The verbiage in variable message signs and traffic diversion during crash incidents

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Abstract

Purpose – WIth limited research on the effects of variable message sign (VMS) message content and verbiage on revealed driver behavior, this study aims to investigate how different verbiage of crash-related messages are related to the diversion rate.

Design/methodology/approach – Using ordered logit models, the associations of message verbiage with diversion rates during crash incidents were assessed using five years of VMS message history within a section of I-15 in the state of Utah.

Findings – A significant impact of message verbiage on the diversion rate was observed. Based on the analysis results, the crash message verbiage with the highest diversion was found to be miles to crash + "prepare to stop," followed by crash location + delay information, miles to crash + "use caution" + lane of the crash, etc. In addition, the diversion rate was found to be correlated to some roadway characteristics (e.g. occupancy in mainline, weather condition and light condition) along with the temporal variations.

Research limitations/implications – These findings could be used by transportation agencies (e.g. state department of transportation [DOTs]) to make informed decisions about choosing the message verbiage during future crash incidents. This study also revealed that higher diversion rates are associated with a shorter distance between the crash location and VMS device location, recommending increasing the number of VMS devices, particularly in crash-prone areas.

Keywords Variable message sign, Verbiage message content diversion rate, Crash, Driver behavior, Congestion

Paper type Research paper

1. Introduction

Variable message signs (VMS), sometimes also referred to as dynamic/changeable message signs, are traffic control devices installed on roadways that impart messages to drivers, primarily about traffic conditions. As a regulatory guideline, the manual on uniform traffic control devices (MUTCD) has outlined 11 situations, where VMS can be used: incident management and route diversion; warning of adverse weather conditions; special events applications associated with traffic control or conditions; control at crossing situations; lane, ramp and roadway control; priced or other types of managed lanes; travel time information; warning situations; traffic regulations; speed control; and destination guidance (MUTCD, 2009). VMS devices are mostly programmable and are often controlled from a central location. Whenever the controller gets information about traffic incidents, the messages are displayed on the devices. Thus, the traffic information displayed in the VMSs is most often real time.

Among the variety of applications of VMS, this study particularly focuses on the messages displayed during crash incidents. Crash incidents have severe negative impacts on roadways, including congestion and secondary crash risks. The congestion during crash incidents might be temporal depending upon the crash clearance time, but it could be severe in terms of travel time and safety risks. Informing drivers about the crash incident along with associated traffic information is important to lower such severe negative impacts, and VMS is a commonly used solution for this task. With appropriate crash information, drivers might consider changing their route for two purposes:

1. to avoid traffic congestion; and
2. to lower the risk of involving in a secondary crash.

Alternatively, drivers might use the same route with additional necessary safety precautions (e.g. considering lower speed, higher headways and focused driving).

Although there are a handful of past studies (summarized in the subsequent Literature Review section) evaluating the

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effectiveness of displaying crash incident messages via VMS in reducing the severe negative effects of crashes, the following research gaps motivate this study:

- Most of the existing studies used drivers' stated preference (survey) or driving simulator experiments to evaluate the performance of VMS messages, but several studies have found large discrepancies between the revealed and stated behavior. This necessitates capturing actual drivers' behavior during crash incident-related messages.
- There are limited existing revealed behavior-related studies (either using survey or loop-detector data) that focus on analyzing the impact of specific message content verbiage on drivers' behavior.

Based on these gaps, this study used the VMS message history and detector data (loop detector and radar data) of a section of I-15 in Salt Lake City, UT to evaluate drivers' behavior during crash incidents and in response to related VMS messages. The specific objective of this study is to identify the association of diversion rate as a result of crash incident messages with different message content verbiage. Here, the diversion rate is defined as the percentage of traffic going off the highway through exits/off-ramps. The authors hypothesize that message content verbiage alters the diversion rate, and that the impact of message verbiage on the diversion rate is also influenced by other factors, such as weather and congestion on the mainline.

2. Literature review

Relevance of the information disseminated via VMS and its understandability is important to achieve the desired response to the message. To avoid driver confusion, the MUTCD has recommended not to use vague wordings in VMS messages (MUTCD, 2009). For example, "incident ahead" should not be used alone and needs to be supplemented by other information, such as the location of or distance to the incident, expected travel time or delay and alternative routes. In the literature, there are many studies that analyzed drivers' responses to different types of messages displayed in VMS and information included in the message. Based on a brief review of the literature (described in subsequent paragraphs), the authors found four categories of methodologies used: stated preference survey, revealed preference survey, lab-based driving simulator experiment and quasi-experiment and analysis of real field data.

The development of detour behavior from VMS messages (using examples of congestion messages) was studied by Kusakabe *et al.* (2012) using a stated preference survey in Japan. The process involves drivers assuming alternate route travel time and comparing it with their expected current route travel time when the level of congestion is displayed on the VMS (with no expected delay information, which is difficult to predict under congestion). This assumed difference in travel time or expected delay triggers the driver's detour behavior. This process was validated by a driving simulator-based study that found an increase in detour rate with an increase in the level of delay (displayed in VMS) (Sharples *et al.*, 2016). Similarly, a 10%–12% increase in detour rate was found from field-collected data in China when the congestion message was varied from "moderate traffic congestion" to "heavy congestion" (Shen and Yang, 2020). This detour behavior development process, explained by Kusakabe *et al.* (2012) and supported by the results of other studies (Sharples *et al.*, 2016; Shen and Yang, 2020), highlights the importance of the level of information that drivers need to comply with VMS messages. In addition to these, by extending the technology acceptance model, Diop *et al.* (2020) found an important role of perceived quality of information sent via VMS and familiarity with the road network in the acceptance of VMS messages and detour or route-switching behavior.

Based on stated preference surveys of travelers on the Borman Expressway (I-94) region in Indiana, Peeta *et al.* (2000) and Peeta and Ramos (2006) found that increased detail of information, such as expected delay occurrence, location, expected delay and detour strategy, increased compliance with the VMS message. Travelers in Greece (Spyropoulou and Antoniou, 2014) and South Korea (Kim *et al.*, 2014) stated that they would be more likely to detour if the incident message was supplemented by expected delay information. Field trials of VMS in nine European cities recommended displaying incident type, severity and location and detour information to attain higher compliance with incident messages (Chatterjee and Mcdonald, 2004). Based on a survey in China, Ma *et al.* (2014) suggested displaying the expected delay on the current route and travel time on the alternate route along with crash information. Yim and Ygnace (1996) found displaying real-time traffic information (level of delay) useful in attaining higher compliance. The importance of VMS message information details was also confirmed by a recent simulator-based study by Morgan State University (Banerjee *et al.*, 2020). However, based on a driving simulator experiment, Xu *et al.* (2020) concluded that an increase in information details in VMS messages increases the information load to the drivers, demanding more cognitive efforts to perceive the information.

Commuters on the Deerfoot Trail in Calgary, Canada, where 12 VMS signs were present, were interviewed to ascertain their response to VMS crash messages (Kattan *et al.*, 2010). Among 500 respondents, 63.3% stated that they wanted to alter their trips in response to VMS crash messaging, either by detouring to alternate routes or by modifying their trip time, trip destination, etc. Compliance with VMS messaging was found to be influenced by driver experience, driver familiarity with alternate routes, trip time, trip length, trip purpose and complementary information provided by radio, TV, etc. Similarly, an on-site revealed preference survey of drivers who had just encountered the alternative placement of VMS before freeway entrances in Milwaukee, WI concluded that compliance with the message depended on drivers' familiarity with VMS, the number of VMS messages encountered, drivers' perceived usefulness and trust toward VMS messages based on past experience, etc. (Peng *et al.*, 2004). Complimentary traffic information via radio and TV allowed commuters to alter their planned trips in a timely manner and increased the overall compliance with VMS messaging (Kattan *et al.*, 2010; Richards and McDonald, 2007).

Among the different types of VMS messages, respondents stated that crash-related messages had the highest compliance and detour likelihood, followed by congestion messages (Gan and Ye, 2015; Peng *et al.*, 2004; Spyropoulou and Antoniou, 2014; Taisir Ratrout and Issa, 2014). The same result was observed in a driving simulator experiment carried out by the University of Nottingham (Sharples *et al.*, 2016) and when analyzing loop detector data in California (Huo and Levinson, 2006). The respondents clarified that the main reasons behind the highest compliance for crash-related messages were the reduction of travel time and avoidance of crashes (Peng *et al.*, 2004). Based on a stated preference survey in China, Gan and Ye (2013) found that those who are not sensitive toward travel time savings do not have any intention to detour and do not actually detour. Thus, in a follow-up study, respondents stated that the detour likelihood increased with the increase in travel time savings on the alternate route (Gan and Ye, 2015).

Few past studies have compared drivers' stated and revealed diversion likelihood in response to different VMS messages. In Southampton, UK, though 53% of the respondents stated that they intended to detour based on different messages, only 1% were found to actually detour (Richards and McDonald, 2007). Similarly, in a study in Saudi Arabia (with one-third of the travelers unfamiliar with VMS), only 0.07% of the travelers were found to actually detour among those who had stated that they would detour (Taisir Ratrout and Issa, 2014). Lower actual detour behavior than the stated behavior was observed in other studies, too (Xu *et al.*, 2011a; Xu *et al.*, 2011b; Yim and Ygnace, 1996).

When analyzing three years of loop detector data from Highway 401 in Canada, a significant decrease in detour rate was observed when the message changed from "moving slowly" to "moving well" (Foo *et al.*, 2008). Thus, the authors confirmed the significant association between delay and detour rate, similar to that of other stated preference studies (described earlier). Using loop detector and license plate reader data in China, Xu *et al.* (2011a) concluded that informing drivers about travel times for the current route was more effective in altering detour behavior than informing drivers of the qualitative congestion level ("low," "medium" and "high"). In addition to providing travel time on the current route, informing drivers about the travel time of alternate routes and coordinating with neighboring VMS signs were found to increase the effectiveness of VMS. Time factors (peak hours, morning or evening peak, daytime, nighttime, etc.), actual visibility of congestion on the route, off-ramp condition, etc. were all found to impact the actual detour behavior. Yim and Ygnace (1996) found higher compliance with the message in the evening peak, which could potentially be explained by the consequence of delay in work start time.

Huo and Levinson (2006) compared the diversion rate (based on loop detector data in Minnesota) before and after the display of VMS messages and found a significant increase in diversion rate after the display of messages. Such change in before and after diversion rate was found to be different for different types of messages, with the highest increase for crash-related messages. Interestingly, the study found no evidence of network-wide travel savings or safety improvement as a result of the VMS only. Høye *et al.* (2011) conducted a network-wide simulation and found that detouring because of crash incident messages on VMS slightly reduced the overall travel time but increased the number of crashes, imposing safety threats across the network. However, a slight benefit in terms of environmental efficiency was observed. The study also claimed that travel time and congestion information from VMS do not have any significant effect on detour behavior as long as there are no incidents. Later, in California, Xuan and Kanafani (2014) evaluated the effectiveness of messages displayed during the times of crash incidents using one year of loop detector data from freeways and offramps. At the time of the incidents, only two pieces of information were displayed on the VMS – the type and location of the incident. After an in-depth analysis of empirical data, the authors concluded that VMS messages were not able to significantly increase the detour rate but that the ultimate increase in detour rate was as a result of visible congestion because of the incident. The authors also claimed that most of the other studies suggesting a significant relationship between detour rate and VMS messaging followed the wrong methodologies or made incorrect interpretations or site-specific differences. Similarly, Basso *et al.* (2021) also reported relatively low compliance with the speed reduction (12.50%) and lane change (28.15%) messages displayed via VMS based on real-field data from Chilean urban highway.

In summary, though the findings of past stated behavior-related studies (summarized earlier) highlighted the importance of detail of information (e.g. miles to crash, location of the crash, precautions needed, expected delay and detour strategy) in crash-related messages, the evidence from real-field data is necessary to validate this finding and to confirm that detailed information does not create information overload for drivers. Very few studies based on real-field data (Foo *et al.*, 2008; Xu *et al.*, 2011a) evaluated the importance of message content verbiage; they were limited to some specific wordings only. A comprehensive evaluation of existing message verbiage used by traffic controllers is necessary to understand and compare their impacts on the effectiveness of VMS messages. In addition, the conflicting finding of Xuan and Kanafani (2014) about no significant impact of VMS messages on diversion rate needs to be re-evaluated under a different data set. To overcome these challenges, the authors estimated the association between the increase in diversion rate during the time of crash-related message displays and message content verbiage and controlled this association by a number of factors, including the congestion level on the mainline.

3. Data and methods

The Utah Department of Transportation (UDOT) provided the data used for this study (UDOT, 2021). First, the history of VMS messages displayed on all the VMS devices across Utah was archived. The messages were updated frequently, at the discretion of the controller, based on real-time traffic conditions available to the controller without a formal algorithm or set of guidelines. Only messages related to crash incidents were used in this study. I-15 between Mileposts 285 and 342 was selected as the study site. A sample study section (not full) is shown in Figure 1. In the study section, 12 and 9 VMS devices were present in northbound and southbound directions, respectively. Second, the crash database to link the message with specific crashes was also provided by UDOT for the required locations and timeframes. Note the information on the weather and lighting conditions (to be used in the analyses later) during the time of the crash were present in the UDOT's crash database. Third, the flow and occupancy data from the high occupancy vehicle (HOV) lane, mainline, on-ramp and

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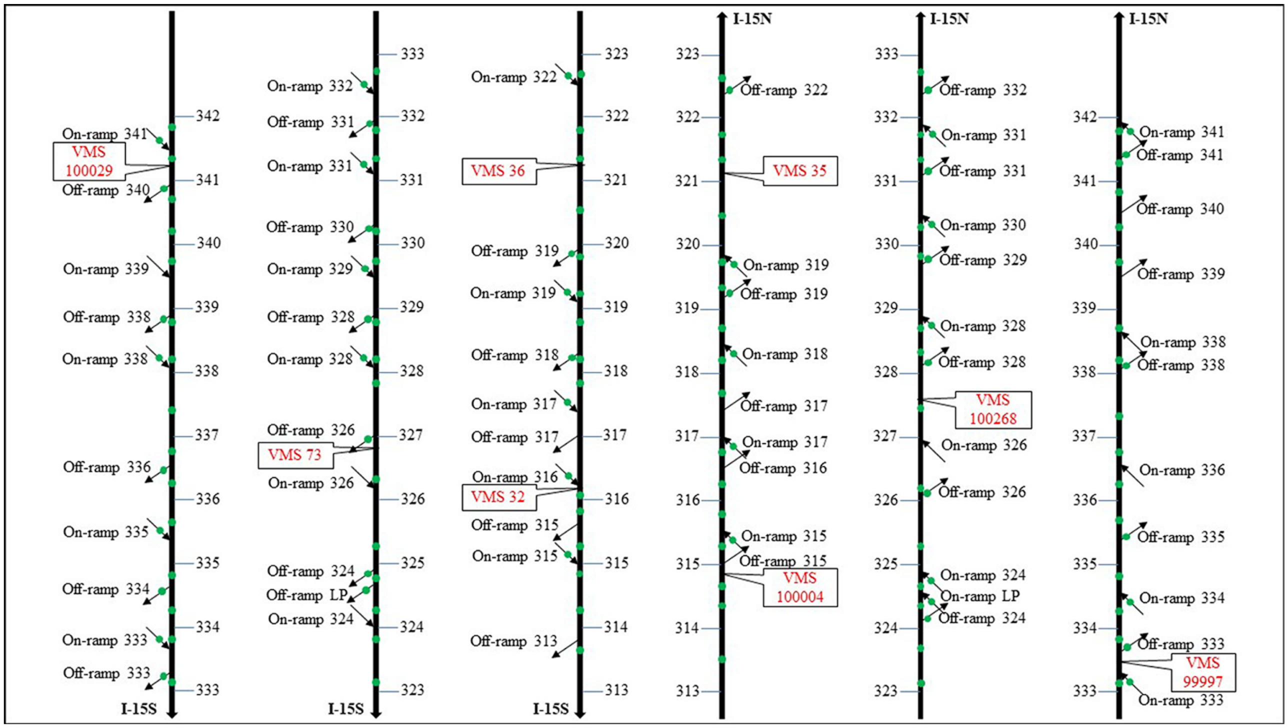
Figure 1 Study site (I-15 between Mileposts 313 and 342)



Note: Green dots indicate the mainline and on/off-ramp detector stations

off-ramp loop detectors were collected from UDOT's performance measurement system (PeMS) (PeMS-UDOT, 2021). These data were available in aggregated granularity of 5 min (lowest granularity available). All data were collected for the period 2016–2020. For the study period, there were 595 VMS records associated with crashes. For more details on data, please refer to Acharya and Mekker (2022).

To achieve the study objective, an ordinal logistic regression technique was used for analysis. Increase in diversion rate as a result of the display of VMS messages was used as the dependent variable. The process adopted to calculate the increase in diversion rate after the display of crash-related VMS messages is presented in Figure 2. The diversion rate for an exit/off-ramp at a point of time was defined as shown in equation (1). Off-ramp volume for a point of time represents either the flow observed from a sensor on the ramp or calculated as the difference between mainline sensors before and after the off-ramp. The mainline volume represents the traffic flow of the roadway just after the off-ramp measured from a sensor. If an HOV lane is present at the location, the mainline volume is the sum of an HOV lane sensor and regular lane sensors. Because there could be a varying number of off-ramps between the location of a VMS device and a crash, weighted averaging in terms of mainline volume was done using equation (2) to find the average diversion rate. Weighted averaging was chosen to account for the differences in mainline volumes of different off-ramps during averaging (Foo *et al.*, 2008).

$$DR = OR/(MV + OR) \tag{1}$$

$$WADR = \sum (DR * MV)/\sum MV \tag{2}$$

where:

DR = diversion rate at an off-ramp location at a timestamp;
OR = off-ramp volume at a timestamp;
MV = main-line volume after off-ramp at a timestamp; and
WADR = weighted average diversion rate of all the off-ramps between the VMS device and crash location at a timestamp.

Also, because the duration of display varied for different crash/VMS incidents (presumably because of varying crash clearance time), a consistent point of time was necessary to calculate the diversion rate across multiple incidents. For this purpose, the start and end time of the message displays were converted to the nearest 5 min (as per the available granularity of traffic flow data), and the diversion rate of each exit between the VMS device and the crash location was calculated for each 5-min interval within the duration of the VMS message display. Then, the weighted averaging of diversion rates of all exits between crash location and VMS device was calculated for each 5-min interval during the message display period using equation (2). As a result, for a message, the weighted average diversion rates of each time interval during the message display period were obtained. The maximum average value among all was determined, which is called the maximum diversion rate.

The stable diversion rate was calculated as the average diversion rate before and after the display of a message. The

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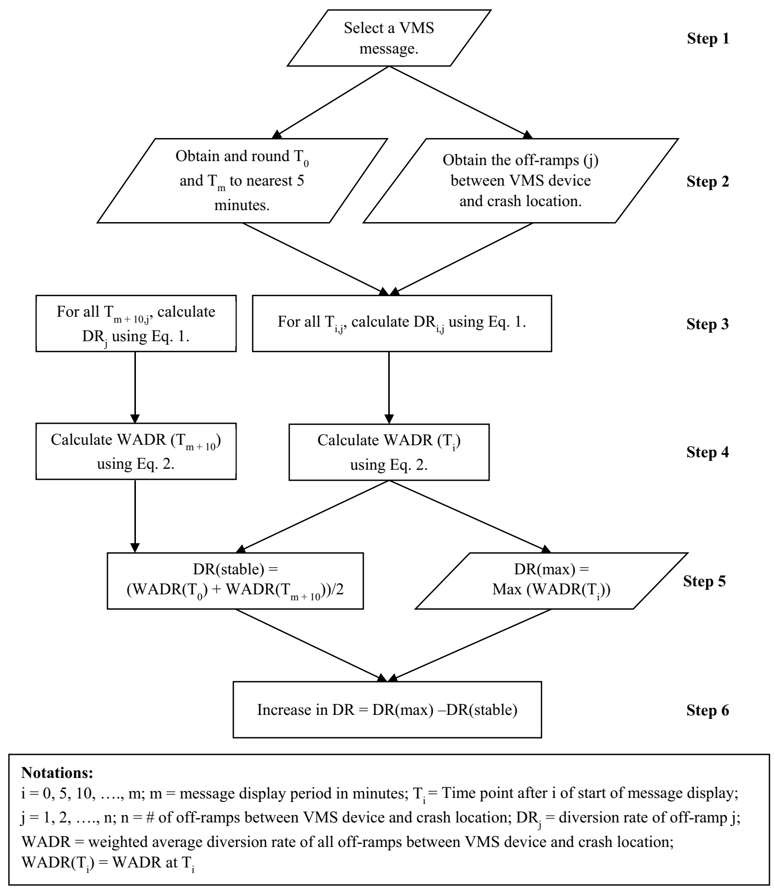
Figure 2 Process to calculate the increase in diversion rate



"before" diversion rate for a message was calculated as the weighted average diversion rate at the point of time of the start of message display. The "after" diversion rate for the message was the weighted average diversion rate 10 min after the end of message display. The arbitrary selection of 0 min before and 10 min after the start and end of the message, respectively, was based on two criteria:

1 It takes some time for the drivers who have seen the message on VMS to pass through the crash location.
2 Using a longer time-period might distort the data because of temporal variations in traffic and exiting behavior.

The selection of 10 min after message end to calculate the stable diversion rate is supported by past studies (Foo *et al.*, 2008). To calculate the diversion rate before the display of the message, we considered the timestamp at which the message display began (i.e. 0 min before the display of the message). Though past studies considered 10 min before the display of message for the before period, we did not find this conceptually intuitive because none of the drivers change the behavior before the message is displayed. Thus, we assumed that the consideration of 0 min for the before period is closest to the reality to analyze the change in driver detour behavior after the display of the message. As a result, the increase in diversion rate was calculated as the difference between the maximum and stable diversion rates for each crash-related VMS message.

An example calculation of the increase in diversion rate is presented here. On 10-29-2020, at 04:40 p.m., the following VMS message was displayed at 316.26 SB: "CRASH 5 MILES AHEAD EXPECT DELAY." There were three exits/off-ramps (potential diversion points) between the VMS and the incident. At the time of the message, T_0, the diversion rates at these exits were 13.51%, 27.29% and 9.74%, with a weighted average diversion rate of 17.67%. Ten minutes after the end of the message display, the diversion rates at these exits were 9.39%, 20.25% and 7.59%, with a weighted average diversion rate of 12.76%. Taking the average of these two values gives the stable diversion rate of 15.17%. During the time of the message display, a weighted average diversion rate was calculated for each 5-min interval across these three exits. The maximum value of these WADRs, 19.09%, was taken as the maximum diversion rate. Then, the difference between DR(stable) and DR(max), 3.92%, was taken as the "increase in diversion rate" for this incident.

The increase in diversion rate was first calculated as a continuous variable. Thus, in such a case with a continuous dependent variable, a parsimonious linear regression model could be fitted to attain the study objective. However, linear regression was found infeasible because of the violation of several assumptions of the model. Hence, we adopted the fixed width unsupervised binning technique (Peng *et al.*, 2009), with an arbitrary width of 5%, to classify the increase in diversion into three bins:

1 low/none, where the increase in diversion rate was less than 5%;
2 medium, where the increase in diversion rate was within 5%–10%; and
3 high, where the increase in diversion rate was more than 10%.

Note that there were 47 observations (out of 595) with a negative or zero increase in diversion rate.

The independent variables used in the analysis are described next. The variables associated with message verbiage were necessary to ascertain the relationship between VMS message verbiage and dependent variables. Based on the content of the message records, 11 such variables (miles ahead, "crash ahead," crash location, delay information, "use caution," traffic slows, speed suggestion, "keep left/right," "prepare to stop," lane of crash and lane blocked) were created. These variables signify whether the specific verbiage/content/information was included in the displayed message or not. For example, if the information about miles to crash is included in the message, the variable "miles ahead" was assigned "yes," otherwise "no". The description of each of these variables and their frequency in the data set are presented in Table 1.

It is to be noted that a VMS message often consists of a combination of the content items presented above. For example, a VMS message "Crash 2 miles ahead, expect delay" consists of two pieces of information or content: miles to crash and delay information. Thus, to investigate driver response to different VMS messages with different combinations of information or content, we ascertained the combinations of content in the data. As a result, we found 68 unique combinations. In total, 13 combinations with high frequencies of use were considered in this study. The frequency of each combination considered in this study is presented in Figure 3. Miles to crash + "use caution" was found to be the most frequent combination followed by crash location + "use caution," crash location + delay information and so on.

To control for the relationship between message verbiage and diversion rate, other independent variables used in the study were the day of the week, peak/off-peak hour, light condition, weather condition, the time difference between message display and crash, the distance between VMS device and crash, duration of message display, the number of frames of the message displayed and increase in occupancy in mainline during the display of the message. The descriptive statistics and definition of the variables considered in the study (except message verbiage-related variables, which are presented in Table 1 and Figure 3) are shown in Table 2.

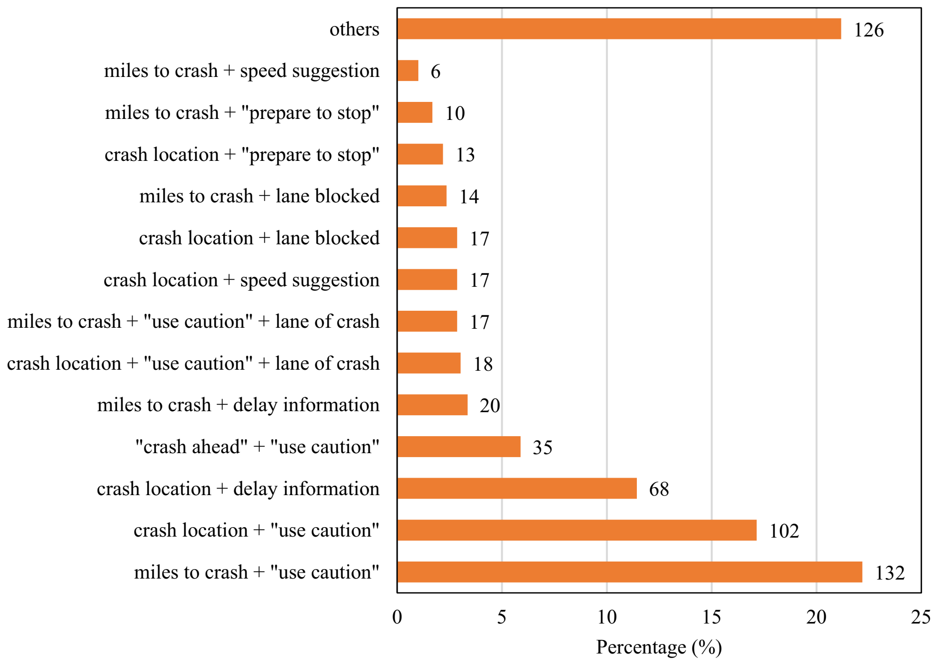
To account for the impact of possible congestion (or reduction in capacity) as a result of a crash on an increase in diversion rate, an increase in occupancy in the mainline at the time of message display was used as an independent variable. As the value of occupancy in the PeMS data set refers to the percentage of time a detector station is occupied by vehicles, a higher value of occupancy indicates a higher level of congestion, as it is a surrogate measure for density (Bham and Benekohal, 2004). Recall that Xuan and Kanafani (2014) had concluded that the increase in diversion after displaying messages in VMS is because of visible congestion rather than the impact of messages. The increase in occupancy was calculated similarly to increase in diversion rate (but without weighted averaging), which is the difference of maximum and stable occupancy in the mainline. For each VMS record, the occupancies of each mainline station just after the exits were calculated for each 5-min interval during the display of the message and the highest arithmetic average (of all stations) was taken as the maximum occupancy. The average occupancies of the before and after period (0 min before the start and 10 min after the end of message display) were calculated. Finally, for each VMS record, the difference between maximum occupancy and stable occupancy (average of before and after period) represented the increase in mainline occupancy during the display of the message.

Finally, two ordered logistic regression models were fitted. The first model was fitted with 11 dichotomous variables associated with message verbiage (shown in Table 1), whereas the second model considered a categorical variable called "message content combination" associated with message verbiage, which had 11 categories each representing a combination of contents of messages (shown in Figure 2). The first model signifies the importance of the presence or absence

Table 1 Description of message verbiage-related variables

Variables	Description of variables	Frequency (N = 595) #	(%)
Whether following information is included in the message or not? (All these variables are binary in nature with two categories: yes and no; "yes" indicates the particular content is present in the message otherwise "no")			
Miles to crash	Miles to crash from VMS device	175	61.0
"Crash ahead"	Distance to crash is not included but "crash ahead" is only mentioned	19	6.6
Crash location	The exact location of the crash either in terms of the street name or by milepost	78	27.2
Delay information	Information about the delay because of the crash; usually displayed as "expect/possible delay"	48	16.7
"Use caution"	Suggestion to use caution ahead; usually displayed as "use caution"	170	59.2
Traffic slows	Traffic ahead is slowing/stopping	9	3.1
Speed suggestion	Suggestion to reduce speed	27	9.4
"Keep left/right"	Suggestion about merging to left/right lane	5	1.7
"Prepare to stop"	Suggestion to prepare to stop ahead	28	9.8
Lane of crash	Information on which lane crash happened (left/center/right lane)	37	12.9
Lane blocked	Closure of left/center/right lane because of the crash	36	12.5

Figure 3 Proportion of VMS messages by different content combinations



of information in the message, whereas the second model compares the impacts of commonly used combinations of content on diversion rate. Both models had all other independent variables (shown in Table 2) as the control variables impacting the associations between the increase in diversion rate and the message verbiage. The whole process of modeling including data preparation was done in R.

4. Results

Two ordered logistic regression models of increase in diversion rate were fitted, and the results are presented in Table 3. Both models were found superior to the null model as indicated by log-likelihood values. Most of the message verbiage content-related variables were found to be significantly associated with an increase in diversion rate. In model A, the increase in diversion rate was significantly associated with the presence of miles to crash, "crash ahead" (without location and miles to crash), location of crash (marginally significant), delay information, traffic ahead (is slowing or slows) and lane of crash (left, center and right) information in the message. However, the presence of "use caution," speed suggestion and "prepare to stop" was found to be negatively associated with the increase in diversion rate.

When considering the combination of contents in the message in model B, message combinations miles to crash + lane blocked, miles to crash + delay information, miles to crash + "use caution" + lane of the crash, miles to crash + "prepare to stop," crash location + "use caution" + lane of the crash, crash location + "use caution" and crash location + lane blocked had a higher increase in diversion rate in comparison to the messages with "crash ahead" + "use caution." However, the message combinations miles to crash + speed suggestion, miles to crash + "use caution," crash location + "prepare to stop" and crash location + speed suggestion had a lower increase in diversion rate than that of messages with "crash ahead" + "use caution" contents.

Messages with two frames had higher diversion rates than messages with one frame (in model B only). A greater distance between VMS devices and crash incidents was negatively associated with an increase in diversion rate. However, the time difference between crash incident and message display and the duration of message display had no significant impact on the increase in diversion rate. In terms of roadway characteristics, occupancy on the mainline was positively associated with an increase in diversion rate. A higher diversion was observed during rain and a marginally lower diversion during snow (in model B only) than that of clear weather conditions. In comparison to daylight conditions, the diversion rate was found to increase more during dark (lighted or unlighted) conditions and less during dawn/dusk light conditions. Both temporal variables considered in the study – peak hour and day of the week – were significantly associated with an increase in diversion rate. In comparison to off-peak hours, morning peak hours observed greater diversion (marginally significant) but evening peak hours observed less diversion. No significant difference in the increase in diversion rate was observed between Saturdays and weekdays, but higher diversion was observed on Sundays in comparison to weekdays.

5. Discussion and conclusion

A VMS message can be presented in many different ways. For example, "crash 13 miles ahead, use caution" and "crash ahead, prepare to stop" could both be used to inform drivers of a crash incident ahead. Past studies based on stated preference (SP) surveys (Peeta and Ramos, 2006; Spyropoulou and Antoniou, 2014; Kim *et al.*, 2014) and simulator-based studies

Table 2 Explanation of the variables and descriptive statistics

Variable	Explanation	Categorical #	(%)	Continuous Mean	S.D.
Dependent variable					
Increase in diversion rate	Difference of maximum and stable diversion rate				
None/low	Increase is diversion <5%	396	66.6		
Medium	Increase in diversion 5%–10%	118	19.8		
High	Increase in diversion > 10%	81	13.6		
Independent variables					
Frames	The number of frames used to display a message				
One		499	83.87		
Two		96	16.13		
Time difference	Time difference between the occurrence of crash and start of message display in minutes			6.51	4.11
Distance	Distance between VMS device and the crash incident in miles			4.24	3.10
Duration	Duration of display of the message in minutes			40.43	34.34
Hour	Whether the message display started during peak or off-peak hours				
Morning peak	7–9 a.m.	364	61.18		
Evening peak	4–6 p.m.	79	13.28		
Off-peak hour	Others	152	25.55		
Day of week	On which day of the week incident happen?				
Weekday		467	78.49		
Saturday		72	12.10		
Sunday		56	9.41		
Increase in occupancy	Difference of maximum and stable occupancy of mainline			4.53	5.55
Weather condition	Weather condition during the display of the message				
Clear		410	68.91		
Cloudy		113	18.99		
Rain		40	6.72		
Snowing		32	5.38		
Light condition	A light condition during the display of the message				
Daylight		426	71.60		
Dark–lighted		79	13.28		
Dark–not lighted/unknown		84	14.12		
Dawn/dusk		6	1.01		

(Banerjee *et al.*, 2020) have concluded that the verbiage of the message matters to the drivers in their response to the message. With limited understanding of diversion behavior of the driver in response to different verbiage of crash message based on real-field data, two ordered logit models of increase in diversion rate were fitted using VMS message history of I-15 in the Salt Lake City metro area.

Results of the models concluded that the verbiage of a crash-related message affects the diversion rate of drivers. This informs an important implication to traffic operation controllers. The choice of message verbiage needs to be done efficiently based on the objective of the message. For example, if the objective is to obtain higher diversion of vehicles from the highway (possibly to ease crash clearance), verbiage associated with higher diversion should be chosen. Models A and B differ based on how the message verbiage information is considered in modeling the increase in diversion rate. Model A signifies the importance of the presence or absence of information in the message, whereas model B compares the impacts of a commonly used combinations of content on diversion rate. As the combination of content is what is actually disseminated by the VMS devices, model B is behaviorally superior to model A. One thing to note is that the results of models A and B are contradicting in some cases. For example, "prepare to stop" was associated with the lowest diversion in model A, whereas the combination of miles to crash + "prepare to stop" was found to have the highest diversion rate in model B. This signifies the importance of the dynamics of the combination of different information in the message. Though "prepare to stop" was found to lower diversion on average, when it was combined with miles to crash, the combination was found to perform better in terms of improving diversion rate. Thus, we suggest the readers make implications based on model B results. With that, based on the estimated coefficients of model B, the combination of message contents with the highest increase in diversion rate was miles to crash + "prepare to stop," followed by crash location + delay information, miles to crash + "use caution" + lane of the crash, etc. The combination with the lowest increase in diversion rate was crash location + "prepare to stop," followed by crash location + speed suggestion, miles to crash + speed suggestion, etc.

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Table 3 Results of ordered logit models of increase in diversion rate

Variable	Model A			Model B		
	B	*SE*	*p*	*B*	*SE*	*p*
Intercepts						
None/low | medium	1.537	0.151	<0.001*	1.604	0.164	<0.001*
Medium | high	3.154	0.204	<0.001*	3.220	0.216	<0.001*
Message verbiage-related variables						
Miles to crash: Yes	0.508	0.161	0.002*	–	–	–
Crash ahead: Yes	0.493	0.195	0.012*	–	–	–
Crash location: Yes	0.308	0.162	0.057~	–	–	–
Delay information: Yes	0.451	0.195	0.021*	–	–	–
Use caution: Yes	−0.574	0.166	0.001*	–	–	–
Traffic ahead: Yes	1.052	0.038	< 0.001*	–	–	–
Speed suggestion: Yes	−0.656	0.120	<0.001*	–	–	–
Keep left/right: Yes	−0.606	0.052	< 0.001*	–	–	–
Prepare to stop: Yes	−0.537	0.068	<0.001*	–	–	–
Lane of crash: Yes	0.560	0.163	0.001*	–	–	–
Lane blocked: Yes	0.150	0.151	0.323	–	–	–
Message content combination (base: crash ahead + Use caution)						
Miles to crash + lane blocked	–	–	–	0.533	0.021	<0.001*
Miles to crash + delay information	–	–	–	0.375	0.008	<0.001*
Miles to crash + use caution + lane of crash	–	–	–	0.567	0.043	<0.001*
Miles to crash + speed suggestion	–	–	–	−0.314	0.005	<0.001*
Miles to crash + prepare to stop	–	–	–	1.825	0.013	<0.001*
Miles to crash + use caution	–	–	–	−0.041	0.188	0.829
Crash location + prepare to stop	–	–	–	−0.784	0.007	<0.001*
Crash location + speed suggestion	–	–	–	−0.380	0.019	<0.001*
Crash location + use caution + lane of crash	–	–	–	0.267	0.021	<0.001*
Crash location + use caution	–	–	–	−0.115	0.208	0.582
Crash location + delay information	–	–	–	0.914	0.179	<0.001*
Crash location + lane blocked	–	–	–	0.098	0.020	<0.001*
Others	–	–	–	−0.158	0.123	0.198
Other VMS message-related characteristics						
# of frames: two	0.263	0.185	0.155	0.463	0.116	<0.001*
Time difference	0.000	0.000	0.642	0.000	0.000	0.582
Distance to crash	−0.212	0.045	<0.001*	−0.201	0.041	<0.001*
Duration of display	0.000	0.000	0.165	0.000	0.000	0.170
Roadway characteristics						
Increase in occupancy	0.206	0.019	<0.001*	0.210	0.019	<0.001*
Weather condition (base: clear)						
Cloudy	−0.203	0.236	0.390	−0.297	0.239	0.213
Rain	0.359	0.104	0.001*	0.313	0.116	0.007*
Snow	0.053	0.052	0.309	−0.103	0.055	0.061~
Light condition (base: daylight)						
Dark–lighted	0.713	0.186	<0.001*	0.758	0.186	<0.001*
Dark–not lighted/unknown	0.379	0.194	0.052~	0.389	0.203	0.055~
Dawn/dusk	−0.122	0.014	<0.001*	−0.107	0.010	<0.001*
Temporal variables						
Peak hour (base: off-peak hour)						
Morning peak	0.273	0.162	0.094~	0.311	0.186	0.095~
Evening peak	−0.576	0.221	0.010*	−0.572	0.229	0.013*
Day of week (base: weekday)						
Saturday	0.233	0.206	0.259	0.079	0.160	0.623
Sunday	0.862	0.158	<0.001*	0.849	0.186	<0.001*

(*continued*)

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Table 3

Variable	Model A			Model B		
	B	*SE*	*p*	*B*	*SE*	*p*
***Model fit statistics* (*N* = 595)**						
McFadden's pseudo-R^2		0.205			0.206	
Log likelihood (null model)		−513.66			−513.66	
Log likelihood (full model)		−408.17			−407.82	
AIC (null model)		1,031.33			1,031.33	
AIC (full model)		872.34			875.65	

Notes: *Indicates statistically significant at 95% confidence interval, ∼ indicates statistically significant at 90% confidence interval and – indicates not applicable

Two-frame messages where more detailed information could be included were found to have significantly higher diversion than one-frame messages. This implies that the detail of information in the message is important to the drivers. This finding is in line with past SP studies (e.g., Kim *et al.*, 2014). However, information overload could occur to the drivers if more information is displayed (Xu *et al.*, 2020); thus, careful interpretation of this result is necessary. Because the results of this study are based on real-field data, the controllers could have already used practices and policies to avoid excess information load. A relatively lower increase in diversion rate was observed when the distance between the VMS device and crash was greater. This indicates that agencies should strive to shorten distances between VMS devices, particularly in crash-prone areas. Realizing this need, a recent study by Zhang *et al.* (2022) has developed an optimization framework to locate the position of VMS devices on the freeways based on weighting the crash occurrence probabilities. A measure of congestion on the mainline (increase in occupancy during the message display period) was found to be significantly related to the increase in diversion rate. This indicates that the increase in the diversion during the message display period is because of the congestion in the mainline or the visible congestion ahead as described by Xuan and Kanafani (2014). However, as opposed to their conclusion, the variance in the diversion was found to be affected by the verbiage of the message in this study.

Apart from these, increase in diversion rate was found to be associated with weather conditions, light conditions and temporal variables. Higher diversion during rain than clear weather could be associated with possible congestion of freeways during rain. Lower diversion during snow than clear weather could be associated with faster snow clearance on freeways (mainline) than on other roads. Drivers could assume that alternative routes would be uncongested compared to the freeway (in conjunction with a crash-related VMS message) during dark conditions (at night), leading to a significant increase in the diversion during dark conditions. However, dusk and dawn light conditions are often considered safety threats to drivers, particularly if the road is not familiar. This could explain the lower diversion during dawn/dusk conditions than daylight conditions. In morning peak hours, particularly, when the commuter volume is high, drivers' demands to reach their work destinations on time might be high. This could explain higher diversion during the morning peak. However, lower diversion during evening peak than off-peak hours could be because drivers consider the time to reach their post-work destination to be more flexible. As explained by Kusakabe *et al.* (2012) about drivers comparing travel time of the main and alternate routes, higher diversion on Sundays could be because lower traffic volumes are expected on alternate routes on that day.

To conclude, an average increase in diversion rate after the display of a crash-related VMS message was found to be 5.43%. The factors associated with this increase were investigated. A commonly accepted understanding of the relation between the message verbiage and increase in diversion rate concluded by past SP studies was verified from this real-field-based study. The findings, especially the impact of different combinations of message verbiage on diversion rate, could be used by the transportation agencies (e.g. state DOTs) to improve crash incident management by using the message verbiage corresponding to the desired objective. However, it is important to note that the data set used in this study was from real-field data of limited spatial and temporal scope. Thus, careful interpretation and application of these results are needed.

This study had some limitations. First, only one section of a freeway was used to estimate the results. More sites could have strengthened the generalizability of the findings. Also, considering the availability of a reasonable alternative route may provide more insight. Second, the flow and occupancy data used in this study were of 5-min granularity. Finer data (of 1-min or 30-s granularity) could produce more accurate results. Third, because of the real-field nature of the data, there were no "control" incidents (where no VMS message was displayed) for comparison. It may be helpful to future studies to assess high-impact incidents in greater detail and individually. Fourth, this study did not account for the possible impact of the use of smartphones and GPS devices in-vehicle by the drivers on the diversion rate. These devices provide advanced notification of the incidents ahead, travel time and re-recommending routes to the drivers and are likely to supplement the VMS information. Similarly, this study also did not consider the impact of the connected vehicles, where drivers are warned about the crash and other hazards ahead via basic safety messaging (Lim *et al.*, 2021), on the diversion rate, as the number of connected vehicles in the US roads is increasing (Acharya and Mekker, 2021). This limitation could be a future research avenue. Lastly, it should be realized that the traffic operator's goal of crash-related messages might not always be a higher diversion. Rather, safety improvement, such as the reduction of secondary crashes by alerting drivers, might be the primary goal of the operator. Thus, safety improvement after displaying crash-related messages could be another future research avenue.

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