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Behavioral Analysis of Drivers Following Winter Maintenance Trucks Enabled with Collision Avoidance System

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Abstract

Winter maintenance trucks (WMTs) often operate at lower speeds during inclement weather and roadway conditions, creating potential safety issues for motorists following close behind. In this study, a new prototype radar-based rear-end collision avoidance and mitigation system (CAMS) was tested to assess its impact on the behavior of drivers following WMTs. The system is designed to flash an auxiliary rear-facing warning light upon detection of a vehicle encroaching within an unsafe relative headway with the rear of the WMT. A series of field evaluations was performed during actual winter maintenance operations to assess the effectiveness of the system compared with normal operating conditions (i.e., without the CAMS warning light) toward improving driver behavior related to rear-end crash risk. Specifically, two measures were assessed: (a) rate of vehicles encroaching beyond a safe time headway threshold to the rear of the WMT, and (b) the reaction–response time of drivers. Classification and regression tree models were created for identifying the relevant factors influential in determining the change in driver response. The results indicate that this warning light was effective in reducing the likelihood of the subject drivers crossing beyond a relative headway of 4.5 s. It was also effective in reducing the reaction and response times of the drivers by 0.83 and 0.55 s (36% and 20% reduction), respectively. Although the results were encouraging, additional field testing is recommended before conclusions are drawn regarding the traffic safety impacts of the system.

Winter maintenance of highways remains a major challenge for roadway maintenance agencies in states with harsh winter climate. Traffic safety and operations are severely affected by poor visibility and snow or ice on the surface of the roadways. Recent research has found that traffic crash rates during winter periods are directly related to total snowfall levels (*1*, *2*). Snow removal and de-icing using winter maintenance trucks (WMTs) are the principal activities accomplished by transportation agencies to mitigate safety and operational issues associated with winter weather. As these operations are typically performed at reduced speeds directly in the roadway travel lanes, often under reduced visibility conditions, the risk of rear-end collision between the WMT and trailing vehicles is elevated. Given the size of such vehicles, collisions involving WMTs can result in substantive property damage, vehicle repair, and medical costs.

To address these concerns, several state Departments of Transportation (DOTs) have invested in technologies and public outreach programs that help in creating a safer operational environment for WMTs. One method is to provide education to motorists to improve driving on ice- or snow-covered roads, particularly around WMTs. For example, drivers are advised to accelerate and decelerate gradually, allowing extra time and distance to stop (*3*, *4*). They are also advised not to follow WMTs too closely and to be mindful of the larger size of these vehicles, which results in potential blind spots, as well as lower travel speeds (*5*). Despite these efforts to optimize safety during winter maintenance, and particularly snow-removal procedures, the number of crashes that involve a WMT remains significant and represents an opportunity area for improvement.

This is especially true in Michigan where significant plowing and deicing operations occur statewide, particularly in the western and northern portions of the state that experience regular lake-effect snow. A review of crash reports in Michigan from 2012 through 2017 conducted by the authors (*6*) revealed an average of nearly

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226 WMT-involved crashes statewide per year. Many of these crashes involved a trailing vehicle colliding with the rear or side of the WMT. Further assessment of the precipitating events and causal circumstances contributing to the collision suggested that approximately 50% of these crashes could have potentially been influenced by a rear-facing collision avoidance system.

To help mitigate such crashes, the Michigan DOT (MDOT) recently procured a prototype collision avoidance and mitigation system (CAMS) that was installed on two WMTs in southeast Michigan in the late fall of 2017. The CAMS setup includes a rear-facing radar sensor that is able to detect vehicles up to 600 ft behind the truck and trigger an independent warning beacon mounted on the rear of the WMT upon detection of a vehicle encroaching too close to the rear of the WMT. This collision avoidance technology had not previously been implemented or tested for winter maintenance operations before this study. As such, the effect on driver behavior and consequent impacts on roadway safety remains uncertain. This study seeks to determine the extent to which CAMS improves driver behavior near WMTs and estimate its potential to reduce WMT-involved crashes.

Literature Summary

Historically, a significant portion of winter maintenance research on improving technology has focused on its operational aspects, such as determining optimal routing strategies for snowplows in consideration of historical and forecasted traffic and weather data (*7–10*). Technologies like automatic vehicle location (AVL) and road weather information systems (RWIS) allow for real-time management of plowing and deicing operations. Studies conclude that AVL and RWIS are fundamental components of effective winter maintenance programs, although they need frequent calibration and modification (*11*, *12*). More recent attempts in improving the operational characteristics of winter maintenance include an Internet of Things (IoT)-based approach with low-cost sensors gathering meteorological data (*13*). However, it should be noted that IoT is a nascent technology and its use in assisting snow removal and deicing suffers the limitations of high deployment and maintenance costs (*13*).

Despite significant advances in the research of operational and logistic characteristics of winter maintenance, there is limited documentation on its impact on traffic safety. Usman et al. analyzed the effect of weather, roadway conditions, and traffic volume on crash frequency and severity during periods of inclement weather in Toronto, Canada (*2*) and concluded that roadway condition is a statistically significant factor in affecting crash frequency during severe winter. As WMTs function to improve roadway pavement condition, they are a necessary component in reducing crash frequency during and after severe weather conditions.

Collision avoidance and advanced safety systems are part of an emerging technology that can help in reducing chances of crash occurrence during inclement winter weather conditions. These are part of advanced vehicle control and safety systems that make typically use of an array of electronic sensors to detect other approaching vehicles and issue a warning when necessary (*14*). Such systems may include forward or rearward crash warning system and adaptive cruise control under the umbrella campaign of intelligent vehicle initiative (IVI), which has been an active topic of research for the automotive industry (*15*) and has primarily been centered on algorithm development (*16*). Although the integration of IVI is popular in the research of consumer vehicles, there is limited development in its specialized use such as winter maintenance (*14*, *17–19*).

Visual information provision strategies have been found more suitable in terms of the influence on travelers' perception–recognition ability in comparison to aural or textual information delivery methods (*20*). CAMS is a type of intelligent transportation system that delivers visual warning information to road users upon detection of vehicles encroaching within close proximity to the rear of the WMT. However, in general, further research on the safety impacts of collision avoidance systems for winter maintenance use is necessary.

CAMS Configuration and Operation

The CAMS evaluated here is an independently functioning system that is retrofit onto the rear of WMTs. The system primarily consists of three units—a radar sensor, a camera, and a warning light bar containing a set of three amber beacons that can be programmed to display various steady or flash patterns. An example the CAMS installed on a WMT used in this study is displayed in Figure 1.

The CAMS is supported by auxiliary components such as a GPS unit enabled with AVL technology, an in-cab computer screen, CPU and portable storage device, and an automated washer unit for cleaning the radar and camera housing. The radar sensor constantly monitors the motion profile of up to 32 vehicles detected in its rear field of view. This information is used to calculate metrics such as the longitudinal and lateral distance, relative speed and acceleration, and relative headway of these vehicles with the truck at every one-tenth of a second. This real-time information is then overlaid with the video and is displayed to the truck driver (see Figure 2). Figure 2 displays the various attributes of the CAMS

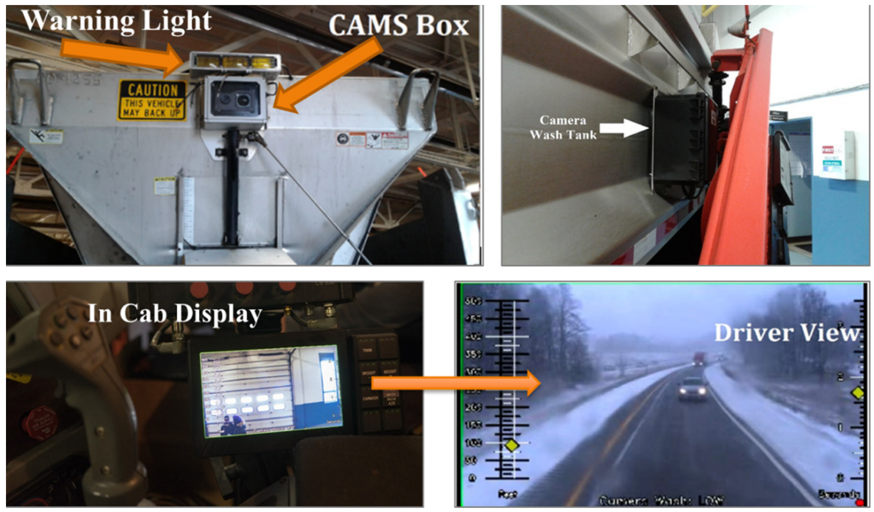

Figure 1. CAMS components installed on a WMT.

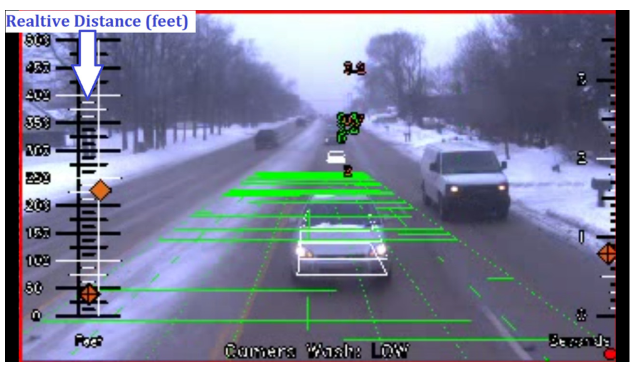

Figure 2. Screenshot of a typical CAMS video.

video display, including the truck's rear exposure zone (green grid), detected vehicles (green and orange numbers), along with their relative distance from the truck (left scale) and time headway.

The CAMS is programmed to trigger the amber beacons upon detection of a vehicle encroaching too close to the rear of the WMT in terms of the vehicle's time headway relative to the rear of the truck. The system is designed to issue up to two levels of warning at two predetermined values of relative headway. The initial flash pattern in the CAMS setup tested in this study, here called "level 1" warning, was programmed for the three beacons to flash simultaneously every 0.75 s. The second flash pattern, which is triggered when vehicles encroach closer despite the first warning and known as "level 2" pattern, was programmed for the three beacons to flash rapidly in an alternating pattern to indicate greater urgency.

In this experiment, after initial controlled roadway testing, the headway values of warning levels 1 and 2 were established at 7 s and 5 s, respectively. Note that the term "relative headway" here refers to the amount of time it would take the front bumper of the following vehicle to hit the rear bumper of the truck if the relative speed between the truck and following vehicle remained the same. It is calculated as the negative of the ratio of relative longitudinal distance (dx in Figure 3) to relative longitudinal speed ($dvx = vx\text{-}vt$). This allows for negative values of relative headway in cases in which the following vehicle recedes from the truck and can therefore be assumed to always improve safety for the following vehicle. Therefore, by design, a warning is set off only when the following vehicle has a positive value of relative headway. Though not by design, level 2 warnings could be triggered without prior level 1 warning for cases where vehicles suddenly entered behind the WMT from an adjacent lane.

The performance of the CAMS was found to be satisfactory in most cases, except in cases of intense occlusion of the camera as a result of heavy snow and malfunction of the washer unit. Although the operational performance of the CAMS was evaluated as a part of the overall study, it is not included within the scope of this manuscript. Only the behavioral impacts of the CAMS system during periods of proper operational performance area are evaluated here.

Methodology

The effect of CAMS warning light on the behavior of the drivers following the subject WMTs was evaluated using

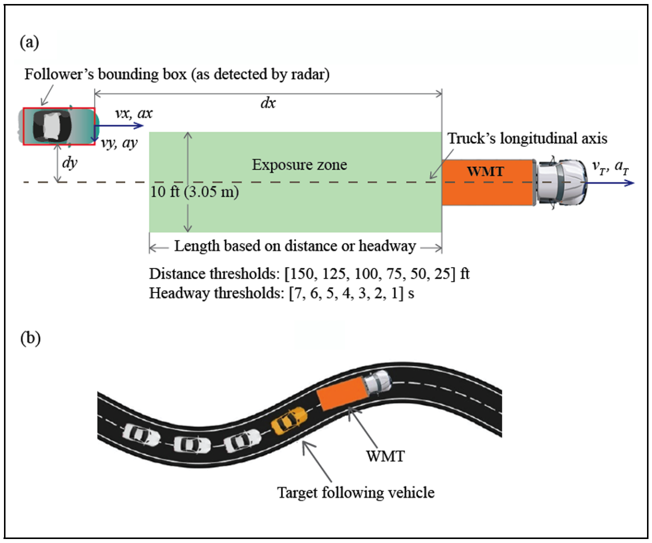

Figure 3. Definition of exposure zone for (*a*) straight segments, (*b*) curved segments.

a case-control study design. In addition to collecting data with the CAMS warning light operational, it was also necessary to establish a baseline for the behavior of drivers when encroaching WMTs without the CAMS warning light to determine the incremental benefits associated with the CAMS warning light. To control for external biases, this evaluation was performed using the same CAMS-implemented trucks with and without the CAMS warning alert light connected. Specifically, the CAMS-equipped trucks operated on the same routes with the radar, video, and data-collection devices active, but with the associated warning light either enabled (the "light on" data-collection period) or completely disconnected ("light off" period). This type of study design was deemed superior to a typical case-control design, that is, comparing CAMS trucks versus other trucks without the CAMS, because it better isolated the effects associated with the warning alert by controlling for effects such as that of the truck, operator, data-collection system, and route.

The behavior of the drivers following the CAMS-equipped trucks was quantified based on two different measures: encroachment rate and reaction–response time, which are each defined in their respective sections that follow. The design of the study ensures that the differences in the behavior of these measures with the warning light enabled and disabled represent the measure of effectiveness provided by the CAMS warning light. These measures were analyzed across different roadway, geometric, and situational conditions. Predictive models using classification and regression tree analyses were developed to better understand the influence of each factor on the driver behavior metrics.

Data Description

In this study, two MDOT WMTs enabled with CAMS performed normal winter maintenance operations on controlled-access and non-controlled-access roadways in Livingston and Washtenaw counties of Michigan with the warning light system enabled and disabled. As mentioned in the prior section, the latter scenario served as the control condition, in which the radar sensor operated and collected data, but the triggered warnings did not activate the warning light. Because of logistical difficulties associated with connecting and disconnecting the warning light during regular winter maintenance operations, the case and control data were collected during different periods between late January 2018 (warning light connected) and early March 2018 (warning light disconnected).

Each dataset consists of detailed trajectory logs of the truck and the following vehicles detected by the radar along with the captured video for every 5 min. The recorded vehicular trajectory data logs were organized to obtain relevant kinematic variables such as relative and absolute longitudinal and lateral distance, speed, and acceleration. A combination of programmatic extraction and manual inspection was used to identify the vehicles responsible for triggering the recorded warnings. In case of the warning light disabled, CAMS still recorded the issued warnings, although they were not reflected to the drivers of the encroaching vehicles. In both scenarios, the trajectory data of the alarm-causing vehicles were extracted at four instants of time, along with roadway features such as the number of lanes and occupancy of the adjacent lane(s) and situational features such as the intention of the driver to either back off or change lane. These instants include (a) warning level 1 issued, if at all, (b) warning level 2 issued, if at all, (c) when the minimum relative headway was attained while occupying the exposure zone, and (d) when the following vehicle reached maximum deceleration. These data points were used to calculate the target features as discussed later. As this study concerns only with the effect of the warning light on the vehicles that triggered them, the resultant dataset was much sparser than the obtained trajectory data.

The target features of the analyses are defined in the subsequent sections. The statistically significant descriptive features extracted after preliminary analysis are listed in Table 1. Notably, three variables—number of lanes, occupancy of adjacent lane, and the identified intended maneuver of the following vehicle's driver—were merged into one feature "maneuver" in order to reduce the dimensionality of the problem.

Encroachment Rate

The concept of encroachment was used to understand the patterns of following a WMT exhibited by the

Table 1. Description of Variables

Variable	Description	Levels
Light	Indicates the presence or absence of the CAMS light when the warning was triggered.	1. On 2. Off
Warning Level	The activated warning level based on the headway threshold.	1. Level 1 only 2. Level 2 only 3. Both level 1 and 2
Geometry	The physical environment of the site/segment.	1. Straight/tangent segment 2. Left/right turn 3. On/off-ramp 4. Merge/diverge lane
Maneuver	Characteristics such as space availability in the adjacent lane and the desired maneuver in response to closing in toward the WMT.	1. Single-lane road, follower backing off 2. Multi-lane road, adjacent lane occupied, follower backing off 3. Multi-lane road, adjacent lane occupied, follower changing lane 4. Multi-lane road, adjacent lane vacant, follower backing off 5. Multi-lane road, adjacent lane vacant, follower changing lane

following vehicles subject to different conditions, especially the influence of flashing warning light. In this study, encroachment was defined as the action of a driver entering into and staying in an exposure zone behind the WMT for a duration greater than a specified dwell time. This is based on the general understanding that a driver should keep a safe distance or headway with the truck at all times. Encroachment rate was accordingly defined as the ratio of the number of vehicles crossing a certain threshold of either distance or time gap to the total number of vehicles detected over a unit period of time. A series of gap thresholds was established for analytical purposes, which are indicated in Figure 3. Distance gap was studied over the range of up to 150 ft at 25 ft intervals, and time/headway gap ranged over 7 s at 1 s intervals.

Some parameters related to the WMT's exposure zone were established after rigorous manual inspection. Specifically, dwell time and zone width were set at 3 s and 10 ft, respectively. However, based on preliminary inspection, exposure zone was defined differently for straight and curved segments (see Figure 3). For straight segments, it was defined as an imaginary rectangle extending from the truck's rear for different lengths corresponding to the aforementioned values of distance and time-based gaps. For curved segments, such a rectangular exposure zone could not effectively capture the reality of warning-causing vehicles because of numerous cases of false negative detection. Therefore, only the nearest following vehicle was considered for the encroachment analysis of curved segments.

The variation in encroachment rate was analyzed based on the cumulative relative frequency distribution. For the purpose of modeling, it was posed as a simple yes/no question: "given a situation of the driver following the WMT, did the driver encroach beyond the specified relative headway threshold?" This was deemed necessary because the measure could then be modeled for different thresholds of headway, and the most relevant value of a "safe gap" could be obtained. The results of encroachment analysis are discussed in later sections.

Reaction–Response Time

Reaction time is a fundamental concept in the study of driver behavior. Its conventional definition takes into account the total time taken by a driver to perceive, interpret and judge the situation, and finally act, such as applying brakes (*21*). In this study, however, reaction time was defined in the context of the issued warning alert as the time difference between the instant of triggering of a warning and the instant when the following vehicle attained its maximum negative acceleration (i.e., deceleration) while occupying the exposure zone. This modified definition was attributed to the availability of only the physical state of the following vehicles, such as their speed and acceleration.

In conjunction with reaction time, another related parameter called response time was considered for understanding driver behavior. It was defined as the time taken by the driver to maneuver to a perceivably safe gap with the WMT after the issuance of the warning. Per the observations, the minimum relative headway between the truck and the vehicle during its stay in the exposure zone was considered the aforementioned safe gap. After the attainment of minimum relative headway, the distance between the subject vehicle and the WMT would

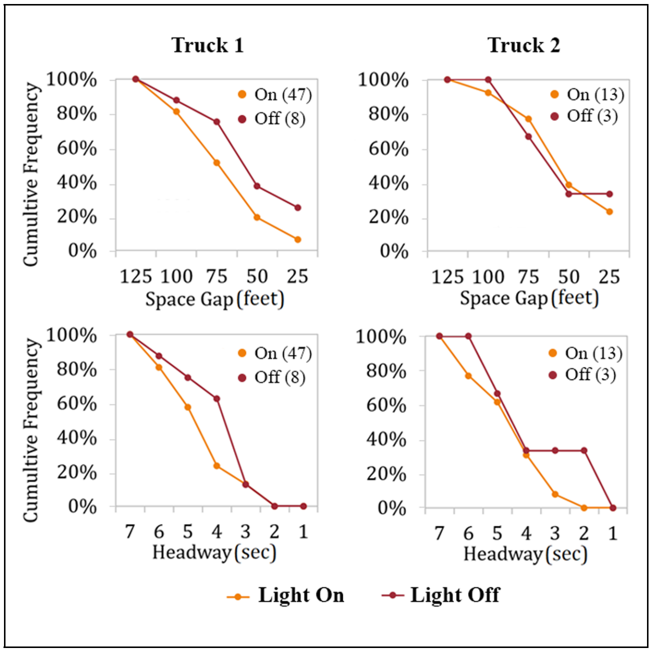

Figure 4. Cumulative frequency distribution of encroachment rate on straight segments only.

increase, intuitively implying a reduction in the risk of crash occurrence.

Reaction and response times are closely linked to each other and were observed to be highly positively correlated in all cases. Therefore, they were used in conjunction with each other. They are mathematically expressed by equations 1 and 2, respectively.

$$t_{\text{react}} = \left| t_{\min(\hat{a})} - t_{\text{warn}} \right| \tag{1}$$

$$t_{\text{resp}} = \left| t_{\min(dt)} - t_{\text{warn}} \right| \tag{2}$$

Behavioral Modeling

Besides the analysis of the distribution of the target features across different segments, maneuvers and gap thresholds, a modeling approach was used to identify the influence of CAMS warning light on the two target features relative to other potentially influential factors. The presence of largely categorical variables necessitated the use of a decision-making oriented modeling approach. As a result of this qualification combined with the issue of a small dataset, decision tree modeling was selected over other popular candidate methods, such as various types of regression models.

Decision tree modeling is a commonly used technique in machine learning that resembles a tree with its branches corresponding to splits constructed based on the amount of useful information its influential descriptive features create. These trees are a visually intuitive means of identifying the importance of descriptive features relative to each other. As such, the features higher up in the tree's hierarchical structure tend to be more informative and therefore more relevant in predicting the outcome of a query passed in as its "state," which comprises its different descriptive features. A program was developed in R to execute the standard "ID3" algorithm to construct these trees.

The two main categories of decision tree—classification and regression tree—differ in the type of their target feature as categorical and continuous, respectively. Therefore, a classification tree was produced for encroachment whereas regression trees were produced for reaction and response times. All three models were developed with the same descriptive features in order to maintain uniformity of inference. They are described in Table 1.

Results

Encroachment Rate Analysis

Frequency Distribution. The encroachment rate of following vehicles was analyzed for both space and time-based gaps for both trucks. The frequency distribution of encroachment rate is shown in Figures 4 and 5. The frequency is labeled as cumulative in these figures because of its cumulative nature, that is, a vehicle having crossed, say, 50 ft of space gap has already crossed 100 ft. The sample sizes of the control and study cases are also labeled in the figures. The small sample sizes are indicative of both the rare nature of the event in general, as well as the limited available datasets.

The results generally show that a larger proportion of drivers cross smaller thresholds of distance- and time-based gaps when the warning light is disabled as opposed to when it is enabled. This can be verified by the general trend of the plots for "light off" period appearing higher than that of "light on" on the vertical axis. This suggests that the CAMS warning light system might be effective in pushing drivers to safer gaps. Evidence from the videos also supports this claim, but also informs that the presence of a flashing light signal redirects them to the adjacent lane in most cases where the difference in cumulative frequency is very high.

The patterns also differ significantly by segment geometry, as can be differentiated in Figures 4 and 5. This may be attributed to the different selection criteria of exposed and warning-causing vehicles. This difference is exacerbated by the small number of warning observations of truck 2 in both the cases of warning light—on and off. In general, however, these results suggest that once the warning alarm was provided to the following vehicles, relatively fewer vehicles crossed the lower and riskier thresholds of gap with the WMT. In the absence

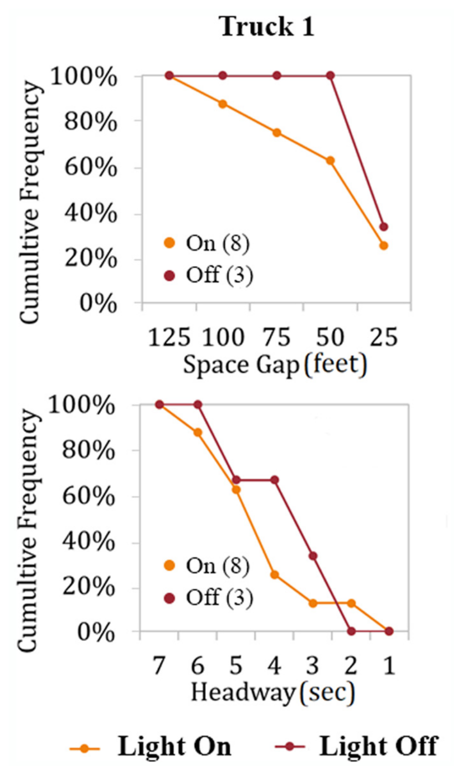

Figure 5. Cumulative frequency distribution of encroachment rate on curved segments only.

of supplementary crash information, it can be intuitively assumed to lead to safer maintenance operations. However, it is crucial to have more observed data supporting this assumption.

Decision Tree. The decision tree of the encroachment likelihood for a specific "safe gap" value of 4.5 s is shown in Figure 6. This value was set as a model parameter and was regulated for different trials. Note that a low value of this safe gap such as 2 or 3 s led to the aggregation of observations under the most important factor: *warning level* and the subsequent dropping of other influential factors. Similarly, a higher value of this parameter led to the development of unrealistic decision sequences. Values of 4 and 4.5 s describe the influence of the descriptive features more accurately.

It was observed that the presence of light prompted drivers to not go closer than the safe gap of 4.5 s. This is evidenced by the observation that 24 out of 33 alarm-causing vehicles were repelled by the warning to fall back of 4.5 s, as opposed to 2 out of 5 in the absence of the light. A similar observation was made in case of a threshold of 4 s. Based on these observations, it can largely be concluded, though not without qualification, that the warning light may be effective in changing the drivers' decision to stay at safer headways.

The structure of the decision tree also provides important information. According to Figure 6, the most informative descriptive feature was observed to be *warning level*, followed by *maneuver* and then by the presence of *light*, which was found relevant for only level 1 warnings. This sheds light on the possibility that the presence of light itself did not lead to a drastic change in drivers' likelihood of crossing a certain threshold of headway, at least not more than warning level issued to them and their intended maneuver.

Reaction–Response Time Analysis

The average values of reaction and response time across different combinations of segment geometry (a physical property) and intended maneuver (a behavioral property) are tabulated in Table 2. The effect of warning light is positive in reducing both of these values. The average reaction time on straight segments was reduced from 2.30 s in the base case to 1.47 s when the warning light was enabled. The 0.83 s (36%) change in reaction time is a considerable reduction that may indicate improvement in driver behavior. The mean response time on straight segments also reduced from 2.71 to 2.16 s, a reduction of about 20%, indicating a positive change in favor of safe driving behavior. Note that these values are significantly higher than standard mean values of braking reaction time, which usually lie in the range of 1.1 to 1.4 s for drivers facing an unexpected situation (*21–23*) and even higher than the design reaction time of 1.5 s as prescribed in the AASTHO Green Book (*24*). This inconsistency is attributed to a different definition that is used in these documents compared with this study, which relies on the observed change in the sign of acceleration.

Although the difference in these values between the two cases of warning light (enabled versus disabled) was found to be numerically significant, the statistical significance of this inference is questionable because of the small number of observations in the case of light disabled. Similarly, too few observations of curved segments imply a statistical insignificance of the results of curved segments.

Decision Tree. The regression trees of the reaction and response time are given in Figures 7 and 8, respectively. The leaf nodes in shades of red indicate the average value of the target feature with the query state outlined in the branches above them. According to Figure 7, the presence of warning light decreased the reaction time of drivers executing maneuvers 2, 3, and 5, all pertaining to multi-lane road segments, compared with the absence of

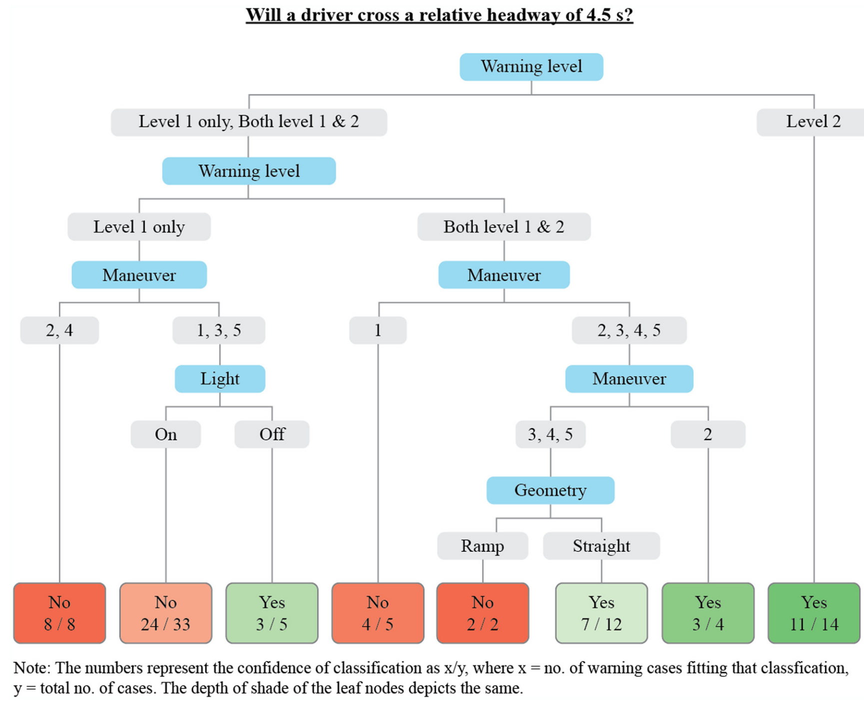

Figure 6. Classification tree of encroachment likelihood for headway level of 4.5 s.

Table 2. Average Values of Reaction and Response Time for Different Segment Geometries and Intended Maneuvers

		Straight segments		All segments	
Maneuver	Light	Average value (s)	No. of observations	Average value (s)	No. of observations
Reaction time					
Both maneuvers	On	1.47	33	1.53	37
	Off	2.30	7	2.30	7
Lane change only	On	1.55	23	1.55	24
	Off	2.40	5	2.40	5
Back off only	On	1.29	10	1.48	13
	Off	2.04	2	2.04	2
Response time					
Both maneuvers	On	2.16	36	2.17	42
	Off	2.71	7	2.46	8
Lane change only	On	2.42	25	2.39	26
	Off	2.94	5	2.57	6
Back off only	On	1.56	11	1.82	16
	Off	2.13	2	2.13	2

the warning light. The average difference of 1.57 s of reaction time corresponds to a subset of observations with a higher difference than the overall observed difference of 0.83 s. These models corroborate the hypothesis that the CAMS warning light can be effective in reducing the drivers' reaction and response time, which in turn can be reasonably conjectured to be associated with an improvement in the following driver behavior. Similar to previous inferences, a more statistically significant analysis should be performed with the help of a richer dataset.

Conclusion

Collision avoidance systems are designed to improve traffic safety by preventing certain types of crashes, including rear-end and sideswipe. Although collision avoidance

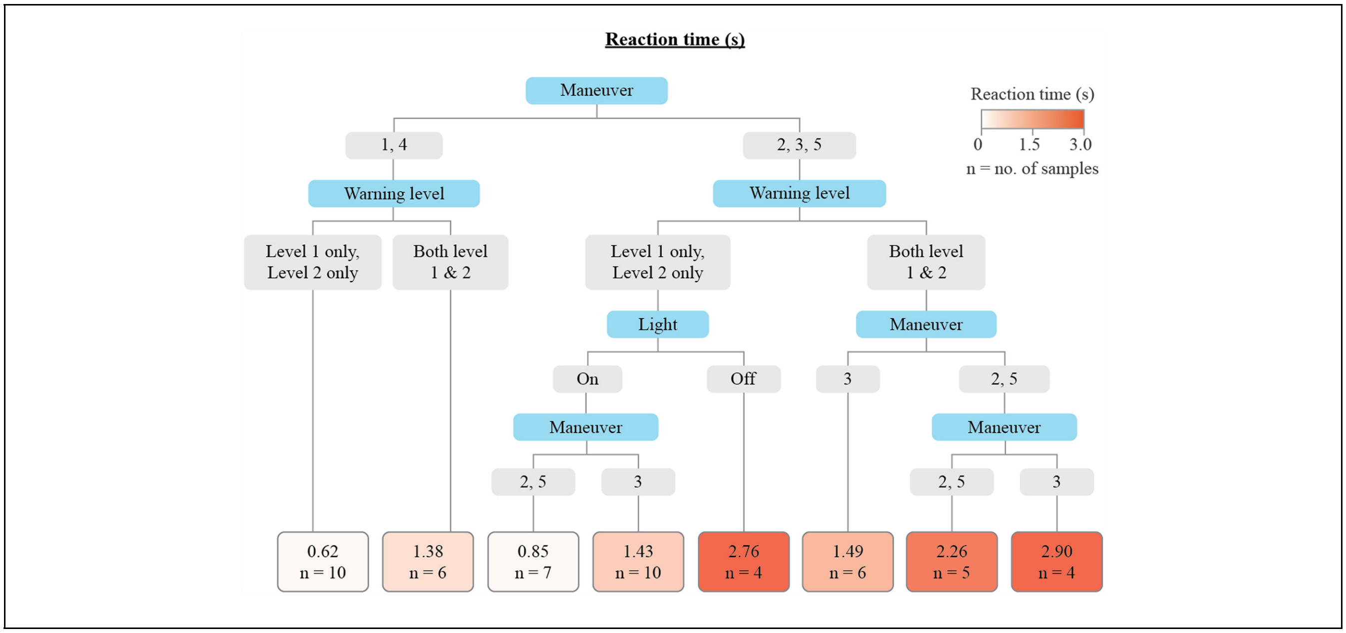

Figure 7. Regression tree of reaction time.

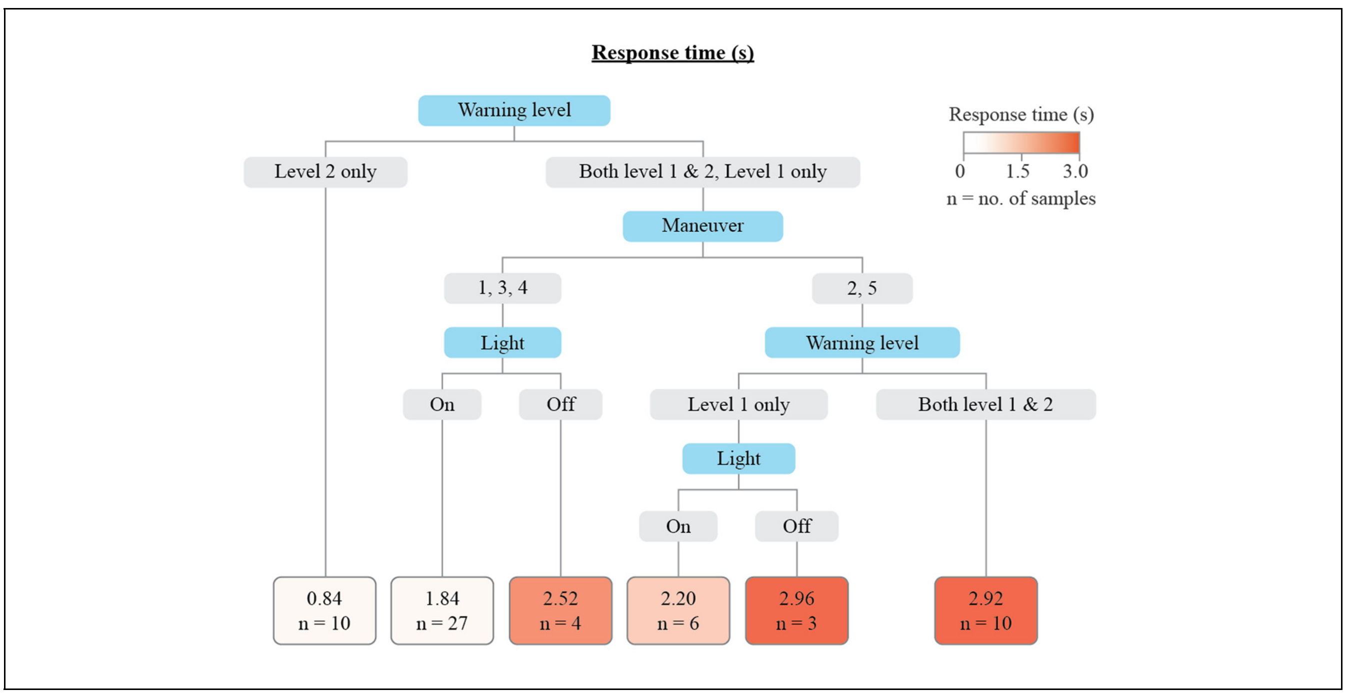

Figure 8. Regression tree of response time.

systems are becoming increasingly common on vehicles, such systems have not experienced extensive implementation or testing on WMTs.

The MDOT recently installed a new prototype CAMS for testing on WMTs that warns drivers following the truck by triggering a rear-facing flashing LED upon detection of a vehicle encroaching beyond a safe time headway. As this collision avoidance technology had not previously been implemented or tested for winter maintenance operation, this study sought to determine the extent to which CAMS improves drivers' behavior in terms of safety when approaching WMTs from the rear.

This study was conducted as a case-control experiment using the same two CAMS-implemented WMTs to control for external biases. Specifically, the CAMS-equipped trucks operated on the same routes with the radar, video, and data-collection devices active, but with the associated warning light either enabled or completely disconnected. Trajectories of vehicles following the WMTs were recorded in the same manner for both cases. The behavior of the drivers following the CAMS-equipped trucks was quantified based on two measures of effectiveness—encroachment rate and reaction–response time. The differences in these behavior measures between the warning light enabled and disabled periods represented the measure of effectiveness provided by the CAMS warning light. These measures were analyzed across different roadway, geometric, and situational conditions. Descriptive models using classification and regression trees were developed to better understand the influence of each factor on the driver behavior metrics.

The results indicate positive effects of the CAMS warning light on improving both of the behavioral metrics. The reaction time reduced from 2.30 s to 1.47 s (a reduction of 36%) and the response time reduced from 2.71 s to 2.16 s (a reduction of 20%). The warning light was also found to be effective in improving the likelihood of drivers encroaching beyond safe headway thresholds of 4 and 4.5 s.

Although these results seem promising, this study was limited by the small number of CAMS-equipped maintenance trucks as well as low number of warning alerts relative to the overall traffic flow during the control data-collection period, when the warning light was disabled. The effect of other potentially important factors such as visibility, precipitation, and roadway conditions could also not be assessed. Human factors such as age and gender, which are found to be effective on driver perception (*25*), were also not evaluated in this study. Nevertheless, the collective findings from this study affirm the hypothesis that even with small crash prevention rates, collision avoidance systems like MDOT's CAMS have the potential to improve important safety-related aspects of driver behavior during winter maintenance operations. Subsequent field testing is recommended before more definitive conclusions are drawn regarding the potential traffic safety impacts of the system.

Author Contributions

The authors confirm contribution of the paper as follows: study conception and design: Ali Zockaie, Timothy J. Gates; data collection: Ramin Saedi; analysis and interpretation: Rajat Verma, Ramin Saedi; manuscript preparation: Rajat Verma. All authors reviewed the results and approved the final version of the manuscript.

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