INTRODUCTION

Front-to-rear-end crashes currently represent approximately one fourth of all collisions. For 1995, the National Safety Council reported that of approximately 10.7 million motor vehicle crashes, 2.8 million were rear-end crashes, about 26.5% of the total (National Safety Council, 1996). According to the General Estimates System and Fatal Analysis Reporting System, in 1995 there were approximately 2.05 million police-reported rear-end crashes (National Safety Council, 1996). These crashes constituted approximately 28% of all police-reported crashes but only about 4.3% of all fatalities. Although many injuries and fatalities are caused by rear-end crashes, such crashes also cause approximately 157 million vehicle-hours of delay annually, which is approximately one third of all crash-caused delays.

Several driver-performance factors contribute to rear-end collisions: driver inattention, perception/reaction time, and perceptual thresholds. Driving an automobile is a complex task that requires the operator to scan the environment and respond properly in order to maintain control, avoid obstacles, and interact safely with other vehicles. Driver inattention is a particularly important factor that can undermine driving performance. Knipling et al. (1993) estimated that driver inattention accounted for 64% of all police-reported rear-end crashes. Inattention associated with following a vehicle too closely represents the cause of 14% of all crashes. The remaining causal factors include alcohol (15%), poor judgment (2%), encroachment of other vehicles (3%), and poor visibility (5%).

Because rear-end crashes account for such a large percentage of automobile crashes, and...
because inattention is the most frequent cause of these crashes, there has been considerable research into the possibility of alerting inattentive drivers to potential collision situations (An & Harris, 1996; Dingus, Jahns, Horowitz, & Knipling, 1998; Hirst & Graham, 1997; Knipling et al., 1993; McGehee, 1995; Shinar, Rothenberg, & Cohen, 1997; Sidway, Fairweather, Sekiya, & McNitt-Gray, 1996). A number of different rear-end collision avoidance systems (RECASs) are under development by Japanese, European, and U.S. automobile manufacturers, in addition to the evaluation efforts sponsored by the National Highway Traffic Safety Administration (NHTSA). These systems all use different algorithms to trigger a driver warning and different displays to present the warning.

The purpose of a collision warning system is to provide drivers with sufficient time to react in a collision situation, so the algorithm that determines the timing of the collision warning is critical. It is essential that the algorithm trigger a warning far enough in advance for the driver to have sufficient time to react without striking another vehicle. However, for a RECAS system to be used and trusted, it is also essential that the warning is not triggered too early in situations that do not pose a hazard to the driver. McGehee, Brown, Wilson, and Burns (1998) found that in situations where there is a possibility of colliding with a stationary vehicle, a warning that provides the driver with more time to react reduces the likelihood of a collision. McGehee et al. also found that a collision warning system that leaves too little time to react results in more collisions than does no system. This result implies that the sooner the driver is warned, the less likely it is that a collision will occur.

However, this conclusion is based on the assumption that a situation exists in which a warning should be given. The problem is that the earlier a warning is provided, the less certain it is that the situation will actually require the driver to act to avoid a collision. Thus the earlier a warning occurs, the greater the chance that it may be interpreted as a nuisance alarm and, therefore, desensitize the driver to future system warnings (Seller, Song, & Hedrick, 1998).

By changing the timing strategy of the warning from early, to avoid all crashes, to a later warning that would prevent only some collisions, it would be possible to develop a system that would produce fewer nuisance alarms. Such a system would seek to warn drivers who fail to react in a collision situation, providing them only with the opportunity to minimize the severity of the impact. This might be a reasonable goal for a collision avoidance system (Seller et al., 1998), given that such systems seek not only to eliminate crashes but also to reduce impact speeds. However, a system developed to accomplish this goal would not provide the driver with sufficient warning to avoid most collisions. It would minimize the number of nuisance alarms but would provide less opportunity to improve safety.

The trade-off between safety and nuisance alarms argues for a careful analysis of the joint performance of the algorithm and the driver. Our objective is to examine this joint performance in different collision situations with a variety of algorithm parameters and driver characteristics. A variety of algorithms can be used to trigger warnings: The two main types are kinematics based and perceptual based. Kinematics-based algorithms trigger warnings using the basic laws of motion. Combining assumptions of deceleration and reaction time with a vehicle’s current state, the algorithm determines a minimum distance required to stop safely. When the vehicle is less than or equal to this distance from another vehicle, a warning is triggered. With perceptual-based algorithms, however, the warning trigger is based on perceptual thresholds such as critical expansion rate or $\tau$ (D. N. Lee, 1976). When the human perceptual threshold is crossed, it triggers a warning to the driver. Because the two types of algorithms make fundamentally different assumptions and behave differently when implemented, we examine each type separately.

First, we consider a kinematics-based algorithm currently under development by NHTSA (Burgett, Carter, Miller, Najm, & Smith, 1998). This algorithm accounts for initial speed, vehicle decelerations, and driver reaction times and includes a safety buffer between the two vehicles. The second algorithm uses a time-to-collision
threshold, with an adjustment for vehicle speed (Hirst & Graham, 1997). The details of these algorithms will be provided in the Method section.

To understand how an algorithm influences RECAS/driver performance, the first issue to consider is the range of conditions for which the algorithm can provide meaningful warnings. Some algorithms may not function properly under all conditions. Analysis of algorithm performance over a range of operating conditions deepens understanding of the algorithm and identifies opportunities for improvement. If conditions exist under which the algorithm does not provide a benefit, this analysis will identify them.

A second issue concerns how variations of the algorithm parameters affect the RECAS-driver system. It is not clear what values are acceptable for the algorithm parameters. For example, how is performance affected if the time-to-collision threshold associated with the time-to-collision algorithm is 3 s rather than 4 s? Answering this question will demonstrate the range of parameters under which the system will function effectively as well as indicate which parameter performance of the RECAS-driver system is most sensitive.

The third issue concerns the effect of driver response variations on RECAS-driver system performance. This will address whether each driver-algorithm system functions appropriately over a range of driver responses, including variations in reaction time to the warning and in degree of deceleration. Understanding the effect of these variations will dictate how best to set the algorithm parameters to account for differences between drivers and to compensate for driver performance limits.

Algorithms can be evaluated using a range of techniques, including models, operator-in-the-loop simulations, and on-road evaluations. Driver-in-the-loop simulation and on-road evaluations provide the most valid estimate of RECAS effectiveness; however, such tests can be expensive and time consuming, particularly if many algorithms are being tested.

Models offer an attractive alternative, but there is a confusing range of model types that vary in complexity and determinism. Potential types of models for evaluating RECAS algorithms include deterministic simulation using a simple driver model, Monte Carlo-type simulation using a simple driver model, and Monte Carlo-type simulation using a complex model of the driver. Each of these model types addresses different questions.

Deterministic simulation using a simple driver model addresses questions about the underlying structure of an algorithm and reveals how a range of conditions would affect its ability to warn the driver in a timely fashion. The Monte Carlo simulation with the simple human model addresses the effects of a representative distribution of initial conditions and driver reaction times on system performance and on the incidence of nuisance alarms (Shinar et al., 1997). Monte Carlo-type simulation using a complex model of the driver, one that includes a detailed description of human information-processing characteristics, addresses questions regarding the interaction between various perceptual and attentional factors of the driver and the warning algorithm.

Each model type examines a different set of RECAS-driver constraints and considerations. Each approach to evaluating algorithms is important, and this paper examines the kinematic constraints of collision situations using a simple deterministic driver model. A simple model provides an economical and expeditious means of clarifying research issues for future model-based and empirical evaluations. The simple, deterministic model reveals how kinematic constraints affect driver-RECAS performance when response variability is ignored. Incorporating that variation could alter the predictions; however, a deterministic representation often provides a useful first approximation.

Figure 1 shows the simple model used in the analyses presented in this paper. It consists of four components. Two of the components are vehicle dynamics blocks that model the behavior of the lead and following vehicles. The third component is the driver. The driver is modeled as a reaction time delay followed by a step response input to the brake. The step brake response is indicative of emergency braking in which a constant brake pressure is applied to stop the vehicle. Finally, the RECAS component is the warning system. In this block, the warning algorithm determines when the driver should be warned. When the warning
threshold is crossed, a warning is sent to the driver, who then initiates braking solely in response to the warning.

The general purpose of this analysis is to develop a deeper understanding of the driver/algorithm interaction. This understanding can help guide the design of expensive human-in-the-loop simulator studies. It can also reveal ways of improving RECAS warning algorithms without running expensive experiments. These analyses address four basic questions:

How do driving situations affect algorithm performance?

How do algorithm parameters affect its performance?

What are the implications of variations in driver response?

What are the benefits of RECAS?

**METHOD**

The model used for these analyses was developed using Simulink 3.0 and MATLAB 5.3 (MathWorks Inc., Natick, MA). All parameters relating to the model components are controllable. This analysis assumes a very simple model of the driver. The transfer function that relates the driver’s braking response to the warning activation includes a reaction-time delay followed by a step function deceleration in response to a warning. The lead and following vehicles brake to a stop based on a basic kinematics model that does not consider the subtle considerations of tire-roadway interaction and brake fade. MATLAB solves the differential equations associated with this model using the Bogacki-Shampine algorithm (MathWorks Inc., 1999). A 4.2-ms maximum time step was selected, and data were written to a file every two time steps, producing a data point at least once every 8.3 ms (120 Hz).

The Kinematics Constraints with Safety Margin (KCSM) Algorithm (Burgett et al., 1998), which is currently under evaluation by NHTSA, and the Time-to-Collision with Speed Penalty (TTCSP) Algorithm (Hirst & Graham, 1997) were both analyzed. Table 1 shows the variable and subscript definitions.

The KCSM algorithm has been refined through a series of studies (Burgett et al., 1998; McGehee, 1995; McGehee et al., 1998) by developing kinematics-based algorithms for three zones of initial conditions: In Zone I the lead vehicle is stopped at the time of the warning; in Zone II the lead vehicle stops before the following vehicle does; and in Zone III the following vehicle stops before the lead vehicle does (Burgett et al., 1998). In Zones II and III, the equations assume that the vehicles are initially traveling at the same speed. Different algorithms apply for each of the three zones.

If different algorithms are to be triggered based upon the zone, then the boundaries separating the zones must be defined. The equations for these boundaries, derived by Burgett et al. (1998), are provided below. These equations define the zone in which the driver is operating and the basis for switching between algorithms. The following equation defines the boundary between Zones I and II. When the current time headway is greater than \( T_h \) from Equation 1, then the driver is in Zone I; otherwise it is in either Zone II or III.

\[
T_h = \frac{1}{2} V_0 \left( \frac{1}{d_L} + \frac{1}{d_F} \right) + \frac{2.0}{V_0} + RT \tag{1}
\]

The boundary between Zones II and III is

\[
T_h = \frac{1}{2} V_0 \left( \frac{1}{d_L} - \frac{1}{d_F} \right) + \frac{2.0}{V_0}. \tag{2}
\]
If the current time headway is less than the $T_h$ from Equation 1 and greater than the $T_h$ from Equation 2, then the driver is in Zone II. If the current time headway is less than the $T_h$ from Equation 2, then the driver is in Zone III.

For Zone I, the warning equations are

$$ R_W = \frac{V_0^2}{2d_F} + RT \times V_0 + 2.0, \quad \text{and} \quad (3) $$

$$ \frac{dR_W}{dt} = V_0. \quad \text{(4)} $$

For Zone II, the following equations define the warning range and range rate.

$$ t_W = \frac{1}{2}V_0 \left( \frac{1}{d_L} - \frac{1}{d_F} \right) + (T_h - RT) - \frac{2.0}{V_0} \quad \text{(5)} $$

$$ R_W = R_0 - \frac{1}{2} d_L t_W^2 \quad \text{(6)} $$

$$ \frac{dR_W}{dt} = -d_L t_W \quad \text{(7)} $$

For Zone III, the equations for warning range ($R_W$) and range rate ($dR_W/dt$) remain the same as for Zone II, but the equation for $t_W$ is altered.

$$ t_W = \left[ \frac{d_f - d_L}{d_F} \right] \left[ \frac{2(V_0 T_h - 2.0)}{d_L \left(1 - \frac{d_L}{d_F}\right)} \right]^{1/2} - RT \quad \text{(8)} $$

The zones associated with each algorithm identify the timing and the range of a warning given a set of initial conditions. It is an underlying assumption of this algorithm that in Zones II and III the vehicles are initially traveling at the same speed. It is important to note that collision avoidance in Zone III is predicated upon the ability of the following vehicle to decelerate faster than the lead vehicle. For additional details about this algorithm, see Burgett et al. (1998).

The first analyses showed that upon initiation of lead vehicle braking, some initial conditions constituted situations in which the warning should have been triggered at a range greater than the current range between the vehicles. In such situations, the time to warning ($t_W$) is negative. Because the warning range is determined by squaring $t_W$, the algorithm will treat a negative time to warning as a positive time to warning, resulting in a warning that is delayed in proportion to the severity of the situation. To alleviate this problem, when the calculated $t_W$ was negative, it was then set

<table>
<thead>
<tr>
<th>TABLE 1: Variable and Subscript Definitions</th>
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<tr>
<td><strong>Variable</strong></td>
</tr>
<tr>
<td>$R$</td>
</tr>
<tr>
<td>$V$</td>
</tr>
<tr>
<td>$t$</td>
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<tr>
<td>$d$</td>
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<tr>
<td>$RT$</td>
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<tr>
<td>$dR/dt$</td>
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<tr>
<td>$g$</td>
</tr>
<tr>
<td>$T_h$</td>
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<tr>
<td>$TTC$</td>
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<td>$SP$</td>
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<table>
<thead>
<tr>
<th><strong>Subscript</strong></th>
<th><strong>Description</strong></th>
</tr>
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<tbody>
<tr>
<td>$0$</td>
<td>Initial, $t = 0$</td>
</tr>
<tr>
<td>$F$</td>
<td>Following</td>
</tr>
<tr>
<td>$L$</td>
<td>Lead</td>
</tr>
<tr>
<td>$W$</td>
<td>Warning</td>
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</table>
to zero in order to produce a more functional kinematics-based algorithm.

Hirst and Graham (1997) approached RECAS warnings from a perceptual basis. They examined pure time-to-collision-based (TTC-based) warnings using different display formats for the warning. They concluded that a TTC-based warning should be augmented with a speed penalty to achieve appropriately timed warnings. This type of algorithm, they suggested, would minimize nuisance alarms but still issue an alarm if the vehicles got too close, even at small relative velocities. Hirst and Graham suggested that the TTC threshold be set to 3.0 s with a speed penalty (SP) of 0.4905 m for each kilometer per hour of following vehicle speed (1 foot/mile/h). Equation 9 shows the warning algorithm.

\[ R_w = \text{TTC} \times \frac{dR}{dt} + \text{SP} \times V_f \]  
(9)

**Independent Variables**

The independent variables examined in this study were severity of collision situation (initial headway time and deceleration of the lead vehicle), algorithm parameters (assumed deceleration of the following vehicle \([A1_d]\), assumed reaction time of the driver \([A1_RT]\), time-to-collision threshold \([A2_TTC]\) and speed penalty \([A2_SP]\), and characteristics of the driver (actual deceleration of the driver and actual driver reaction time). These independent variables were systematically manipulated in eight analyses. Ranges and specific values used in the simulation model were chosen based on a review of the literature. The details of these analyses are summarized in Table 2.

Ranges and specific values used in the simulation model were chosen based on previous findings. Examining a realistic range of driver characteristics is essential to understanding how the RECAS-driver system responds. The two main driver characteristics are reaction time and deceleration. Reaction time varies greatly between drivers and situations. A good estimate of the mean reaction time in a rear-end-collision situation is 1.2 to 1.5 s, with a maximum reaction time of 2.5 s (McGehee, 1995). Others studies have found 1.6 s to be an upper limit of reaction time to a road hazard (Lerner, 1993; Wilson, 1987). In a simulator study of inattentive drivers and RECAS, a mean reaction time of 2.5 s was found for drivers without a system, whereas having RECAS resulted in shorter reaction times (1.9 and 2.3 s; McGehee et al., 1998).

What constitutes reasonable values for the deceleration depends on the situation. In this study, where imminent collisions are being examined, drivers will respond as they would in an emergency situation. Realistic decelerations for an emergency-braking situation range from 0.40 g (low end of emergency braking) to 0.85 g (maximum braking with antilock brakes). A re-examination of the data obtained by McGehee et al. (1998) confirmed that this is a reasonable range. Their data showed an overall mean deceleration of 0.50 g, a mean maximum deceleration of 0.75 g, and an overall maximum deceleration of 0.86 g.

It takes approximately 300 ms for a human to redirect attention from one task to another (Klapp, Kelly, & Netick, 1987; Pashler, 1998). Therefore, compared with the situation in which the driver receives an alert, with no alert, 300 ms must be added to account for the time taken to redirect attention to the roadway and determine that the vehicle ahead is slowing or stopped. This provides a conservative estimate of the benefit of a RECAS, as some inattentive drivers will require more than 300 ms to return their attention to the roadway.

A total of 2574 conditions were examined. To address these questions using human participants would have required at least 20 672 participants (8 per condition) for a between-subject experimental design.

**Dependent Measures**

The goal of the rear-end collision warning algorithm is to prevent collisions. As relative velocity at the time of a collision is a measure of both collisions and their severity, it is an appropriate measure for evaluating algorithm effectiveness. Where a collision does not occur, the velocity is 0 m/s.

**Comparison with Driver-in-the-Loop Simulator Results**

To validate this model, data obtained from it were compared with data obtained from a
<table>
<thead>
<tr>
<th>Question</th>
<th>Analysis</th>
<th>Driving and Initial Conditions</th>
<th>Algorithm or Response</th>
<th>Number of Conditions</th>
</tr>
</thead>
<tbody>
<tr>
<td>What conditions are too severe for the algorithm to prevent a collision?</td>
<td>1</td>
<td>$d_L = 0.40$ $0.85(0.05)\quad d_F = 0.75\quad T_h = 1.00 \ 3.00(0.25)\quad V_0 = 56.32, 88.51\quad RT = 1.5$</td>
<td>KCSM $A_{df} = 0.75\quad A_{RT} = 1.5$</td>
<td>360</td>
</tr>
<tr>
<td>How do the algorithm parameters affect performance in avoiding the rear-end collision?</td>
<td>2</td>
<td>$d_L = 0.5\quad d_F = 0.75\quad T_h = 1.00 \ 3.00(0.25)\quad V_0 = 56.32, 88.51\quad RT = 1.5$</td>
<td>KCSM $A_{df} = 0.75\quad A_{RT} = 1.0 \ 2.5(0.1)$</td>
<td>180</td>
</tr>
<tr>
<td></td>
<td>3</td>
<td>$d_L = 0.5\quad d_F = 0.75\quad T_h = 1.00 \ 3.00(0.25)\quad V_0 = 56.32, 88.51\quad RT = 1.5$</td>
<td>TTCSP $A_{TTC} = 3.0\quad A_{SP} = 0.0\quad 1.4716(0.123)$</td>
<td>288</td>
</tr>
<tr>
<td></td>
<td>4</td>
<td>$d_L = 0.5\quad d_F = 0.75\quad T_h = 1.00 \ 3.00(0.25)\quad V_0 = 56.32, 88.51\quad RT = 1.5$</td>
<td>TTCSP $A_{TTC} = 2.0 \ 5.0(0.25)\quad A_{SP} = 0.4905$</td>
<td>216</td>
</tr>
<tr>
<td></td>
<td>5</td>
<td>$d_L = 0.5\quad d_F = 0.75\quad T_h = 1.00 \ 3.00(0.25)\quad V_0 = 56.32, 88.51\quad RT = 1.5$</td>
<td>TTCSP $A_{TTC} = 3.0\quad A_{SP} = 0.4905$</td>
<td>234</td>
</tr>
<tr>
<td>What are the implications if the driver response varies?</td>
<td>6</td>
<td>$d_L = 0.5\quad d_F = 0.40 \ 0.85(0.05)\quad T_h = 1.00 \ 3.00(0.25)\quad V_0 = 56.32, 88.51\quad RT = 1.5$</td>
<td>KCSM $A_{df} = 0.75\quad A_{RT} = 1.5\quad TTCSP$</td>
<td>360</td>
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<tr>
<td></td>
<td>7</td>
<td>$d_L = 0.5\quad d_F = 0.75\quad T_h = 1.00 \ 3.00(0.25)\quad V_0 = 56.32, 88.51\quad RT = 1.0 \ 2.5(0.1)$</td>
<td>KCSM $A_{df} = 0.75\quad A_{RT} = 1.5\quad TTCSP$</td>
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<tr>
<td></td>
<td>8</td>
<td>$d_L = 0.40 \ 0.85(0.05)\quad d_F = 0.75\quad T_h = 1.00 \ 3.00(0.25)\quad V_0 = 56.32, 88.51\quad RT = 1.8$</td>
<td>KCSM $A_{df} = 0.75\quad A_{RT} = 1.5\quad TTCSP$</td>
<td>360</td>
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Note: The numbers in parentheses indicate the increment between conditions. $d_L$ and $d_F$ given in g; $T_h$, RT, and TTC given in seconds; SP given in m/km/h; $V_0$ given in km/h.
controlled operator-in-the-loop simulator study examining emergency braking in response to a rear-end collision warning. The mean decelerations and brake reaction times for 154 participants in a study examining the KCSM warning algorithm were used as inputs to the model. The deceleration profiles and outcomes predicted by the model were then compared with those of the 154 participants. Three sets of inputs were considered. The first input set consisted of 154 pairs of reaction time and mean deceleration measures, one pair for each participant. The second input set contained eight pairs of reaction time and mean deceleration measures, one pair for each of the eight conditions used in the simulator study. The third input set involved a single pair of reaction time and mean deceleration measures, which was the grand mean over all conditions. The conditions examined were two levels of velocity (56.32 km/h [35 miles/h] and 88.51 km/h [55 miles/h]), two levels of situational severity (1.7 s headway with 0.4 g lead vehicle deceleration and 2.5 s headway with 0.55 g lead vehicle deceleration), and two levels of assumed deceleration (0.4 and 0.75 g, both with 1.5 s reaction time and a 2-m [6.67-foot] buffer).

The data were compared at two levels: deceleration profile and outcome. A correlation compared each driver’s deceleration profile with the profile produced by the model. One correlation was calculated for each of the three sets of model inputs. For the first correlation, the model input was each driver’s reaction time and mean deceleration. This comparison examined how closely the delay followed by a step response braking profile of the model matched the driver’s data. The second correlation used the condition means to determine how well a model using such means and ignoring individual differences can explain individual driver responses. The third correlation used the overall mean reaction time and deceleration of the drivers to address the question of how well a model using overall means that ignore the specific driving conditions and individual differences explains individual driver’s responses.

An overall correlation was determined for each of the three models by transforming each corresponding correlation to a z score, averaging the z score, and then back-transforming the z score into a correlation (Neter, Wasserman, & Kutner, 1985). The predicted outcome of the model – collision or no collision based on each driver’s reaction time and mean deceleration – was compared with the simulator study to determine how accurately the model can predict outcomes where individual drivers are involved. (This comparison was not done using either the condition means or the grand means, as that would have required comparing a dichotomous value from the model with the condition average of a dichotomous value – e.g., comparing either a collision or no collision outcome with percentage of collisions in a condition.) Comparing the model output with the actual deceleration profiles and collision/no collision outcomes show how well the model predicts the joint RECAS-driver collision avoidance behavior.

**RESULTS AND DISCUSSION**

The output of the simulation is a time history of each condition. This history includes the velocities, positions, and deceleration rates of the lead and following vehicles; the range and range rate; time to collision; and the state of the warning (present or absent). This data were then reduced to provide the velocity at collision (the primary dependent measure). Timeline plots of two sets of data are shown in Figures 2 and 3. The first plot, Figure 2, is an example of a condition in which a crash occurs. Figure 3 is an example of a timeline in which no crash occurs. Each of these plots represents one of the 2574 conditions considered in the eight analyses.

Many of the analyses confirmed prior expectations of how the system would behave. These intuitive results can be summarized briefly. First, with these RECAS algorithms, the frequency and severity of collisions is greater at higher speeds than at lower speeds. Second, as lead vehicle deceleration increases, so does the frequency and severity of collisions. Third, longer initial headways generally result in less-severe collisions. Results that differ from these general findings will be discussed in the following sections.

**How Do Driving Situations Affect Algorithm Performance?**

The question of how driving situations affect algorithm performance was addressed by
varying headway, speed, and lead vehicle deceleration for both algorithms. For this analysis, the KCSM algorithm parameters are fixed at $A_{1_{\text{df}}} = 0.75 \text{ g}$ and $A_{1_{\text{RT}}} = 1.5 \text{ s}$. The TTCSP parameters are fixed at $TTC = 3.0 \text{ s}$ and $SP = 0.4905 \text{ m/km/h} (1 \text{ foot/mile/h})$. The driver parameters are fixed at $d_{\text{f}} = 0.75 \text{ g}$ and $RT = 1.5 \text{ s}$.

**KCSM algorithm.** At both 56.32 km/h (35 miles/h) and 88.51 km/h (55 miles/h), no crashes occurred when the initial headway was 1.75 s or greater. At 1.5 s headway and below, the number and severity of collisions increased as initial headway was reduced.

It is clear that with the algorithm parameters $A_{1_{\text{df}}} = 0.75 \text{ g}$ and $A_{1_{\text{RT}}} = 1.5 \text{ s}$, a driver would be unable to avoid a collision under certain combinations of small headway times and moderate to high levels of lead vehicle deceleration at initial speeds of both 56.32 and 88.51 km/h. Therefore, even with the RECAS warning, headway times of 1.00, 1.25, and 1.50 s produce situations so severe that the algorithm does not enable the driver to avoid a collision.

**TTCSP algorithm.** At 56.32 km/h (35 miles/h), no collision occurred when the initial headway was greater than 2.5 s, and there were no collisions at lower lead vehicle decelerations when the initial headways were between 2.0 and 2.5 s. At 88.51 km/h (55 miles/h), collisions did occur at most combinations of initial headway and lead vehicle deceleration, with the exception of small initial headways and low lead-vehicle decelerations. It is clear that with the algorithm parameters $A_{2_{\text{TTC}}} = 3.0 \text{ s}$ and $A_{2_{\text{SP}}} = 0.4905 \text{ m/km/h} (1 \text{ foot/mile/h})$, the algorithm does not perform well under many combinations of decelerations and initial headways.

Figures 4 and 5 show a surprising effect of initial headway: At higher speeds, shorter initial headways lead to fewer collisions, whereas at lower speeds, longer initial headways lead to fewer collisions. As can be seen in Figure 4, at 56.32 km/h (35 miles/h) there were no collisions when the headway was 2.75 or 3.00 s. Generally, as headway gets shorter the collision velocity increases, although there is exception for 1.00-s headway when the lead vehicle decelerates at less than 0.7 g and for 1.25-s headway when the lead vehicle decelerates at less than 0.5 g. However, at 88.51 km/h (55 miles/h), when the lead vehicle decelerated at 0.4 g, a 3.00-s headway produced the greatest collision velocity whereas, a 1.00-s headway produces the smallest collision velocity. Figure 5 shows that as lead vehicle deceleration increases, longer headways begin to produce relatively lower collision velocities. However, even when the lead vehicle decelerated at 0.85 g, a 1.00-s headway still resulted in lower collision velocities than did a 2.00-s headway, although a 3.00-s headway resulted in the lowest collision velocity.

**Discussion.** Several general observations can be made concerning situational severity. First, certain combinations of headways less than 1.75 s and lead-vehicle decelerations...
greater than 0.5 g result in conditions too severe for the kinematics-based algorithm to provide drivers with sufficient warning to avoid a collision. Second, larger headways produce more severe collisions when the TTCSP algorithm is used for high-speed collision situations. Because one goal of collision avoidance systems is to encourage larger following distances, the TTCSP algorithm could undermine safety in such situations. Finally, with the TTCSP algorithm, collisions were unavoidable for almost all combinations of initial speed, initial headway, and lead vehicle deceleration, suggesting a mismatch between the values of the algorithm parameters and assumptions regarding driver response.

How Do Algorithm Parameters Affect Performance in Avoiding Rear-End Collisions?

This question was addressed by varying the headway, speed, and algorithm parameters associated with the following vehicle deceleration ($d_{f}$) and assumed driver reaction time ($A_{1\text{RT}}$), TTC ($A_{2\text{TTC}}$) and SP ($A_{2\text{SP}}$). The results reveal how different parameter values affect the performance of KCSM and TTCSP algorithms. For this analysis, the driver parameters are fixed at $d_{f} = 0.75$ g and $RT = 1.5$ s. The lead vehicle deceleration ($d_{L}$) was set to 0.50 g.

KCSM algorithm. The assumed deceleration of the following vehicle ($A_{1\text{df}}$) will be examined first. At both 56.32 and 88.51 km/h, the driver avoids collisions when $A_{1\text{df}}$ is less than that produced by the simple driver model (0.75 g). At 56.32 km/h (35 miles/h), when the $A_{1\text{df}}$ exceeds the deceleration of the following vehicle by more than 0.05 g, the vehicles collide. At 88.51 km/h (55 miles/h), the driver cannot avoid a collision if the $A_{1\text{df}}$ is less than the driver’s reaction time. When the vehicles collide, larger initial headway increases.

Turning to the assumed reaction time ($A_{1\text{RT}}$) of the driver at both 56.32 and 88.51 km/h, the driver avoids collisions when $A_{1\text{RT}}$ is greater than the reaction time (1.5 s) in the simple driver model. At 56.32 km/h (35 miles/h), when the assumed reaction time is 0.2 s less than the actual reaction time, collisions will occur. At 88.51 km/h (55 miles/h), the driver cannot avoid a collision if the $A_{1\text{RT}}$ is less than the driver’s reaction time. When the vehicles collide, larger collision velocities are, again, evident as initial headway increases.
To fully understand the effects of algorithm parameter selection on driver-RECAS performance, assumed deceleration and reaction time must be considered jointly. Overestimates of driver deceleration and underestimates of driver reaction time both resulted in crashes over the range of headways tested, whereas underestimates of deceleration and overestimates of reaction time did not. Additionally, larger headways, when assumed reaction time is less than the actual reaction time or the assumed deceleration is greater than the actual deceleration, result in greater impact speeds. Thus, if used in a RECAS, this algorithm would penalize safer driving (larger initial headways). For best performance, the assumed deceleration parameter of the algorithm must be less than or equal to that of the driver and the assumed reaction time must be greater than or equal to that of the driver.

Another important finding of the study is that changes in the assumed reaction time have a greater effect on performance than do changes in assumed deceleration. This has important implications for the analysis of driver response to RECAS warnings as well as for the development of more sophisticated models of driver performance. Specifically, these results suggest that a more precise estimate of a driver’s reaction time is more useful than a precise estimate of the driver’s braking profile.

**TTCSP algorithm.** The TTCSP algorithm has two parameters: the speed penalty ($A_{2_{SP}}$) and the time-to-collision threshold ($A_{2_{TTC}}$). The speed penalty will be examined first. At 56.32 km/h (35 miles/h), a penalty of 0.4905 m/km/h (1.0 foot/mile/h) is insufficient to prevent a collision for all but the 2.75- and 3.00-s headway conditions. A 0.7358 m/km/h (1.5 feet/mile/h) speed penalty is sufficient to prevent all collisions at this speed. At 88.51 km/h (55 miles/h), the algorithm is unable to prevent collisions with a 0.4905 m/km/h penalty for any of the headways tested. With a 1.0-s headway, collisions can be avoided if the speed penalty is 0.6377 m/km/h (1.3 feet/mile/h) or greater, and all collisions can be avoided with a 0.8338 m/km/h (1.7 feet/mile/h) penalty. As shown by Figures 6 and 7, the nonlinearity of the warning algorithm produces a complex relationship among headway, speed penalty, and relative velocity at collision.

Figures 8 and 9 show the results of various levels of the TTC threshold with the $A_{2_{SP}}$ set

![Figure 5](image-url). Collision severity for deceleration of the lead vehicle and initial headway times ($T_h$) from 1 to 3 s at 88.51 km/h (55 miles/h) for the TTCSP algorithm.
at 0.4905 m/km/h (1.0 foot/mile/h). At 56.32 km/h (35 miles/h), a collision cannot be avoided for any value of $A_2^{\text{TTC}}$ when the initial headway is 1.00 or 1.25 s. Larger initial headways reduce the severity and occurrence of collisions. At 88.51 km/h (55 miles/h), smaller initial headways produce less-severe crashes at TTC thresholds between 1.0 and 3.5 s, but

**Figure 6.** Collision severity for speed penalty ($A_2^{\text{SP}}$) and initial headway times ($T_h$) from 1 to 3 s at 56.32 km/h (35 miles/h) for TTCSP algorithm.

**Figure 7.** Collision severity for speed penalty ($A_2^{\text{SP}}$) and initial headway times ($T_h$) from 1 to 3 s at 88.51 km/h (55 miles/h) for TTCSP algorithm.
larger initial headways produce fewer collisions when the TTC threshold is greater than 3.5 s. It appears that a single TTC threshold cannot provide acceptable outcomes at both speeds. The nonlinearity of the warning algorithm complicates the relationship among headway, TTC threshold, and the relative velocity at collision.

Figure 8. Collision severity for TTC threshold ($A_2TTC$) and initial headway times ($T_h$) from 1 to 3 s at 56.32 km/h (35 miles/h) for TTCSP algorithm.

Figure 9. Collision severity for TTC threshold ($A_2TTC$) and initial headway times ($T_h$) from 1 to 3 s at 88.51 km/h (55 miles/h) for TTCSP algorithm.
Based upon these results, it appears that the best way to improve results with this algorithm is to vary the speed penalty ($A_{2sp}$) while leaving the TTC threshold constant. A speed penalty of 1.7 s or greater, coupled with the 3.0-s assumed TTC, would avoid collisions for the conditions tested.

**Discussion.** These results show several important findings concerning the effect of algorithm parameter selection. First, for the kinematics-based algorithm (KCSM), the assumed reaction time of the driver has greater impact on system performance than does the assumed deceleration of the following vehicle. Second, adjusting the parameters of the TTCSP algorithm had a mixed effect. It was not possible to avoid collisions by adjusting the TTC threshold only, whereas adjusting the speed penalty improved algorithm performance. Third, assuming a driver reaction time of 1.5 s, it is recommended that the TTCSP algorithm parameters be set to 3.0 s for the TTC (the initial value proposed by Hirst & Graham, 1997), and that the speed penalty be increased to between 0.8338 m/km/h and 0.9810 m/km/h to allow for a 1.5-s reaction time (Hirst & Graham proposed a 0.4905 m/km/h [1.0 foot/mile/h] speed penalty).

**What Are the Implications of Variations in Driver Response?**

This simulation uses a very simple model of driver performance that contains only two parameters: reaction time and a step response deceleration. One analysis examined deceleration at initial speeds of 56.32 and 88.51 km/h; the other examined reaction time at initial speeds of 56.32 and 88.51 km/h. These analyses were conducted for both the KCSM and TTCSP algorithms and examined the effects of variations in driver behavior on the joint driver-algorithm performance for the two algorithms. The KCSM algorithm contains two parameters related to drivers’ reaction to the RECAS warning. The $A_{1df}$ represents the assumed deceleration of the driver, and $A_{1rt}$ represents the assumed reaction time of the driver. If drivers respond exactly as assumed by the algorithm, they avoid collision. This analysis examined the effect of violating the assumptions of the KCSM algorithm. For this analysis, the KCSM algorithm parameters were

![Figure 10](image)
fixed at $A_{1df} = 0.75 \text{ g}$ and $A_{1RT} = 1.5 \text{ s}$. The TTCSP parameters were fixed at $TTC = 3.0 \text{ s}$ and $SP = 0.4905 \text{ m/km/h (1.0 foot/mile/h)}$. The deceleration of the lead vehicle ($d_l$) was set to $0.50 \text{ g}$.

**KCSM algorithm.** The effect of variations in the deceleration of the following vehicle will be examined first. It is possible to avoid collisions at both 56.32 and 88.51 km/h in all cases when the deceleration is greater than $A_{1df}$. When the deceleration is less than $A_{1df}$, a collision always occurs at 88.51 km/h (55 miles/h) and at 56.32 km/h (35 miles/h) if the headway is 1.00 s. At 56.32 km/h (35 miles/h), collisions occur with larger headways when the deceleration is less than $A_{1df}$ by more than 0.05 g.

At both 56.32 and 88.51 km/h, the vehicles did not collide if the reaction time was less than or equal to the $A_{1RT}$. At 56.32 km/h (35 miles/h) collisions occurred if the reaction time was more than 0.1 s greater than $A_{1RT}$ and the initial headway was less than 1.25 s. However, at 88.51 km/h (55 miles/h), it was not possible to avoid a collision if the reaction time was greater than the $A_{1RT}$.

The difference between following vehicle deceleration and $A_{1df}$, as well as the difference between the reaction time and $A_{1RT}$ is particularly important at higher speeds. Figures 10 and 11 show that longer headways lead to more severe crashes when following vehicle deceleration is less than $A_{1df}$ or reaction time exceeds $A_{1RT}$ at higher speeds.

These findings indicate it is essential that the algorithm does not assume the driver will react faster than is likely. If such an assumption is made and the driver relies on the system, the driver will not be able to avoid collisions at any of the initial headways that were tested for these two speeds. Moreover, collisions will be more severe with longer initial headways. For the assumed deceleration, it is better to use a warning parameter based on an underestimation, rather than an overestimation, of how fast the driver will decelerate. Overestimations will lead to collisions that are worse at longer initial headways, whereas underestimations will not; however, underestimations may lead to more nuisance alarms. Although the results are somewhat intuitive, they show that the 2-m safety margin of this algorithm is not sufficient.
to compensate for poor calibration of algorithm parameters.

TTCSP algorithm. Figures 12 and 13 show the effect of variations in driver deceleration using the TTCSP algorithm. At 56.32 km/h (35 miles/h), a collision cannot be avoided when the following vehicle decelerates at less than 0.70 g. When the following vehicle travels at 88.51 km/h (55 miles/h), a collision cannot be avoided except with 0.85-g deceleration and a 3.0-s initial headway. Again, the effects of the nonlinearity of the warning algorithm are evident in the results. These results suggest that the TTCSP assumes drivers will react faster than 1.5 s to avoid a collision.

Variations in the drivers’ reaction time have important consequences for the TTCSP algorithm. At 56.32 km/h (35 miles/h), collisions can be avoided regardless of headway if the driver’s reaction time is less than 1.5 s. As initial headway increases, the number of collisions decreases. At 88.51 km/h (55 miles/h), collisions can be avoided when the driver’s reaction time is less than 1.2 s. Interestingly, the number and severity of collisions increases as headway increases. These findings indicate that with the proposed algorithm, drivers will be able to avoid a collision in all test conditions if they can react in 1.2 s or less from warning onset. The results suggest that the TTCSP implicitly assumes a driver reaction time of 1.2 s, a value substantially shorter than the 1.5-s assumed reaction time in the KCSM algorithm. Although a 1.2-s headway may be consistent with the performance of an attentive driver, the literature suggests that a 1.5-s reaction time is more reasonable for an inattentive driver (Hankey, 1996; Lerner, 1993; McGehee, 1995; McGehee et al., 1998; Wilson, 1987). It is likely that the TTCSP algorithm was developed based on the shorter reaction time associated with an attentive driver rather than on the longer time of the inattentive driver assumed in these analyses of imminent collision situations. The analysis shows that violating this assumption severely undermines the algorithm performance.

Discussion. Two overall conclusions can be drawn about driver response to these warnings. First, overestimations of human performance (e.g., faster reaction times or greater deceleration) do not allow the driver sufficient time to avoid the collision. Second, improper selection of algorithm parameters can result in disadvantages for safe driving.
What Are the Potential Benefits of a RECAS?

The potential benefits of a RECAS were examined by comparing a driver responding to a warning with a driver returning attention to the roadway. We assumed that the driver without the warning would require an additional 300 ms to respond. The situations considered were the same as in the first analysis.

Table 3 shows the percentage reduction in collisions and collision velocity for both the KCSM and TTCSP algorithms at 56.32 and 88.51 km/h. The greatest benefit of the warning comes from the KCSM algorithm, which reduces collisions and collision velocities by more than 80%. The TTCSP algorithm produces a smaller benefit, a relatively small reduction in collision velocity (20% to 40%). This analysis shows that if the warning produces even a small decrease in response time (300 ms) for inattentive drivers, significant reductions in collisions and collision velocities can be achieved.

Comparison with Driver-in-the-Loop Simulator Results

A comparison was made between model output and actual driver performance to determine how well the model captures driver-RECAS performance in rear-end crash situations. The first question addressed was “How well does the deceleration profile obtained from the model correspond to the actual data from the

TABLE 3: Benefit Analysis

<table>
<thead>
<tr>
<th>Algorithm</th>
<th>Speed (km/h)</th>
<th>Accident Reduction</th>
<th>Collision Velocity Reduction</th>
</tr>
</thead>
<tbody>
<tr>
<td>KCSM</td>
<td>56.32</td>
<td>84.4%</td>
<td>82.7%</td>
</tr>
<tr>
<td></td>
<td>88.51</td>
<td>85.6%</td>
<td>86.0%</td>
</tr>
<tr>
<td>TTCSP</td>
<td>56.32</td>
<td>27.8%</td>
<td>44.7%</td>
</tr>
<tr>
<td></td>
<td>88.51</td>
<td>3.4%</td>
<td>21.4%</td>
</tr>
</tbody>
</table>

Figure 13. Collision severity for following vehicle deceleration and initial headway times ($T_h$) from 1 to 3 s at 88.51 km/h (55 miles/h) using the TTCSP algorithm.
When the model outputs, based on individual reaction times and decelerations, were compared with driver deceleration profiles, the mean correlation was .853, with a minimum correlation of .489 and a maximum correlation of .980 (profiles provided in Figures 14 and 15, respectively). Additionally, 75 of the braking responses from the actual drivers can be categorized as single-step braking maneuvers, and 85 are some form of modulated responses. Of those that modulated their response, many followed a step response and modulated their braking toward the end of the event. Very few drivers modulated their response in the extreme manner shown in Figure 14. This implies that the simple step response of this model matches most drivers’ deceleration response.

When the model outputs, based on the condition means, were compared with driver profiles, the mean correlation was .798, with a minimum correlation of .327 and a maximum of .980. Ignoring individual differences between participants, the model adequately captures drivers’ deceleration response, although it did not do as well as when individual driver data were used as input. This indicates that a large portion of the driver response can be explained without considering individual differences.

When the model outputs, based on the grand means, were compared with driver profiles, the overall correlation was .857, with a minimum of .243 and a maximum of .989. When both the condition and the individual driver differences are excluded from the input, the correlation remains high. This indicates that the kinematics of the situation may be the main factor, rather than the conditions or individual drivers.

These relatively high overall correlations indicate that the step function model of driver deceleration adequately describes actual driver deceleration in imminent collision situations. However, there were 19 cases with low correlations (12.3%), indicating that not all drivers respond with a step function deceleration. As shown in Figure 14, drivers often seem to modulate their brake use based on what they perceive in the environment. The model does not describe these cases accurately.

Given that the model adequately describes deceleration profiles, the next question was “How accurately does it predict collision outcomes?” For those cases where we had empirical data, the model correctly predicted 78% of the outcomes, whereas in 6% it incorrectly predicted an avoided collision and in 16% it incorrectly predicted collisions. In six cases where the model incorrectly predicted collisions, the driver changed lanes to avoid the collision. If we exclude these cases, the model correctly predicted 81% of the outcomes (in 6% it incorrectly predicted an avoided collision, and in 12% it incorrectly predicted a collision). The \( \phi \) coefficient (Siegel & Castellan, 1988) was calculated to the association between the driver outcomes and the model outcomes. The association, \( \phi = .41 \), between...
the two sets of data was found to be significant at $\alpha < .001$ for $\chi^2(1) = 22.1$. Where the model was incorrect, the cause of the discrepancy was examined. The primary causes of discrepancies included the driver traveling at a different speed than assumed by the model and deceleration profiles that differed greatly from a step function response.

Although the model does not describe all driver behaviors, the high correlation between the deceleration profiles combined with its accuracy in predicting outcomes indicates that the model is a useful tool for evaluating RECAS. This analysis suggests that improvements to outcome prediction and deceleration profiles may be best achieved by developing a better model of driver braking to address cases in which drivers’ braking profiles differ from a step function response.

**CONCLUSIONS**

This paper demonstrates the value of using a simple deterministic model to examine the various scenarios that lead to rear-end crashes. The ability of this model to analyze several critical issues without conducting operator-in-the-loop simulations saved testing of more than 2000 conditions, an impractical alternative. Addressing questions using the deterministic model provided insight into how the algorithms, drivers, and driving scenarios interact, revealing a number of subtle but important behaviors. These analyses made it possible to identify important characteristics of the algorithms that govern RECAS-driver performance. From this study, it is evident that even a simple computational model of RECAS-driver interaction can identify important design issues and guide subsequent simulator data collection (Kantowitz, 1997; Moray, 1990).

These analyses reveal a number of important implications for the design of RECAS algorithms. They define the problem space and identify the areas that need the most attention; they also provide guidance for future work on RECAS algorithms. Several general conclusions can be made concerning RECAS design. First, the model confirms that particular attention should be paid to high-speed, short-headway conditions in which the lead vehicle brakes sharply because the analyses indicate that it is under such conditions that the algorithms are least effective. Second, when selecting the algorithm parameters, it is essential that the algorithm parameters underestimate rather than overestimate driver performance. Although underestimates may lead to more false alarms, these analyses have shown that overestimations will result in collisions. Third, the TTCSP algorithm parameters should be set to 3.0 s for the TTC (the initial value proposed by Hirst & Graham, 1997) and to between 0.8339 and 0.9811 m/km/h for the speed penalty to allow for a 1.5-s driver reaction time (compared with the 0.4905 m/km/h [1.0 foot/mile/h] proposed by Hirst & Graham). Fourth, the complex, nonlinear relationship between initial
headway and collision severity for the TTCSP algorithm may generate confusing results in evaluations of this algorithm. Although particularly pronounced with the TTCSP algorithm, analyses showed that both algorithms can produce counterintuitive results, with larger headways leading to more severe collisions. This argues strongly for a careful analysis of algorithm parameters, collision situations, and driver characteristics in the design of RECAS algorithms.

These analyses can also help guide future human-in-the-loop evaluations of RECAS algorithms. Three specific findings will help in the selection of experimental conditions for future analyses. First, for the kinematics-based algorithm (KCSM), the assumed reaction time of the driver has a greater impact on system performance than does the assumed deceleration of the following vehicle. Second, if further adjustments are required to make the TTCSP algorithm operational, adjustments should be made to the speed penalty, as the TTC threshold has only a marginal effect on algorithm performance. Third, the nonlinearities and complex interactions revealed in this paper can help guide the selection of experimental conditions as well as the interpretation of results. For example, given certain conditions, more-severe collisions at longer headways would be expected. This paper demonstrates that such results should not be attributed to the complexities of driver behavior but to the kinematics of the situation. The use of this simple deterministic model served to reduce the design space to be considered and the parameters of the algorithms to be evaluated without costly human-in-the-loop experiments.

These analyses used a deterministic, simplified model of the human operator. This type of model is sufficient for answering questions about how the various components of a system work together and can also provide insight into the nature of the complex interactions between algorithms and driver performance. In this case, the model identified how various algorithm parameters and scenarios affect performance of the driver-RECAS system. As evidenced by the accuracy of the deceleration profiles in this study, a model of the environment and a very simple model of the driver can account for much of the variability in a system. Although this model is a reasonable first approximation, the addition of a more precise braking model should produce great improvements in the accuracy of outcome prediction as well as in the correlation between the deceleration profiles. In addition to this weakness, the model cannot address the effects of stochastic response, the likelihood of nuisance alarms, or the general performance of the driver-RECAS system with an undistracted driver.

Another critical aspect not included in the current model is driver compliance with the warning. Factors such as trust in the warning system could have a very large effect on the overall benefit of the system (J. D. Lee & Moray, 1992, 1994; Muir, 1987). The human model used in these analyses has low complexity and is deterministic; it does not account for the distributions associated with responses. As the complexity is increased, the model provides a more accurate representation of the manner in which the system actually functions, but it may also mask properties of other components in the model. Moving from deterministic to stochastic, the model can be used to examine variability in response, which provides a more accurate representation of how the actual system functions. However, this added realism might hide certain small differences and behaviors that may be inadvertently attributed to the stochastic features of a model. For example, subtle nonlinear difference found in this study through the deterministic model might have been attributed to normal variation in a stochastic simulation and thus discounted and ignored unless many trials were run. Although a stochastic simulation could be used to generate enough data to reduce the variability to an arbitrarily small level, it is possible that counterintuitive results might be discounted and the data might never be generated.

This paper demonstrates the value of a simple deterministic model of a human-machine system, showing that it can provide a useful description of the joint performance of the driver and the warning system that may be impractical or impossible to achieve by other means. This paper also shows that a detailed analysis of the kinematics constraints of the collision avoidance situation can help researchers avoid inadvertently attributing complex behavior to
cognitive mechanisms when it is actually the product of relatively simple interactions between the driver and the kinematics of the driving situation. More generally, this paper shows that a comprehensive analysis of the constraints of the work domain, as exemplified by our model, can explain a large amount of variance in the behavior of human-machine systems (Vicente, 1999).

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