

Content of Variable Message Signs and On-Line Driver Behavior

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Variable message signs (VMS) are programmable traffic control devices that convey nonpersonalized real-time information on network traffic conditions to drivers encountering them. Especially useful under incidents, VMS aim to influence driver routing decisions to enhance network performance. This study investigates the effect of different message contents on driver response under VMS. Presumably, if the message content is a significant factor in driver response, the traffic controller can use it as a control variable to influence network traffic conditions positively without compromising the integrity of information. This issue is addressed through an on-site stated preference user survey. Logit models are developed for drivers' diversion decisions. The analysis suggests that content in terms of the level of detail of relevant information significantly affects drivers' willingness to divert. Other significant factors include socioeconomic characteristics, network spatial knowledge, and confidence in the displayed information. Results also indicate differences in the response attitudes of semitrailer truck drivers compared to other travelers. They provide substantive insights for the design and operation of VMS-based information systems.

Advanced traveler information systems (ATIS), a key component of the intelligent transportation systems architecture, assist motorists in making more informed decisions on departure time, congestion avoidance, route selection, and en route diversion. In a prescriptive mode, they can be used by traffic controllers to improve network performance by triggering favorable route choice, or diversion decisions, or both by travelers. This implies the need to understand the factors that influence drivers' response to supplied information.

Variable message signs (VMS), the most visible manifestation of ATIS, are programmable traffic control devices located in close proximity to the roadway. They display nonpersonalized real-time information on traffic conditions, either as advisories or as proactive guidance, to drivers encountering them. While VMS have an obvious role under incidents in terms of improving network performance, they have the potential to contribute positively under endemic recurrent congestion and special events as well. In all cases, VMS' effectiveness in real-time traffic operations is highly dependent on user response to the displayed information. This motivates the need to study the relationship between information displayed through VMS and user response behavior. A compounding factor is that, unlike an in-vehicle navigation system which can provide personalized routing information, VMS are constrained to display generic information. This places a higher premium on the message displayed through a VMS vis-à-vis its relative effect on system performance. This is further accentuated by the path-specific access to VMS information and the limited ability to display messages.

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This paper focuses on the relationship between the content of VMS messages and driver route diversion rates. Presumably, if different message contents to describe the same situation prompt different diversion rates, then message content can be used as a control variable by the traffic controller to generate favorable network conditions in the real-time operation of the system, while conserving the integrity of information. This has key implications for the design and operation of VMS-based traffic information systems, primarily in terms of credibility and effectiveness of information for motorists. Controlling the level of detail of displayed VMS information without impinging on its veracity can potentially aid user confidence in VMS-based information provision. Also, solution methodologies for networks installed with VMS can focus on message content as a primary mechanism to improve network performance. It should be noted here that message content in our study does not imply human factor-related details such as number of words or lines, size of words, or graphics issues. Message content refers to the amount of information provided on the incident situation.

The task of eliciting relationships between VMS message content and driver response is not trivial; it is characterized by several technical, technological, and logistical impediments. Previous studies, including Bonsall (1), suggest that some messages conveyed through VMS are not understood or are perceived to be irrelevant, while yet others may be misinterpreted. Others report a wide range of diversion rates due to a VMS message (2). Yet other studies have suggested that driver response to traffic information conveyed through any dissemination source is highly dependent on the information content (3, 4). While these studies further strengthen the case for the value of VMS message content and highlight the technical issues, the key problem is nevertheless how to capture the relationship between VMS message content and driver diversion behavior under different scenarios. In a technologically sophisticated scenario, each vehicle could be equipped with tracking devices (subject to the adequate resolution of privacy issues) that provide the analyst with user response to the displayed VMS message in the field. In the absence of such capabilities, revealed preference surveys entail impractical logistic mechanisms such as stopping and interviewing motorists on the road after they encounter a VMS message. Although such studies exist (5, 6), their results are limited to the messages displayed during the survey period.

Stated Preference Studies

Previous studies have focused on driver response to VMS through stated preference (SP) methods involving user surveys (7), on-screen driving simulators (8) or full-scale driving simulators (9). The SP methodology is a valuable tool to test the behavior of indi-

viduals under a variety of controlled scenarios. It has been used to understand the effect of well-observed factors vis-à-vis VMS, such as network spatial knowledge, message content, and confidence in the supplied information. However, the methodology suffers from a number of key limitations. Its main shortcoming is that users may not respond the way they state, in a real situation. In the VMS context, this is primarily because SP is not effective in capturing the situational behavior of users; it is not a reliable method for capturing the effect of variables such as weather, time of day, destination, and actual traffic conditions, all of which are key situational elements in the driver’s decision-making process given the generic nature of VMS messages. The ability of SP approaches to reasonably infer on these factors requires recreating driving environments that closely replicate real world conditions (e.g., flight simulator technology used by the aviation industry to train pilots). Second, stated preference surveys can be lengthy depending on the key variables that need to be considered. To illustrate this issue, let us assume that we are trying to capture the effect of a set of situational variables X_i ($i = 1, 2, 3, \dots, n$) on the dependent variable Y (divert or not divert). For simplicity, assume that each of these n variables contain m categories. Then, there are m^n unique combinations of these variables. Ideally, we would like to observe the value of the dependent variable for each of these m^n combinations. In an SP survey, since each of these scenarios represents a question for the respondent, the survey may become impractical. And as discussed earlier, users’ actual actions may be different.

Study Objectives

The main objective of this research was to build driver behavior models that predict the diversion probability of an individual under a specific VMS message type (content). In building these models, the study examined the relative importance of various VMS message types in influencing drivers to divert. For more effective use of VMS in on-line traffic operations, the study also sought insights on attitudinal differences among different population segments.

The remainder of this study is organized as follows. SP survey design and implementation are described in the next section. This is followed by a brief summary of survey results. The modeling framework for VMS route diversion using the survey data is then discussed. Insights and limitations of the estimated models are then described, and, finally, some concluding comments are presented.

METHODOLOGY

VMS Messages

VMS messages are classified into two main categories from the perspective of their utility for drivers: passive and active. A passive message provides descriptive information of the problem the driver may encounter. This information could include type of incident, its location, and expected delay. Passive information may be further classified as qualitative or quantitative. Qualitative information refers to the problem generically (e.g., accident, work zone, congestion) whereas quantitative information focuses on specifics (expected delay, location, etc.). An active message provides the driver explicit route guidance, such as the best available alternate route, for avoiding the bottleneck. This study analyzes whether route diversion rates differ based on the amount and type of VMS information displayed.

Survey Design

A stated preference study was conducted via an on-site survey in the form of a questionnaire. The questionnaire was designed as follows after identifying key factors that influence driver route diversion decisions under VMS. First, respondents were asked about their socioeconomic characteristics including gender, age, education level, and household size. Next, they were asked a series of questions concerning their preferences and attitudes toward traffic information conveyed through VMS and their propensity to divert under certain situations. The last part of the questionnaire addressed diversion intentions under generic descriptions of VMS messages in terms of the level of detail of information, as illustrated in Table 1. The messages were specified in random order to avoid potential directional bias for the messages. Responses were recorded on a five-point Likert scale (1 to 5), where 1 meant low willingness to divert and 5 meant high willingness to divert.

The survey was conducted in the Borman Expressway region in northwestern Indiana. This region consists of the Borman Expressway, a 16-mi segment of interstates 80 and 94 that is characterized by heavy traffic volumes, surrounding arterials, and the nearby interstates I-90 and I-65. The Indiana Department of Transportation is currently installing an advanced traffic management system (ATMS) on the Borman Expressway (10) to alleviate congestion and incident situations, both of which are magnified by the high percentage of

TABLE 1 Effect of VMS Message Content

VMS Message Type	Message Content	Relative Willingness to Divert				
		1 %	2 %	3 %	4 %	5 %
1	Occurrence of accident only	13.7	33.9	26.6	13.3	12.5
2	Location of the accident only	20.2	33.1	22.6	11.3	12.9
3	Expected delay only	9.3	12.9	39.5	23.8	14.5
4	The best detour strategy only	7.7	18.5	30.2	25.0	18.5
5	Location of the accident and the best detour strategy	2.0	4.0	22.6	35.1	36.3
6	Location of the accident and the expected delay	0.8	0.8	19.8	38.3	40.3
7	Expected delay and the best detour strategy	2.0	2.0	13.7	33.5	48.8
8	Location of the accident, expected delay, and the best detour strategy	1.2	2.0	5.6	19.8	71.4

trucks (30 percent during peak periods and up to 70 percent at night). VMS is the primary information dissemination source being planned for this ATMS.

Two survey locations were identified. The first was a truck stop on the Borman Expressway, hence most respondents at this location were truck drivers. Because there are no rest areas on the Borman Expressway, a rest area on I-65 a few miles south of the Borman Expressway was used as the other survey location. The Borman Expressway represents part of the journey for most drivers who stop at this rest area. Most drivers surveyed here were not truck drivers. The surveys at both locations were conducted using a four-person crew of interviewers for two days each. Potential respondents were approached and informed about the objectives of the survey. The refusal rates were 20 percent and 10 percent at the truck stop and rest area, respectively. The data collection effort resulted in 248 respondents—116 truck drivers and 132 nontruck drivers.

SURVEY RESULTS

Socioeconomic Characteristics

Table 2 shows the socioeconomic characteristics of the sample. About 79 percent of the respondents were males. The distribution of respondents in terms of age groups was mostly even, except for the less-than-20 and greater-than-65 age groups. Almost 60 percent had at least some college experience, and 41 percent had at least one college degree.

Network Familiarity

About half the respondents (50.4 percent) stated they were regular drivers in the Borman Expressway region. This does not necessarily imply they were familiar with alternate routes over their regular route. Hence regular drivers in the region were asked about their familiarity with alternate routes. Among this group, 65 percent indicated they were familiar with at least one alternate route. And 61 percent stated they would divert to an alternate route under a work-related trip if that alternate route offered travel time savings

ranging from 5 to 30 min. However only 47 percent stated they would divert on a personal trip for identical savings. This reaffirms the notion of higher value of time for work-related trips.

Diversion Characteristics

When the expected delay on the current route is at least 10 min, 53 percent of respondents indicated they would divert. More than 70 percent of respondents stated they would divert to an alternate route under adverse weather conditions if a VMS message suggested it. This could be due to the effect of incident clearance time, as bad weather conditions may increase it. In such situations, drivers prefer to avoid excessive delays by diverting to the suggested alternate route. Also, a significant number of participants (65 percent) stated they would consider diverting to an alternate route at night. While the survey obtained responses on weather and night variables, these responses are not based on the consideration of other factors (such as incident severity) that make driver responses to these variables more meaningful. Such a capability entails providing the drivers several specific situations involving many factors through SP to elicit their response attitudes. As discussed earlier, this is a limitation of the SP approach.

Content of Messages

Table 1 summarizes the drivers' willingness to divert to an alternate route when different types of VMS messages are displayed. The table shows that as information content increases, driver propensity to divert also increases, provided the information type is considered valuable. The survey suggests no significant difference in diversion response to VMS message Types 1 and 2. In other words, messages displaying occurrence of accident and location of accident have similar effects on driver behavior, all other factors being equal. Expected delay and best detour strategy are considered valuable information in terms of influencing drivers' route diversion decisions. Location of accident and occurrence of accident have added value only in conjunction with information on expected delay or best detour strategy.

TABLE 2 Socioeconomic Characteristics

Attribute	Range	Non-Truck Drivers (%)	Truck Drivers (%)	Aggregate (%)
Gender	Male	63.6	95.7	78.6
	Female	36.4	4.3	21.4
Age Group	< 20	4.5	2.6	3.6
	20-29	21.2	26.7	23.8
	30-39	28.0	27.6	27.8
	40-49	22.7	24.1	23.4
	50-64	12.9	15.5	14.1
	≥ 65	10.6	3.4	7.3
Education Level	High School or Less	18.2	35.3	26.2
	Some College	15.2	52.6	32.7
	College Graduate	40.2	12.1	27.0
	Post Graduate	26.5	0.0	14.1
Persons in Household	1	17.4	11.2	14.5
	2	26.5	22.4	24.6
	3	25.0	22.4	23.8
	≥ 4	31.1	44.0	37.1

MODELING FRAMEWORK

We now develop VMS route diversion prediction models for the Borman Expressway using the survey data. The focus is on estimating the diversion rate in response to information conveyed through a specific message type.

Model Structure

The choice set C_n of each individual consists of only two alternatives—divert or not divert—motivating the use of a binary logit model to predict the probability of a user diverting under a VMS message. The utility functions are represented by

$$U_{in} = V_{in} + \epsilon_{in} \tag{1}$$

$$U_{jn} = V_{jn} + \epsilon_{jn} \tag{2}$$

where

- i = alternative representing user diverting,
- j = alternative representing user not diverting,
- V_{in} = systematic component of the utility of diverting from the current route,
- V_{jn} = systematic component of the utility of not diverting from the current route, and

ϵ_{in} and ϵ_{jn} = disturbances or random components.

The probability of an individual n diverting is equal to the probability that the utility of alternative i (U_{in}) is greater than or equal to the utility of alternative j (U_{jn}) ($1I$). This can be written as follows:

$$P_n(i|C_n) = Pr[U_{in} \geq U_{jn}, \forall j \in C_n] \tag{3}$$

Then, the probability of user n diverting is given by

$$P_n(i) = \frac{1}{1 + e^{-(V_{in} - V_{jn})}} \tag{4}$$

$$P_n(j) = 1 - P_n(i) \tag{5}$$

In the current context, the difference in the systematic components can be represented as follows:

$$V = (V_{in} - V_{jn}) = ONE + \beta X + \alpha VMS \tag{6}$$

where

- ONE = alternative specific constant corresponding to divert,
- X = vector of those explanatory variables other than VMS message type that may influence a driver's decision to divert,
- β = vector of estimated parameters corresponding to X ,
- VMS = vector of dummy explanatory variables representing each of the VMS message types provided to drivers, and
- α = vector of estimated parameters corresponding to VMS .

The third element of the right side of Equation 6 can be represented as

$$\alpha VMS = \sum_{k=2}^8 \alpha_k VMS_k \tag{7}$$

where VMS_k is the dummy variable representing VMS message k and α_k is the coefficient of VMS_k . The list of all explanatory variables included in the utility function is shown in Table 3.

Construction of Dependent Variable

As illustrated in Table 1, the diversion propensities of respondents under the various VMS message types are obtained in the form of a five-point Likert scale where 5 indicates a strong willingness to divert and 1 indicates a strong unwillingness to divert. However, the dependent variable in the modeling process is a binary (Yes or No) variable to indicate diversion decision. This is because the response of the driver in actual situations is discrete: either the driver diverts or does not. In the context of VMS message display for incident management, the objective is to display messages that optimize network performance. The VMS message aims at influencing users' decisions to divert or not to divert under incident scenarios. Therefore the binary logit model is chosen for our analysis. While use of the Likert scale lends itself to the estimation of models such as ordinal logit or ordered probit, the current focus is on estimating diversion probabilities rather than probabilities of the different degrees of willingness to divert. However, there are some advantages to using the Likert scale instead of the Yes/No format in the survey. The Likert scale enables the collection of a richer array of data to better understand the differences in responses to the eight VMS message types. It allows the acquisition of finer insights on response attitudes toward message types that otherwise seemingly produce similar responses or responses that are not significantly different. More importantly, a finer resolution than Yes/No—for example a tertiary dependent variable such as Yes/Neutral/No—is more versatile in the context of on-line operations, where some on-line factors (such as weather, time of day, destination data, traffic conditions) can be weighted in conjunction with the survey data to obtain the diversion decisions of the Neutral drivers. A Yes/No approach is not as flexible in the context of on-line implementation. Thereby, use of the Likert

TABLE 3 Explanatory Variables in the Driver Response Model

Explanatory Variable	Mnemonics
Alternative specific constant	ONE
Sex = 1, if male = 0, if female	SEX
Age group = 1, if age ≥ 40 years = 0, if age < 40 years	AGE
Level of education = 1, if education ≤ some college = 0, if education ≥ college	EDU
Dummy variable for truck drivers = 1, if respondent is a truck driver = 0, otherwise	TRUCK
Regular driver in the Borman Expressway region = 1, if Yes = 0, if No	DRIV
Familiarity with alternate routes = 1, if familiar = 0, if not familiar	FAM
Trust in information provided = 1, if high = 0, otherwise	TRUST
Dummy variables corresponding to each VMS message type, k = 1 to 8	VMS _k

scale allows the exploration of several alternative on-line models in determining the most representative ones.

In the current context, the focus is on the binary Yes/No choice for obtaining insights from the survey. To compromise the Likert scale used in the survey with the binary choice, the actual survey responses can be grouped in different ways to obtain the dependent variable for model estimation. Two possible ways are

$$y_n = \begin{cases} 1, & \text{if willingness to divert} \geq 4 \\ 0, & \text{otherwise} \end{cases} \quad (8)$$

$$y_n = \begin{cases} 1, & \text{if willingness to divert} \geq 3 \\ 0, & \text{otherwise} \end{cases} \quad (9)$$

In the first method, respondents who answered 4 or 5 are assumed to divert while those who answered 1, 2, or 3 are assumed unwilling to divert. In the second method, respondents answering 3, 4, and 5 are assumed to divert while respondents answering 1 or 2 are assumed unwilling to do so. The difference between the two methodologies lies in the treatment of the respondents answering 3. If respondents answering 3 are assumed to divert, the models may overestimate the final diversion rates. However, if respondents answering 3 are assumed not to divert, the opposite effect is likely. While a limitation here, the Likert scale is beneficial in practice because it allows more refined modeling, as discussed earlier. The models here use the first method in determining the dependent variable.

ANALYSIS OF MODELS

Preliminary Models

As a first step in the model-building procedure, a general model was constructed with the survey data (8 VMS message types per person

× 248 persons = 1,984 pooled observations). Table 4 shows the results from the estimation of this binary logit model. All explanatory variables were included in the estimation procedure. Insignificant variables, as determined from intermediate models, were omitted at the corresponding stages. Also, the categories shown in Table 3 for some variables (SEX, AGE, EDU, TRUCK, DRIV, FAM, TRUST, VMS_k) were obtained after grouping survey sub-categories that were not statistically different. Since the estimation procedure uses pooled data over individuals, the models were tested for the presence of heterogeneity using a Hausman specification test (12). Test results indicate no evidence of the presence of heterogeneity.

The variable ONE is the alternative specific constant. It represents the utility of diverting for a driver exposed to VMS₁, whose socioeconomic and other characteristics are given by the base cases of the relevant variables (that is, the variables take a zero value) included in the model. The negative sign implies a natural aversion to diversion. It illustrates the potential of information systems to convince drivers to divert through information provision. When any of the message types VMS₁, VMS₂, or VMS₃ are displayed, there is no combination of socioeconomic variables that will produce a positive utility difference. This suggests that users exhibit an inclination to stay on their current route when they do not have much information on the incident, which reaffirms the conclusions of previous studies (3, 13, 14).

SEX and AGE are socioeconomic characteristics that significantly influence the diversion behavior of an individual. SEX has a positive sign implying that males are more likely to divert than females under similar conditions. AGE has a negative coefficient indicating that younger drivers are more likely to divert compared to older drivers when all other conditions are the same. These results are intuitive because females and older drivers are, on average, more risk averse than males and younger drivers.

TABLE 4 Logit Models for Driver Response Under VMS

Variable	Model			
	General Coeff. (t-ratio)	Truck Drivers Coeff. (t-ratio)	Non-Truck Drivers Coeff. (t-ratio)	Interaction Coeff. (t-ratio)
ONE	-1.897 (8.92)	-1.665 (-5.30)	-2.586 (-10.52)	-2.426 (-10.90)
SEX	0.433 (3.26)	+0.643 (-1.63)	0.416 (2.45)	0.266 (1.91)
AGE	-0.458 (-4.17)		-0.238 (-1.53)	-0.422 (-3.77)
EDU	-0.308 (-2.74)			
TRUCK				0.371 (1.29)
DRIV	0.207 (1.87)	0.434 (2.36)		
FAM		0.570 (2.73)		
TRUST	0.666 (5.84)	0.435 (2.58)	0.916 (5.61)	0.924 (5.82)
VMS ₂	-0.090 (-0.43)	-0.158 (-0.56)	1.27E-04 (3.62E-04)	-0.095 (-0.44)
VMS ₃	0.611 (3.05)	0.191 (0.69)	1.154 (4.48)	1.004 (3.90)
VMS ₄	0.842 (4.23)	0.781 (2.83)	1.046 (4.03)	0.890 (4.34)
VMS ₅	2.083 (10.00)	1.636 (5.56)	2.671 (10.10)	2.511 (9.59)
VMS ₆	2.490 (11.38)	2.372 (7.12)	2.864 (10.60)	2.636 (11.59)
VMS ₇	2.731 (12.02)	1.995 (6.43)	3.577 (11.78)	3.395 (11.39)
VMS ₈	3.548 (13.02)	3.231 (7.68)	4.057 (11.92)	3.729 (13.27)
DRIV*TRUCK				0.549 (2.92)
FAM*TRUCK				0.713 (3.35)
TRUST*TRUCK				-0.525 (-2.27)
VMS ₃ *TRUCK				-0.712 (-2.31)
VMS ₅ *TRUCK				-0.762 (-2.33)
VMS ₇ *TRUCK				-1.279 (-3.45)
Sample size	1984	928	1056	1984
L(0)	-1375.20	-643.24	-731.96	-1375.20
L(β)	-1037.66	-490.92	-519.34	-1009.68
ρ ²	0.245	0.237	0.290	0.266

Note: See Table 3 for definition of variables.

The models also suggest that the education level of a driver (EDU) may be an important factor. Well-educated individuals exhibit greater compliance with VMS compared to their less educated counterparts under similar conditions. Since education is a proxy for income, well-educated people are likely to have a higher value for time and hence may be more sensitive to delays on their planned route. Another aspect vis-à-vis education relates to the level of comfort with technology. Well-educated individuals are likely to be at greater ease with technological innovations, at least initially, and hence may not exhibit as much a priori inertia to VMS messages. A related issue is that most truck drivers in the sample belonged to the less educated category and a large proportion of the nontruck drivers belonged to the well-educated category. Therefore, EDU might act as a proxy for truck drivers, as discussed in the next subsection.

Dummy variables corresponding to VMS Messages 2 to 8 were included in all models (VMS₁ is the base case). The VMS variables are very significant and provide the largest increases in log-likelihood among all variables. As mentioned earlier, VMS Messages 1 to 8 are in order of increasing amount of information (Table 1). In all models presented, coefficient values increase with information, implying that more relevant information on a VMS leads to higher diversion. These results are important because they suggest that drivers' diversion behavior can be influenced by controlling the amount of information displayed on VMS. The traffic controller can use this variable to improve network performance without compromising the integrity of the system. There is no statistical difference between messages VMS₁ and VMS₂, seemingly suggesting no value for the location of the incident. This highlights the limitations of the SP approach in the VMS context. Location plays a significant role in the diversion decision based on the actual destination. However, unlike expected delay, which can be perceived irrespective of the actual situation, the value of the location of incident is revealed only in real situations. Thus the lack of statistical differences between one or more VMS variables might be an artifice of the SP methodology as opposed to a behavioral effect. Therefore, irrespective of the t-statistic, all VMS variables were included in the models.

Models for Truck and Nontruck Drivers

We now explore whether significant differences in response attitudes exist between truck drivers and other travelers in the Borman Expressway region. By assuming the same coefficients for both groups in the general model, truck and nontruck drivers are assumed to exhibit similar diversion behavior. However, the diversion behavior of truck drivers can be significantly different than that of nontruck drivers. This is because not all alternate routes available to a nontruck driver are feasible for trucks. Hence truck drivers may exhibit more resistance to diversion than other drivers. These issues are especially important in commercial highway corridors such as the Borman Expressway region, where trucks can represent a significant fraction of the total traffic. To address these issues, the survey data were separated into truck and nontruck observations, and separate binary logit models were estimated for them. The results are illustrated in Table 4.

A major difference between the truck and nontruck models is the effect of the DRIV (regular driver) and FAM (familiarity with alternate routes) variables. These variables are significant for truck diversion but not for nontruck diversion, suggesting that being a regular driver in the Borman Expressway region and being familiar with alternate routes is important for truck drivers in route diversion deci-

sions. This implies that truck drivers may a priori hesitate to consider all alternate routes as legitimate alternatives. Therefore, unless a truck driver is familiar with alternate routes, they may not risk diverting. TRUST is an important explanatory variable in all three models (General, Truck, Nontruck). The positive sign of TRUST suggests that people who trust messages displayed through VMS are more likely to divert as compared to those who do not.

The trends in the VMS variables for the truck and nontruck models are similar to those observed in the general model. There is a small decrease in coefficient values as one goes from VMS₆ to VMS₇ in the truck model and from VMS₃ to VMS₄ in the nontruck model; however, these are not statistically significant differences. For the truck model, VMS₂ and VMS₃ are not statistically different from the base case (VMS₁). Similarly, for the nontruck model there is no statistical difference between VMS₁ and VMS₂. These cases are possibly a result of the limitations of the SP approach, as discussed in the previous subsection.

Interaction Model

The preceding subsection concentrated on specific trends for the truck and nontruck models. However, the models cannot compare their coefficients. For instance, is the effect of TRUST on diversion probability different for truck and nontruck drivers? To address such questions, truck and nontruck data was pooled, and a combined model with interaction variables was estimated as shown in Table 4.

The effect of age on diversion propensities is similar for truck and nontruck drivers and is therefore not a significant interaction variable. As discussed earlier, DRIV and FAM are important factors for truck drivers. Thus (DRIV*TRUCK) and (FAM*TRUCK) are significant variables in this model. Also, the effect of the TRUST variable seems to differ for truck and nontruck drivers. In Table 4, the TRUST variable has a coefficient value of 0.924 and the interaction variable (TRUST*TRUCK) has a coefficient value of -0.525. Hence the contribution of the TRUST variable will be $(0.924 - 0.525) = 0.399$ for a truck driver but 0.924 for a nontruck driver. The positive sign for the combined coefficient (0.399) for truck drivers implies that trusting truck drivers exhibit a higher diversion propensity compared to nontrusting ones. Also, unfamiliar and trusting truck drivers exhibit a slightly lower propensity to divert than corresponding nontruck drivers. Hence the TRUST variable does not have similar effects on truck and nontruck drivers. The same line of reasoning can be extended to the VMS interaction variables: (VMS₃*TRUCK), (VMS₅*TRUCK), and (VMS₇*TRUCK) are all negative. This implies that if the message VMS₃, VMS₅, or VMS₇ is shown, a truck driver is less likely to divert than a nontruck driver. This highlights the relatively greater importance of location for truck drivers. However, when one of the other VMS messages is displayed, there is no significant difference in the diversion probabilities among truck and nontruck drivers.

CONCLUSIONS AND FURTHER RESEARCH

This study focused on the potential of VMS to improve system performance under real-time traffic operations by analyzing the relationships between driver route diversion propensity and the content of VMS messages. Toward this end, an on-site SP survey was conducted on the Borman Expressway in northwestern Indiana, and logit models were developed using the survey data.

The commonly used SP methodology has a number of well-understood limitations. First, the SP responses may not satisfactorily reflect actual behavior. Second, in the context of VMS driver response, SP surveys can be lengthy (to address the multiple actual scenarios possible). However, the current sparsity in VMS behavior field data suggests SP methodology is a valuable tool to address driver behavior under a variety of scenarios. Ongoing research focuses on the effective use of available technology in SP surveys. The interactive and dynamic capabilities of the Internet are being used to enhance the reliability of stated responses, compared to on-site surveys. The aim is to develop more reliable and cost-effective SP surveys.

The current SP study provides some important insights into VMS survey design and driver attitudes for on-line traffic operations. The strong correlation between VMS message type and driver response suggests message content is an important control variable for improving system performance without impinging on the integrity of the information provided. Also, significant differences were found in the attitudes of truck and nontruck drivers. This is important for the use of VMS-based information systems to influence network performance in commercial corridors such as the Borman Expressway region, where trucks represent a significant percentage of the traffic. The use of a Likert scale in the SP survey in the context of VMS message content enables a finer resolution for understanding the differences between driver responses to various message types. It also provides flexibility in practice while developing hybrid driver response models. A shortcoming of using generic variables is illustrated by the perceived relative values of expected delay and location. While expected delays are perceivable in terms of magnitude without the need for specific scenarios in SP surveys, the value of location is perceivable only in actual situations or specifically constructed SP scenarios for a particular network. Thus information on the location of an incident was not a significant VMS message in this study, although it is in the real world.

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