose MD-295, and 2 chose Washington Blvd. in the DS scenario-*1*. Conversely, among the 56 people who chose I-95 in the DS scenario-*1*, only 39 people had stated such choice in the survey. Table 8 evaluates the consistency between the SP responses and DS choices for all experiments. For comparison purposes, I-95 was designated as the likely SP choice to those who scored it 4 or 5 in the 5-point Likert scale. The consistency rate, computed from Table 8, was found to be only 55 percent. The results demonstrate that travelers' reaction to traffic information in the DS environment is not fully consistent with their stated choices, fairly in line with the findings of a field-based study [15].

TABLE 7 Disaggregate Comparison of SP and DS for Scenario-*1*

		DS choice			
		I-95	MD 295	Wash Blvd	Total
SP	I-95	39	6	2	47
	MD 295	11	4	0	15
	Wash Blvd	6	4	0	10
	Total	56	14	2	72

TABLE 8 Disaggregate Comparison of SP and DS for All Scenarios

		DS choice		
		I-95	Not I-95	Total
SP	I-95	150	75	225
	Not I-95	178	160	338
	Total	328	235	563

3.4. Bivariate and Multivariate Analysis

Bivariate correlation analysis was performed to verify the significant contributors prior to multivariate analysis. Efficiency-related attributes, driver-specific variables, and information-specific variables were the initial explanatory variables. The binary nature of the outcome variable (compliance and non-compliance with DMS) initially led to the use of a logistic regression structure to develop a compliance model. While the result of a binary logit model was presented in [29], diagnostic tests revealed that ordinal scale outcome can better explain driver compliance behavior and resulted in a better model fit. Compliance level is hypothesized to be different for different △TT value displayed on the DMS. The proposed ordinal measuring scheme for compliance (Comp) which appears to be more sensitive to drivers' reactions is illustrated in Figure 6. Compliance is scored positive when the driver chose the shorter route and is negative when the choice is the longer route; however, in each end, the compliance takes values of 1, 2, and 3 proportional to 5, 10, and 15 minutes △TT.

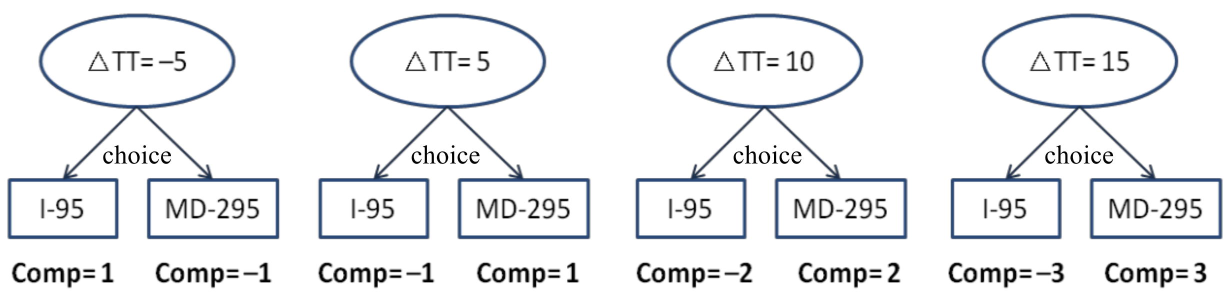

FIGURE 6 Ordinal measuring system of compliance variable for any choice in each scenario.

The correlation coefficients and significance values of the explanatory variables with the dependent variable (ordered compliance) are presented in Table 9. A Chi-square test was conducted to measure the correlation of the categorical (ordinal or nominal) variables with the dependent variable, while point-biserial test computed the correlation of the quantitative variables with compliance. Among drivers' characteristics, income level, household size, and car ownership appeared to be significantly correlated with DMS compliance, and gender, age, education level, job status, and driving mileage had no significant association with DMS compliance. None of the information-specific variables, actual and perceived travel times, and route familiarity was a significant predictor. However, drive frequency, travel time savings, and the reliability of DMS information were strongly correlated with DMS compliance.

Table 10 presents the results and goodness-of-fit of the multiple regression model with ordered logit structure congruous with the proposed quantification scheme of the compliance variable. The final model employs four predictors and has five thresholds for the six compliance categories. Except the first threshold which isolates compliance levels –3 and –2, the remaining four cut-points are strongly significant. The overall goodness-of-fit indicators demonstrated the superiority of the ordinal regression model over the logistic model previously developed in [29].

Aligned with a past field-based study [16], travel time difference was deemed to be highly significant with a positive coefficient. This is intuitive not only because of the importance of travel time variable, but also due to the mechanism that the ordered compliance variable was coded as a function of $\triangle$TT. For a one-minute increase in travel time savings, the odds of compliance at each level is 1.37 (=exp(0.316)) times greater than the next lower compliance level, with the other variables in the model being constant. Travel time uncertainty is identified as an important factor in drivers' departure times and route choices [30]. Reliability of DMS information had a close positive relationship with DMS compliance in our model, affirming past studies based on SP data [31]. The odds of compliance increases 53 percent as the travel time information displayed on DMS becomes 20 percent more reliable, with the other variables being constant. Income level and drive frequency are treated as multi-valued factors. Setting the first income group (<$20K) as the reference group, none of the other 3 groups was distinct from the first group, indicating income level as an insignificant determinant in route guidance compliance.

With the first drive set as the control group, the second and third drives were observed to have significant declining effects on compliance behavior compared to the first drive. This may be because drivers tended to explore new routes in their second and third experiments rather focusing on travel time optimization. The effect of experience learning on compliance behavior with travel information has also been addressed in the recent literature. Using a simulated DMS, information had an increasing effect on initial risk-seeking and a decreasing effect on initial exploration [8]. In a hybrid SP and laboratory experiments study, recent experience decreased compliance rate under information provision [32]. Our study results indicate that learning process materialized during the first three experiences in a typical 20-25 minutes long trip.

While past studies indicate that route familiarity leads to more efficient route choice behavior [5, 33], our study found no significant correlation between them. While familiarity with the study area was not a strong predictor, it could potentially act as a moderator in the relationship between compliance behavior and driving experience. To test this hypothesis, an interaction analysis was performed to evaluate the combined effect of route familiarity and driving experience on compliance behavior. Figure 7 depicts the extent of driving experience effect on compliance for three levels of route familiarity. Since the lines are parallel and adjacent, there is no significant difference between the behavior of familiar and unfamiliar drivers in choosing the recommended route. However, the “somewhat familiar” group demonstrated a significantly different compliance behavior compared to the other two groups as the dotted line crosses the other two lines. A correlation analysis revealed that while familiarity was not correlated with DMS guidance compliance (Pearson correlation coefficient: 0.054, sig.: 0.240), the product term of familiarity and driving experience was correlated (Pearson correlation coefficient: 0.093, sig.: 0.043). This illustrates that familiarity with the road network has an interaction effect on the relationship between driving experience and compliance with travel information.

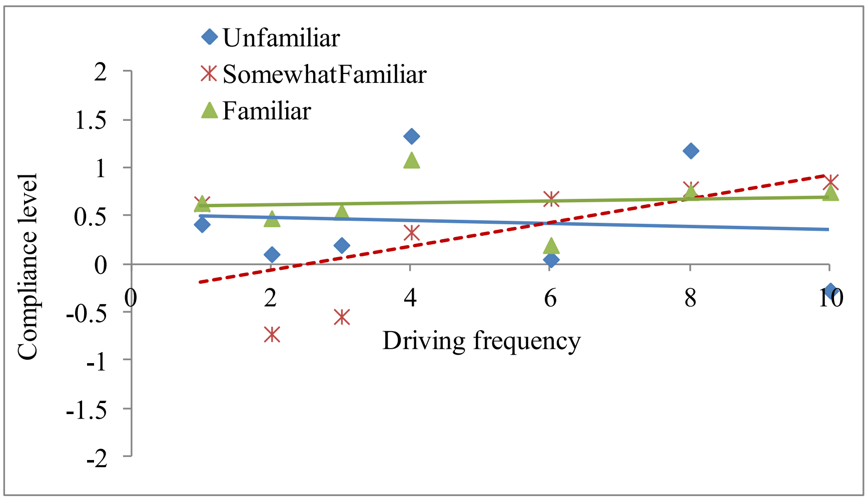

FIGURE 7 Interaction effect of driving experience and familiarity on DMS compliance.

TABLE 9 Correlation Coefficient of Independent Variables And Dependent Variable

Variable	Value	Significance	Decision
Gender	3.33 [1]	0.649	Reject
Age	10.62 [1]	0.779	Reject
Education level	4.70 [1]	0.910	Reject
Job status	4.94 [1]	0.895	Reject
Income level	–0.09 [2]	0.088	
Household size	–0.08 [2]	0.074	
Car ownership	–0.10 [2]	0.036	
Driving mileage	13.96 [1]	0.529	Reject
DMS exposure	5.30 [1]	0.871	Reject
DMS attention	15.59 [1]	0.409	Reject
DMS helpful belief	9.66 [1]	0.471	Reject
Navigation systems usage	6.23 [1]	0.796	Reject
Drive frequency	314.46 [1]	0.000	
Actual travel time	–0.01 [2]	0.933	Reject
Perceived travel time	–0.02 [2]	0.651	Reject
▵TT (travel time saving)	970.00 [1]	0.000	
Route familiarity	0.05 [2]	0.240	Reject
DMS info reliability	0.21 [2]	0.000	

[1] Two-tailed Pearson chi-square
[2] Two-tailed point-biserial correlation (Pearson’s r)

TABLE 10 Ordinal Regression Model Results

Variable		Estimate	Standard error	Wald *	Significance
Threshold	Comp = –3	0.152	0.717	0.05	0.832
	Comp = –2	1.408	0.691	4.15	0.042
	Comp = –1	2.333	0.692	11.37	0.001
	Comp = +1	4.465	0.772	37.70	0.000
	Comp = +2	6.237	0.779	64.06	0.000
Variables	△TT	0.316	0.038	70.76	0.000
	DMS reliability	0.424	0.142	8.88	0.003
	Income level (stratum1)		Reference group		
	Income level (stratum2)	–0.285	0.279	1.04	0.307
	Income level (stratum3)	–0.110	0.287	0.15	0.701
	Income level (stratum4)	–0.591	0.384	2.37	0.124
	Drive frequency (1st drive)		Reference group		
	Drive frequency (2nd drive)	–1.550	0.395	15.37	0.000
	Drive frequency (3rd drive)	–1.014	0.423	5.74	0.017
	Drive frequency (4th drive)	–0.193	0.467	0.17	0.680
	Drive frequency (5th drive)	–0.042	0.481	0.01	0.930
	Drive frequency (6th drive)	0.198	0.490	0.16	0.686
	Drive frequency (7th drive)	–0.103	0.468	0.05	0.826
	Drive frequency (8th drive)	–0.140	0.518	0.07	0.787
	Drive frequency (9th drive)	–0.044	0.478	0.01	0.926
	Drive frequency (10th drive)	–1.084	0.602	3.24	0.072
	Drive frequency (11th drive)	–0.522	0.734	0.50	0.478
	Drive frequency (12th drive)	0.824	1.110	0.55	0.458

– 2 log likelihood for the intercept-only model= 856.12

– 2 log likelihood for the final model= 763.97

Pearson chi-square = 4642.78 (0.000)

Nagelkerke R^2 = 0.280

* The Wald chi-square that tests H_0: Estimate = 0 (calculated by dividing the square of Estimate by the square of SE)

4. CONCLUDING COMMENTS

This empirical study seeks to address some key issues related to the collection of appropriate route choice data under information provision. Both SP and driving simulator (DS) techniques were used to evaluate the effects of driver characteristics and efficiency-related attributes on route compliance behavior with DMS-based travel time information. The majority of the subjects believed that DMS is a useful tool for traveler information provision. Drivers with higher exposure to DMS were more likely to read DMS than those with lower exposure. Thus, more recent studies can better exhibit driver's attitude since drivers are now more exposed to DMS driving in the highways. Drivers were generally responsive to the travel time information provided by DMS. When the major route became slower, the probability of choosing the alternative route became gradually higher. While the change was uniform in SP data, DS results evidenced latent inertia in route choice behavior and suggested that compliance is not linearly correlated with DMS guidance and travel time savings. Despite faster alternative route for 5 minutes, nearly half of the drivers were anchored to the study's major route which was wider, faster (in normal traffic), and had a higher speed limit. Even for 15 minutes $\triangle$TT, the major route was selected in one-third of the tests. For an equal $\triangle$TT, DMS compliance was much superior when $\triangle$TT was in favor of the major route than the alternate route. While more drivers initially complied with DMS under $\triangle$TT=15 than $\triangle$TT=10, the learning pace was sharper in the latter case, arguing the rational behavior of drivers.

Consistent with the recent literature, the study concluded that travel time is not the only factor affecting route choice. Driving experiences and DMS information accuracy were also significant determinants. Familiarity with the study area had an interaction effect on the relationship between driving experience and DMS compliance. Drivers demonstrated significantly different route choice behavior in their second and third drives compared to their first drive, indicating lower compliance and higher exploration behaviors. Compliance with DMS-based travel time guidance was about 65 percent in the DS experiments and 59 percent in the corresponding SP scenarios. This finding illustrates that the estimated compliance rate can vary with the approach used. Compliance with DMS information appeared to be higher in DS experiments than in similar SP scenarios, possibly due to the perception of travel time and cognition of driving task in the DS. Further, there was a nearly 40 percent difference in individuals' route choices under similar scenarios using the SP and DS approaches, challenging the validity of stated route choice data.

A limitation of this study is its lack of use of nomadic personalized navigation systems, such as GPS and smart phone, as a supplement to the generic traffic information providers (DMS). In the real world, more drivers equip their vehicles with real time navigators and use it frequently or occasionally. When observing a message, one may be willing to divert, but may not know how to reroute if an in-vehicle navigator is not available. A future research direction is to perform a study with personalized route guidance available to the subjects. An additional step is the integration of DS with a traffic simulator to enhance the traffic flow characteristics by creating a more realistic and interactive traffic environment.

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6. REFERENCES

[1] Levinson, D., and H. Hua. Effectiveness of Variable Message Signs Using Empirical Loop Detector Data. *Transportation Research Board Annual Conference*, Washington, D.C., 2003.

[2] Erke, A., F. Sagberg, and R. Hagman. Effects of Route Guidance Variable Message Signs (VMS) on Driver Behaviour. *Transportation Research Part F*, Vol. 10, No. 6, 2007, pp. 447–457.

[3] Haghani, A., M. Hamedi, R. L. Fish, and A. Nouruzi. *Evaluation of Dynamic Message Signs and Their Potential Impact on Traffic Flow*. Report MD-13-SP109B4C, Maryland State Highway Administration, 2013.

[4] Koutsopoulos, H. N., T. Lotan, and Q. Yang. A Driving Simulator and Its Application for Modeling Route Choice in the Presence of Information. *Transportation Research Part C*, Vol. 2, No. 2, 1994, pp. 91–107.

[5] Lotan, T. Effects of Familiarity on Route Choice Behavior in the Presence of Information. *Transportation Research Part C*, Vol. 5, No. 3-4, 1997, pp. 225–243.

[6] Katsikopoulos, K. V., Y. Duse-Anthony, D. L. Fisher, and S. A. Duffy. The Framing of Drivers' Route Choices When Travel Time Information Is Provided under Varying Degrees of Cognitive Load. *Human Factors*, Vol. 42, No. 3, 2000, pp. 470–481.

[7] Adler, J. L. Investigating the Learning Effects of Route Guidance and Traffic Advisories on Route Choice Behavior. *Transportation Research Part C*, Vol. 9, No. 1, 2001, pp. 1–14.

[8] Ben-Elia, E., I. Erev, and Y. Shiftan. The Combined Effect of Information and Experience on Drivers' Route-Choice Behavior. *Transportation*, Vol. 35, No. 2, 2008, pp. 165–177.

[9] Peeta, S., J. L. Ramos, and R. Pasupathy. Content of Variable Message Signs and On-Line Driver Behavior. *Transportation Research Record*, Journal of Transportation Research Board, No. 1725, 2000, pp. 102-108.

[10] Sikka, N., and P. Hanley. How Do Drivers' Respond to Risk and Ambiguity in Travel Times? An empirical Approach to Behavioral Decision Theories. *Transportation Research Board Annual Conference*, Washington, D.C., 2013.

[11] Wardman M., P. W. Bonsall, and J. D. Shires. Driver Response to Variable Message Signs: A Stated Preference Investigation, *Transportation Research Part C*, Vol. 5, No. 6, 1997, pp. 389–405.

[12] Jindahra, P., and K. Choocharukul. Short-Run Route Diversion: An Empirical Investigation into Variable Message Sign Design and Policy Experiments. *IEEE Transactions on Intelligent Transportation Systems*, Vol. 14, No. 1, 2013, pp. 388-397.

[13] Peeta, S., and J. L. Ramos. Driver Response to Variable Message Signs-Based Traffic Information. *IEE Proceedings Intelligent Transport Systems*, Vol. 153, No. 1, 2006, pp. 2–10.

[14] Zhong, S., L. Zhou, S. Ma, and N. Jia. Effects of Different Factors on Drivers' Guidance Compliance Behaviors under Road Condition Information Shown on VMS. *Transportation Research Part A*, Vol. 46, No. 9, 2012, pp. 1490-1505.

[15] Chatterjee, K., N. B. Hounsell, P. E. Firmin, and P. W. Bonsall. Driver Response to Variable Message Sign Information in London. *Transportation Research Part C*, Vol. 10, No. 2, 2002, pp. 149–169.

[16] Xu, T. D., L. J. Sun, Z. R. Peng, and Y. Hao. Modelling Drivers' En-Route Diversion Behaviour under Variable Message Sign Messages Using Real Detected Traffic Data. *IET Intelligent Transport Systems*, Vol. 5, No. 4, 2011, pp. 294–301.

[17] Divekar, G., H. Mehranian, M. R. E. Romoser, J. W. Muttart, P. Garder, J. Collura, and D. L. Fisher. Predicting Route Choices of Drivers Given Categorical and Numerical Information on Delays Ahead: Effects of Age, Experience, and Prior Knowledge. *Transportation Research Record*, Vol. 2248, 2011, pp. 104–110.

[18] Tian, H., S. Gao, D. L. Fisher, and B. Post. A Mixed-Logit Latent-Class Model of Strategic Route Choice Behavior with Real-time Information. *Transportation Research Board Annual Conference*, Washington, D.C., 2012.

[19] Qian, Z., and H. M. Zhang. A Hybrid Route Choice Model for Dynamic Traffic Assignment. *Networks and Spatial Economics*, Vol. 13, No. 2, 2013, pp. 183-203.

[20] Tian, H., S. Gao, D. L. Fisher, and B. Post. Route Choice Behavior in a Driving Simulator with Real-time Information. *Transportation Research Board Annual Conference*, Washington, D.C., 2011.

[21] Tawfik, A. M., J. Szarka, L. House, and H. A. Rakha. Disaggregate Route Choice Models Based on Driver Learning Patterns and Network Experience. *14th International IEEE Conference on Intelligent Transportation Systems*, Washington, D.C., 2011, pp. 445-450.

[22] Paz, A., and S. Peeta. Information-Based Network Control Strategies Consistent with Estimated Driver Behavior. *Transportation Research, Part B*, Vol. 43, No. 1, 2009, pp. 73-96.

[23] Paz, A., and S. Peeta. On-line Calibration of Behavior Parameters for Behavior-Consistent Route Guidance. *Transportation Research, Part B*, Vol. 43, No. 4, 2009, pp. 403-421.

[24] Paz, A., and S. Peeta. Paradigms to Deploy a Behavior-Consistent Approach for Information-Based Real-time Traffic Routing. *Networks and Spatial Economics*, Vol. 9, No. 2, 2009, pp. 217-241.

[25] FORUM 8. UC-win/Road New Features, http://www.forum8.co.jp/english/uc-win/ucwin-road-e1.htm, Accessed April 14, 2013.

[26] Ben-Elia, E., and Y. Shiftan. Which Road Do I Take? A Learning-Based Model of Route-Choice Behavior with Real-Time Information. *Transportation Research Part A*, Vol. 44, No. 4, 2010, pp. 249–264.

[27] Srinivasan, K. K., and H. S. Mahmassani. Modeling Inertia and Compliance Mechanisms in Route Choice Behavior under Real-Time Information. *Transportation Research Record*, Journal of Transportation research Board, No. 1725, 2000, pp. 45-53.

[28] Bekhor, S., G. Albert. Accounting for Sensation Seeking in Route Choice Behavior with Travel Time Information. *Transportation Research, Part F*, Vol. 22, 2014, pp. 39-49.

[29] Ardeshiri, A., M. Jeihani, and S. Peeta. Driving Simulator Based Analysis of Driver Compliance Behavior under Dynamic Message Sign Based Route Guidance. *Transportation Research Board Annual Conference*, Washington, D.C., 2014.

[30] Kaparias, I., M. G. H. Bell, Y. Chen, and K. Bogenberger. ICNavS: A Tool for Reliable Dynamic Route Guidance. *IET Intelligent Transport Systems*, Vol. 1, No. 4, 2007, pp. 225–233.

[31] Kerkman, K., T. Arentze, A. Borgers, and A. Kemperman. Car Drivers' Compliance with Route Advice and Willingness to Choose Socially Desirable Routes. *Transportation Research Record*, Vol. 2322, 2012, pp. 102–109.

[32] Shiftan, Y., S. Bekhor, and G. Albert. Route Choice Behaviour with Pre-Trip Travel Time Information. *IET Intelligent Transport Systems*, Vol. 5, No. 3, 2011, pp. 183–189.

[33] Al-Deek, H., S. R. C. C. Venkata, J. Flick, and A. Khattak. Dynamic Message Sign Deployment and Diversion Behavior of Travelers on Central Florida Toll Roads. *Transportation Research Record*, Vol. 2129, 2009, pp. 24-34.