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Contents

Foreword

The papers contained in this volume were among those presented at the 79th Annual Meeting of the Transportation Research Board in January 2000. Nearly 1,600 papers were submitted by authors; more than 1,000 were presented at the meeting; and approximately 600 were accepted for publication in the 2000 *Transportation Research Record* series. The published papers will also be issued on CD-ROM, which will be available for purchase in late 2000. It should be noted that the preprint CD-ROM distributed at the 2000 meeting contains unedited, draft versions of presented papers, whereas the papers published in the 2000 Records include author revisions made in response to review comments.

Starting with the 1999 volumes, the title of the Record series has included "Journal of the Transportation Research Board" to reflect more accurately the nature of this publication series and the peer-review process conducted in the acceptance of papers for publication. Each paper published in this volume was peer reviewed by members of the sponsoring committee listed on page ii. Additional information about the *Transportation Research Record* series and the peer-review process can be found on the inside front cover. The Transportation Research Board appreciates the interest shown by authors in offering their papers and looks forward to future submissions.

Abbreviations used without definitions in TRB publications:

AASHO	American Association of State Highway Officials
AASHTO	American Association of State Highway and Transportation Officials
ASCE	American Society of Civil Engineers
ASME	American Society of Mechanical Engineers
ASTM	American Society for Testing and Materials
FAA	Federal Aviation Administration
FHWA	Federal Highway Administration
FRA	Federal Railroad Administration
FTA	Federal Transit Administration
IEEE	Institute of Electrical and Electronics Engineers
ITE	Institute of Transportation Engineers
NCHRP	National Cooperative Highway Research Program
NCTRP	National Cooperative Transit Research and Development Program
NHTSA	National Highway Traffic Safety Administration
SAE	Society of Automotive Engineers
TRB	Transportation Research Board

Transportation Research Record 1724
Paper No. 00-1480

Cellular Telephone Conversation While Driving

Effects on Driver Reaction Time and Subjective Mental Workload

Roberto Abraham Tokunaga, Toru Hagiwara, Seiichi Kagaya, and Yuki Onodera

The effects of conversation through a cellular telephone while driving on driver reaction time and subjective mental workload (SMWL) were investigated. Two vehicles equipped with measurement devices were used to measure reaction time. The drivers' SMWL was measured by the National Aeronautics and Space Administration Task Load Index procedure. The experiment was conducted on an expressway in Japan. Thirty-one subjects participated in the experiment; 19 were young and 12 were elderly drivers. Each subject was asked to follow a leading vehicle and to keep a constant distance while following. The subjects performed four tasks: (*a*) following a leading vehicle, (*b*) operating a cellular telephone while following the leading vehicle, (*c*) performing a simple conversation task, and (*d*) performing a complex conversation task on a cellular telephone with the experimenter while following the leading vehicle. The results of these experiments indicated that the performance of the telephone tasks increases the reaction time and SMWL of the drivers, as was shown in a previous study. The results also indicated that the complex conversation task produced an increase in reaction time as compared to the simple conversation task, independent of age group. Furthermore, the experiment indicated that the SMWL also increased significantly in the complex conversation task as compared to the other tasks.

In 1996, the authors conducted an experimental study using a driving simulator developed by the Civil Engineering Research Institute of the Hokkaido Development Bureau (*1*). The primary objective of this study was to investigate how the location of a cellular telephone in a vehicle affects driver reaction time and subjective mental workload (SMWL). In the experiment, a cellular telephone with a hands-free system (HFS) was placed on the left side of the dashboard, and a cellular telephone with no HFS was placed on the front-passenger seat. The results of the experiment showed that the location of the cellular telephone significantly affected the drivers' reaction times and that the SMWL of the subjects using an HFS telephone was less than that of the subjects using a cellular telephone placed on the front-passenger seat. However, since this experiment was conducted in a driving simulator, the question remained of how driver reaction time and SMWL would be affected under real driving conditions.

Alm and Nilsson conducted a number of studies on drivers' behavior as a function of mobile telephone tasks while driving (*2, 3*). These studies were conducted in a Swedish Road and Traffic Institute driving simulator. In the most recent study, they investigated the effects of a mobile telephone task in a car-following situation on the reaction time and SMWL of the driver (*2*). They concluded that using a mobile telephone while driving had negative effects on driver behavior. However, there are, naturally, differences between the feeling of risk while driving in a simulator and that of driving on a real road, and this may affect driver behavior.

In 1997, an experimental study was conducted on an expressway (*4*). The primary objective of this study was to investigate how conversation through a cellular telephone with an HFS while driving affects driver reaction time and SMWL. Sixteen subjects participated in the experiment. Half of the subjects had experience in using a cellular telephone while driving. The number of participants was small; however, the results of that investigation indicated that conversation affects both drivers' reaction times and SMWL. Nevertheless, it could not clarify how much the driver was affected according to the conversation type.

The objectives of this study were

- To investigate whether talking through a cellular telephone while driving has negative effects on driver reaction time and SMWL according to conversation type, and
- To determine whether the reaction time and SMWL of an elderly driver using a cellular telephone while driving are better than those of a young driver.

In this study, changes in driver reaction time and SMWL were investigated as a function of conversation type. The experiment consisted of two types of conversations through cellular telephone while driving: the first an easy conversation and the other more complex. The experiment was carried out on an expressway in Hokkaido, Japan.

METHODS

Subjects

Thirty-one subjects, 22 to 65 years old, participated in the experiment. The subjects had a minimum of 3 years driving experience and traveled an average of 12 480 km annually. All subjects had previous experience using cellular telephones. Nineteen subjects (mean age, 23.95 years) were young drivers (16 male and 3 female), and the other 12 subjects (mean age, 62.75 years) were elderly drivers (all male). Table 1 shows the subject demographics.

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TABLE 1 Subject Demographics

Young Subjects	Age	Driving Exp. (years)	Annual Driving (km)
Average	23.95	5.11	12211
SD	2.78	3.07	6630
Average + SD	26.73	8.18	18840
Average - SD	21.17	2.03	5581
Subjects	19	19	19

Elderly Subjects	Age	Driving Exp. (years)	Annual Driving (km)
Average	62.75	39.17	12750
SD	2.26	3.86	5941
Average + SD	65.01	43.02	18691
Average - SD	60.49	35.31	6809
Subjects	12	12	12

Experimental Site and Vehicles

The experiment was conducted on the Central Expressway in Hokkaido in May 1999. The total length of the test section was 50.6 km, between the West-Ebetsu interchange (start and end point) and the Iwamizawa interchange (turnaround point). Most of the test section was flat and straight. One test section (25.3 km) was completed in about 20 min. Two vehicles were used in the experiment. The experiment staff drove the leading vehicle and controlled the driving speed during each experimental run. The subject drove another vehicle following the leading vehicle. Instruments installed in the leading vehicle driven by the experiment staff and the following vehicle driven by the subject measured the driver's reaction time.

Cellular Telephone with HFS

A cellular telephone with an HFS was fixed on the left side of the dashboard in the experimental vehicle driven by the subject. The HFS consisted of an external microphone and antenna. During each run, the experimenter in the leading vehicle called the subject using a cellular telephone. Figure 1 shows the cellular telephone under driving conditions.

Subjective Mental Workload

The National Aeronautics and Space Administration Task Load Index (TLX) procedure was used to estimate the drivers' SMWL (*5*). NASA-TLX is a multidimensional rating procedure that provides a global SMWL score based on the average of subjective ratings of six factors: mental demand, physical demand, time pressure, effort,

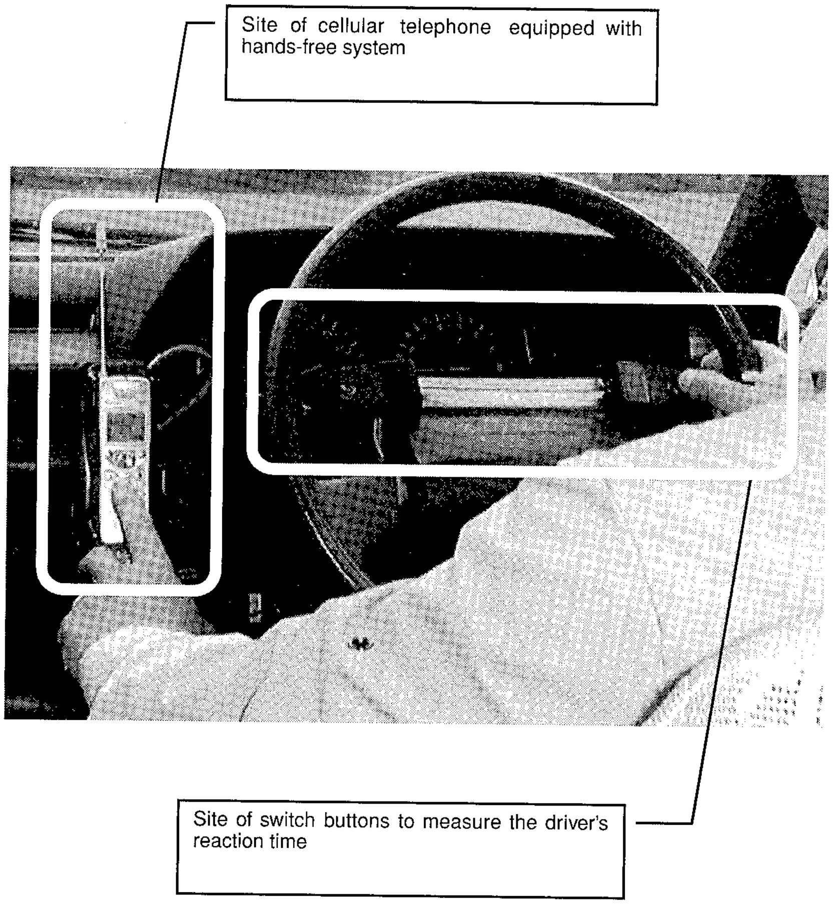

FIGURE 1 A cellular telephone with a hands-free system and switch buttons on the steering wheel to measure the driver's reaction time.

performance, and frustration. Each factor was presented as a 12-cm line with a title explanation and bipolar descriptors at each end (e.g., high/low). After driving, the subjects were asked to rate on a paper form each of these factors. Then numerical values (1 to 10) were assigned to scale positions during data analysis in the laboratory. Finally, the global SMWL rate was computed from the six ratings given by the subject.

TABLE 2 Contents of Sensor Data File

Leading Vehicle (4WD NISSAN SAFARI)	
Sampling Number	20 data per second
Time Record	hh:mm:ss
Counter	counting number
Brake Lamp	on/off

Following Vehicle (4 Door Sedan TOYOTA VISTA)	
Sampling Number	20 data per second
Time Record	hh:mm:ss
Following Distance	meters
Counter	counting number
Lateral Acceleration at the Center of Gravity (X)	G
Longitudinal Acceleration at the Center of Gravity (Y)	G
Throttling Data	volts
Braking Data	volts

Multiple Data Recording System

Reaction time is defined as the interval from the time when the emergency warning lights of the leading vehicle come on to the time when the subject presses the switch buttons installed on the steering wheel. Due to the large number of measurements required for the computation of reaction time, it was necessary to develop a multiple data recording system, as shown in Figure 2. The sampling rate of the multiple data recording system is 20 data per second. This system was installed in the subject's vehicle, and a similar system without a laser radar system was installed in the leading vehicle. Table 2 shows the data by the multiple data recording system. The computer program of the multiple data recording system integrates the data through a serial port.

The following distance—that is, the distance between the front of the following vehicle and the rear of the leading vehicle—was measured continuously by a laser radar system. The system generated short laser pulses, and it received those pulses reflected from the rear of the leading vehicle. The following distance was calculated by multiplying the travel time by the speed of light. A potentiometer was employed to monitor the position of the accelerator pedal, and a pressure sensor was employed to measure the position of the brake pedal. For accurate electronic measurements of distance of the vehicle, a transmission sensor was used. The transmission sensor generated an electrical pulse when the vehicle moved. Six pulses were generated with each revolution of the front tire. After the signals were amplified, the computer program converted them from analog to digital data. The digital data were transferred through a serial port to the multiple recording systems.

An onboard digital video camera was installed in the rear of the passenger compartment to record the driving scene and subject's voice. The emergency warning lights of the leading vehicle could

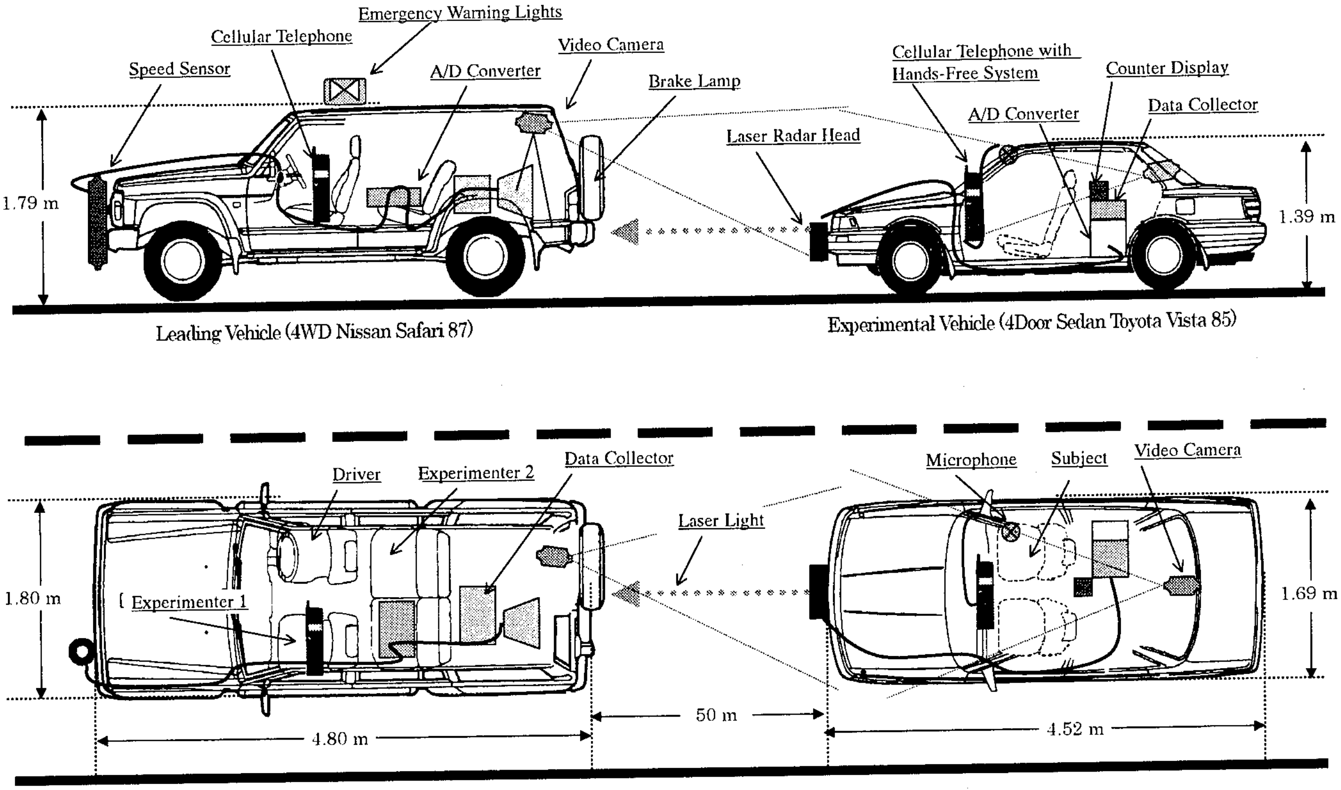

FIGURE 2 Instrumented vehicles and multiple measurement system.

be recognized in the driving scene. The driving scene contains a counter display that allows synchronization between the recording video frame and the sampling data number recorded by the multiple recording systems. The counter displays the pulse number generated by the transmission sensor.

Task and Experimental Design

The dependent variables in this study were the reaction time and the SMWL of each driver. Major independent variables were the following four tasks and the drivers' groups (elderly or young). During the experiment, an experimenter in the leading vehicle suddenly turned on the emergency warning lights during the driving task and once during the conversation task in order to measure the subject's reaction time. Each subject was required to perform the following four tasks:

- Driving task (round-trip): to drive the experimental vehicle on the test section at a constant distance behind the leading vehicle.
- Operation task (round-trip): to push the "ON" key for receiving a telephone call while performing the driving task. During the experiment, each subject received two calls from the experimenter.
- Simple conversation task (one time): to engage in a simple conversation with the experimenter over the cellular telephone while performing the driving task. The conversation was about current driving conditions and navigation of the test section (time of conversation: approximately 2 min).
- Complex conversation task (one time): to engage in a conversation with the experimenter answering a series of mathematical problems. For example: "How much is 7 + 1 − 1 + 1 + 1?" After two problems, the experimenter asked the subject to remember the first and second answers. Then the experimenter repeated the process adding one more problem (time of conversation: approximately 2 min).

Experimental Procedure

Before the experiment, the subjects were given instructions regarding their tasks. They also were allowed time to become familiar with the operation of the experimental vehicle and the cellular telephone. The subjects were instructed to maintain a distance of about 50 m behind the leading vehicle, and to use the distance between illuminated delineators along the center of the test road as a reference distance. The above-mentioned four tasks were performed during each run, and the task order was completely randomized. The driver of the leading vehicle maintained a speed of 90 km/h. The driver of the leading vehicle suddenly turned on the emergency warning lights for a period of 5 s. Each subject drove one round-trip of the test section. As soon as the run was completed, each subject was asked to rate the six SMWL factors for each of the four tasks after reading the rating scale definitions and instructions. Each subject first provided ratings on six subscales for each task. The subject also answered a few questions concerning the use of the cellular telephone system while driving.

RESULTS

Drivers' Reaction Time

Analysis of the recorded data was conducted in the laboratory after the experiment. Due to technical problems, data were not recorded for two runs involving elderly subjects, and data for only 10 of the 12 subjects in the elderly group were available for analysis.

TABLE 3 Average and Standard Deviation Values of Drivers' Reaction Time

Time (sec.)	Young Subjects			
	Task Conditions			
	Driving Task (Northbound)	Driving Task (Southbound)	Simple Conversation	Complex Conversation
Average	0.63	0.66	0.85	0.97
SD	0.20	0.26	0.40	0.35
Average+SD	0.83	0.92	1.25	1.32
Average-SD	0.43	0.40	0.45	0.62
Subjects	19	19	19	19

Time (sec.)	Elderly Subjects			
	Task Conditions			
	Driving Task (Northbound)	Driving Task (Southbound)	Simple Conversation	Complex Conversation
Average	0.76	0.61	0.82	0.99
SD	0.32	0.16	0.22	0.08
Average+SD	1.08	0.77	1.04	1.07
Average-SD	0.44	0.45	0.60	0.91
Subjects	10	10	10	10

Table 3 shows the average and standard deviation values of drivers' reaction time during the performance of driving and different conversation tasks. Drivers' reaction time during the driving task (round-trip) was less than 0.76 s. Drivers' reaction time during the simple conversation task was longer than that for the driving task. In addition, drivers' reaction time during the complex conversation task increased even more than during the simple conversation task. Thus, a negative effect was found on both groups' reaction times during telephone tasks. Moreover, the complexity of conversation directly influenced the increase in drivers' reaction time. Figure 3 shows a box-plot diagram of the drivers' reaction times. The edges of each box indicate the 25th and 75th percentiles of the data. The horizontal line in the middle of the box indicates the median of the data.

A two-way analysis of variance (ANOVA) was performed to compare the four tasks and the groups. There were no significant differences between the groups. The Tukeys pairwise multiple

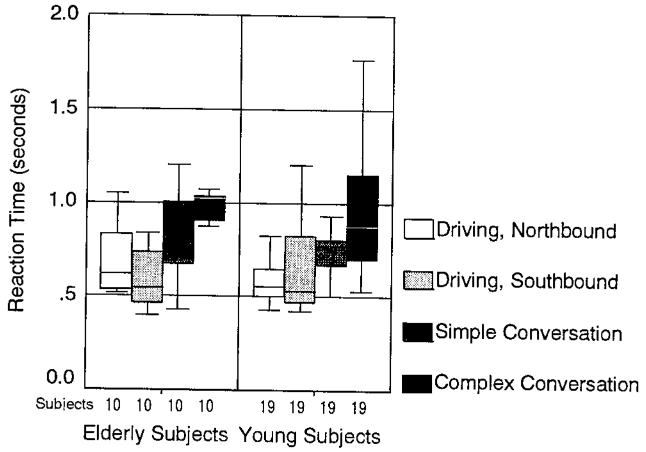

FIGURE 3 Drivers' reaction times as a function of age and task.

TABLE 4 Average and Standard Deviation Values of Drivers' SMWL

Rate (pts.)	Young Subjects					
	Task Conditions					
	Driving Task (Northbound)	Driving Task (Southbound)	Operation Task (Northbound)	Operation Task (Southbound)	Simple Conversation	Complex Conversation
Average	3.86	3.83	5.03	4.74	5.04	6.90
SD	1.68	1.84	1.93	2.01	1.90	1.69
Average+SD	5.54	5.67	6.96	6.75	6.94	8.59
Average-SD	2.18	1.99	3.10	2.73	3.14	5.21
Subjects	19	19	19	19	19	19

Rate (pts.)	Elderly Subjects					
	Task Conditions					
	Driving Task (Northbound)	Driving Task (Southbound)	Operation Task (Northbound)	Operation Task (Southbound)	Simple Conversation	Complex Conversation
Average	4.00	3.63	4.72	4.15	4.49	5.31
SD	1.32	1.24	1.57	1.50	1.43	1.79
Average+SD	5.32	4.87	6.29	5.65	5.92	7.10
Average-SD	2.68	2.39	3.15	2.65	3.06	3.52
Subjects	12	12	12	12	12	12

comparisons method was performed to see the differences among pairs. There were significant increases in drivers' reaction times between the southbound driving task and the simple conversation task and between the round-trip driving task and the complex conversation task.

Drivers' SMWL

Analysis of drivers' SMWL from NASA-TLX data was conducted in the laboratory after the experiment. Table 4 shows the average and standard deviation values of drivers' SMWL points rated on driving and different telephone tasks. Drivers' SMWL values for the driving task (round-trip) were less than 4.00 points in both groups. Young and elderly drivers' SMWL values for the operational task (round-trip) were bigger than that of the driving task. Meanwhile, drivers' SMWL values for the simple conversation task were close to their operational task. Finally, drivers' SMWL values for the complex conversation task increased more than that of the simple conversation. Nevertheless, elderly drivers' SMWL value for the complex conversation task was less than that of the young drivers' SMWL value. Thus, a significant effect was found on both drivers' SMWL for telephone tasks, and the complexity of conversation directly influenced drivers' SMWL. Figure 4 shows a box-plot diagram of the drivers' SMWL. The edges of each box indicate the 25th and 75th percentiles of the data. The horizontal line in the middle of the box indicates the median of the data.

A two-way ANOVA was performed to compare the six tasks and the groups. There were significant differences in the variation pattern between the groups [F (5, 145) = 3.254, P-value < 0.05]. The Tukeys pairwise multiple comparisons method was performed to see the differences among pairs of tasks. There were no significant differences except for the increase in drivers' SMWL for the complex conversation task as compared with the other tasks.

DISCUSSION OF RESULTS AND CONCLUSION

In this study, driver reaction time and SMWL were investigated as a function of conversation type and age group. The results of this study showed that using a cellular telephone while driving had negative effects on driver reaction time and SMWL, as was shown in a previous study conducted in 1997. The drivers' reaction times were longer in both groups while performing the complex conversation

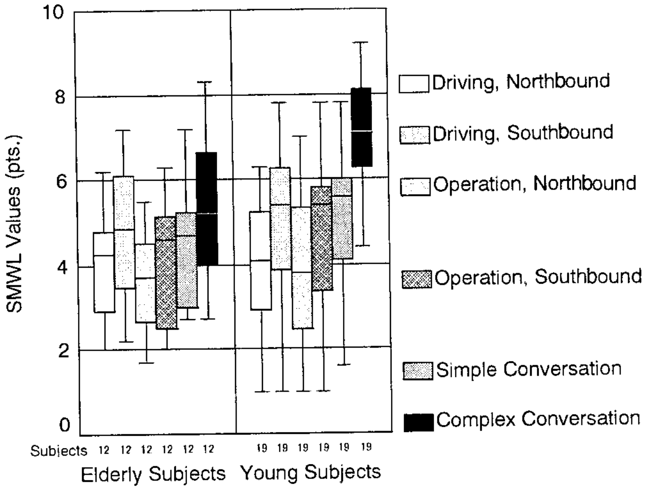

FIGURE 4 Drivers' SMWL as a function of age and task.

task than while performing the simple conversation task. Furthermore, for both age groups the SMWL increased significantly in the complex conversation task as compared to the other tasks.

The authors predicted that cellular telephone use as a function of two types of conversation while driving would increase elderly drivers' reaction times and SMWL more than that of the young drivers. However, there was no significant difference between the increment of elderly drivers' reaction times and SMWL and that of young drivers. The elderly drivers' performance may have been related to extensive annual driving distance and driving experience. In addition, it should be noted that the elderly drivers participating in this experiment were carefully selected for safety according to driving experience and psychophysics capabilities.

Conversation more complex than that used in this study could increase the driver reaction time and SMWL even further. In this study, the experiments were conducted under limited conditions. Thus, further investigations are needed.

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Paper No. 00-1453

Aggressive Driving and Road Rage Behaviors on Freeways in San Diego, California

Spatial and Temporal Analyses of Observed and Reported Variations

Sheila Sarkar, Alanna Martineau, Mohammad Emami,
Mohammad Khatib, and Karen Wallace

The California Highway Patrol in San Diego County receives cellular telephone calls reporting unsafe driving. The content of the calls varies, with drivers complaining about speeding cars driving over 161 km/h (100 mph) and other drivers weaving and cutting off or tailgating. In some cases, the driving conditions were even more volatile with drivers describing harassment, assaults with a weapon, or running other vehicles off the road. There were about 1,987 reported incidents from the freeways of San Diego for the months of April, June, and September 1998. The information received by the dispatchers was tabulated and put into five different categories. Analyses indicated that 24.6 percent of the calls were for "Aggressive Driving 1" (speeding plus some other behavior, such as unsafe lane changes or passing); "Aggressive Driving 2" (weaving and cutting) was reported most frequently (27.1 percent of all calls); about 12.5 percent of the calls were for "Aggressive Driving 3" (tailgating); "Speeding Alone" calls comprised 19.8 percent of the total; and the rest were for "Road Rage" (16.1 percent). Of the 1,987 calls, 33 percent were generated on Interstate 5, the busiest and longest in the county, followed by Interstate 15, which accounted for 22 percent of the calls. The high number of calls can be attributed to the high average daily traffic volumes at each interchange and the longer interstate lengths. Similarly, Interstate 8 seemed to have a lower number of calls than expected, because the urban portion of the freeway is not as long and the remaining distance had fewer vehicles at each interchange. This was further corroborated and both volume and length were robustly correlated with the number of phone reports per freeway. Additionally, chi-square tests indicated that the time of the day and day of the week influenced the type and number of calls received.

This paper analyzes the data set that consists of reports made by drivers on their cellular telephones. Drivers often call in to report various types of transgressions that they observe on the San Diego, California, freeways. These include traffic violations, excessive speeding, threats, and verbal assaults. Data were compiled for 3 months (April, June, and September) of 1998 within San Diego County. This is with the exception of 5 consecutive days in April for which the data were unavailable (April 11–15).

All calls (1,987 incidents) made to the California Highway Patrol (CHP) dispatchers reporting perceived driving transgressions were included in these analyses. Callers would report the driving behaviors that they felt were dangerous. The reported incidents were assigned a computer-aided dispatch (CAD) number, a reference number for CHP records. Other information recorded was date, time, location, type of offense, and, sometimes, a description. The information provided in the CAD records then was classified for analysis under six categories: speeding, tailgating, running vehicles off the road, weaving, cutting vehicles off, and other. The applicable categories were checked off and if any additional information was provided above and beyond that accounted for by the categories, a description also was recorded. Table 1 shows an example of the compiled data.

This paper investigates both the frequency and patterns for aggressive driving and road rage on the freeways of San Diego County. The problem of aggressive drivers has been around for a long time. In 1968, Parry wrote an entire book about aggression on the road (*1*).

Although the two terms "aggressive driving" and "road rage" often have been used interchangeably, the National Highway Traffic Safety Administration (NHTSA) has chosen to separate them into two disparate categories. There has been little consensus in the literature thus far as to an adequate definition of these terms. Connell and Joint state that road rage can be used to refer to anything from "any exhibition of driver aggression" (*2*, p. 27) to roadside assault (including murder). In some cases, aggressive driving is seen as a traffic offense and road rage is seen as a criminal offense (*3*). In a presentation at the Aggressive Driving Conference (October 19, 1998, Los Angeles, California), Richard Compton gave a specific definition of aggressive driving as a combination of certain traffic offenses. Aggressive driving has been said generally to include excessive horn honking, running red lights, traffic weaving, tailgating, headlight flashing, braking excessively, excessive speeding, profanity or obscene gestures, and blocking the passing lane. NHTSA describes road rage as the more extreme cases of aggressive driving (*3*).

The types of behaviors included under these umbrella terms often vary and it is not necessarily useful to take a checklist approach. This is especially true in the case of road rage if it is to be considered a "criminal offense." Joint similarly has referred to road rage in a broad sense as any display of aggression by a driver but also suggests that the term often is used to refer to the more extreme acts of

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TABLE 1 Example of Recorded Information for Five Cellular Telephone Reports, June 1, 1998

CAD #	Date	Time	Location	Speeding	Tailgating	Running vehicle off road	Weaving	Cutting vehicle off	Other	Description
111	6/1/98	0711	SB 805 JNO Palm Ave.	1			1			In and out of traffic
183	6/1/98	0831	NB 805 JNO EB 94						1	Throwing objects at vehicle
246	6/1/98	0950	SB 5 JSO Via De La Valle	1					1	Slamming brakes in front of vehicle
351	6/1/98	1218	SB 805 JSO Telegraph Canyon Rd		1		1			Unsafe lane changes
352	6/1/98	1215	SB 15 JSO Mission Rd.				1			In and out of traffic

NOTE: The reported information was sometimes relevant to more than one category, and in some cases a description also was provided. JNO = just north of; JSO = just south of; NB = northbound; SB = southbound; and EB = eastbound.

aggression (*4*). The line between aggressive driving and road rage is even blurrier, with Mizell's definition stating that aggressive driving is "an incident in which an angry or impatient motorist or passenger intentionally injures or kills another motorist, passenger, or pedestrian, or attempts to injure or kill another motorist, passenger, or pedestrian, in response to a traffic dispute, altercation, or grievance" (*5*, p. 5). Ellison-Potter et al. indicate that aggressive driving is any driving behavior fueled by frustration, anger, or both, that psychologically and physically endangers others whereas road rage refers to the more extreme and psychopathological cases of aggressive driving involving homicidal intent (*6*). Shinar has used the frustration aggression model that was first proposed by Dollard et al. in 1939 (*7*, *8*). According to him, aggressive driving is a syndrome of frustration-driven behaviors enabled by a driver's environment. These behaviors can either take the form of "instrumental aggression," which allows the aggressive driver to move ahead at the cost of infringing on other road users' rights (weaving, cutting, running red lights), or "hostile aggression," which is directed toward the object of frustration (*7*, *9*).

Obviously, both aggressive driving and road rage need to be operationally defined in such a way that they can be used both for practical and legal purposes. From a legal perspective, *mens rea* or the state of mind at the time of an offense is an essential factor to consider for criminal prosecution (*6*). If the distinction between aggressive driving and road rage includes a traffic versus criminal offense differential, the definition of these terms should in some sense address the state of mind of the perpetrator. First and foremost, "road rage" as the term implies is associated with a state of anger or hostility directed at some driver. This may not necessarily be true of aggressive driving. This paper proposes that aggressive driving be described as driving that is intentionally inconsiderate of other drivers (i.e., negligent), as Shinar describes, intentionally infringing on the rights of others (*7*). This type of driving is not directed at any one individual, but rather toward other drivers in general. For example, this would include such behaviors as weaving and cutting, passing on shoulders, and following too closely. The intentional component of this definition precludes certain types of actions from being classified as aggressive driving. Thus, if a driver makes a lane change and does not see a vehicle in the next lane, this driver may inadvertently cut someone off. This would not be considered aggressive. This driver is inattentive and probably would be apologetic for the action. Someone who is driving aggressively, however, would not feel apologetic because he or she is intentionally ignoring the rights of others on the road. That is not to say that these actions differ in terms of dangerousness. However, if the victim in this scenario realizes that the act was unintentional, he or she might be less likely to retaliate against this inattentive driver. One of the most detrimental consequences of aggressive driving is that it may cause another driver to become angry and retaliate—a stage that would be considered road rage.

Whereas aggressive driving is directed toward other drivers in general, road rage is considered to be directed toward a specific driver. The driver exhibiting road rage also is clearly, intentionally inconsiderate of other drivers' rights. However, the road rager—unlike the aggressive driver—is targeting a particular individual. As implied earlier, aggressive driving may instigate retaliation and thus a state of road rage. Anger is a necessary condition of road rage but not of aggressive driving, and road rage further includes an intent to cause emotional or physical harm. Road rage therefore would include behaviors such as running a vehicle off the road, throwing objects at a vehicle, threatening another driver, assaulting another driver, using a vehicle as a weapon, and directing verbal threats or obscene language toward another driver. Note that behaviors such as tailgating or slamming brakes in front of another vehicle could be considered either road rage or aggressive driving, depending on the circumstances. For example, if a driver exhibits weaving, cutting, and tailgating as a pattern in general, then this would be considered aggressive driving. Conversely, if a driver is cut off by someone and retaliates by following this individual too closely (i.e., tailgating), this would be considered road rage. Similarly, if a driver frequently weaves in and out of traffic and slams on the brakes, the behavior would fall into the aggressive-driving category. If, however, a driver slams on the brakes to retaliate against someone following too closely, the behavior would be considered road rage. By this line of reasoning it can be seen that inattentive driving, aggressive driving, and road rage are each dangerous in their own right. However, it is especially important to note that aggressive driving can very easily result in anger and retaliation and thus escalate to road rage.

Because this paper discusses incidents of aggressive driving and road rage according to these definitions, the offense category information is used to form five new categories (see Figure 1). In some cases, the information available for a particular phone call is not suf-

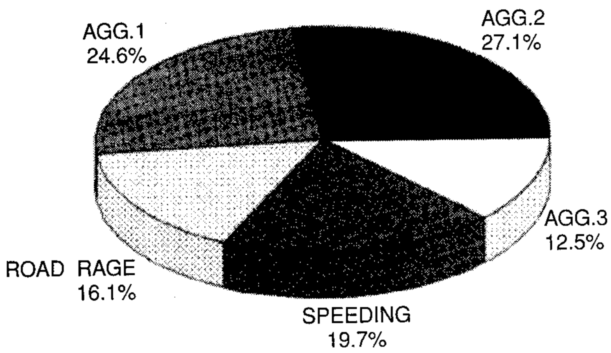

FIGURE 1 Percentage of cellular telephone calls reported for the five categories (AGG. = aggressive driving; 1 = speeding plus other unsafe activity; 2 = weaving or cutting; 3 = tailgating).

ficient to determine whether the incident is aggressive driving or road rage. Furthermore, when the call is merely reporting something such as excessive speeding, by these definitions the incident cannot necessarily be classified as aggressive driving. If someone is just speeding and there are no other drivers in his or her path, then the behavior is not necessarily inconsiderate of others. Of course, this is open to debate. It might be that someone speeding excessively is inconsiderate in the sense that even if traffic is minimal, the speeder is still putting others at risk and therefore is inconsiderate of others' rights on the road. Because of this ambiguity, isolated reports of speeding are put into their own category. This category is considered a type of aggressive driving because this reported speeding behavior probably was accompanied by some other aggressive act, although this is not certain. The category was labeled "Speeding Alone" and there were 393 calls (19.7 percent of all calls) reporting incidents of this type for the months of April, June, and September 1998.

On a related note, aggressive driving that involved speeding with any other type of transgression was labeled "Aggressive Driving 1." This means that the report was speeding and one or more of the other categories (unsafe lane changes, unsafe passing). There were 489 such incidents (24.6 percent) reported by callers from the freeways of San Diego.

Another very frequent pattern of aggressive driving is drivers weaving and cutting through traffic. This type of incident likely occurs during times of major congestion and therefore is less likely to involve speeding. For this reason, a separate category labeled "Aggressive Driving 2" included incidents of reported weaving or cutting or both, without any mention of speeding. There were 537 calls (27 percent) reporting such incidents.

The final category for aggressive driving ("Aggressive Driving 3") consists of incidents that reported tailgating. Tailgating is a more severe form of aggressive driving, and in some cases these reports probably are referring to incidents of road rage, although this cannot be determined from the information available. There were 248 incidents (12.5 percent) of Aggressive Driving 3.

The last category is for incidents that could not be classified as aggressive driving and are assumed to be primarily incidents of road rage. Any reported incidents of running vehicles off the road were included in this category, as were any incidents that were only checked off as "other." Furthermore, some of the reports were not placed into any of the original offense categories (see Table 1) so are included in this final category as well. This category was labeled "Road Rage" and there were 320 incidents (16 percent) of this type.

The description data (see Table 1) were coded and aggregated into five content categories. The first pertains to unsafe lane changes and is labeled as such. It consists of reports such as "all over the road," "swerving," and "using all lanes to pass." This type of description was significantly correlated with incidents of Aggressive Driving 1—$r(1{,}987) = .33$, $p < .001$—and with Aggressive Driving 2—$r(1{,}987) = .12$, $p < .001$. This makes sense, of course, because both of these categories contain incidents related to unsafe lane changes. The second content category pertains to inappropriate passing and contains statements such as "passing on the shoulder, center divide, turn lanes, and across double solid lines." This type of comment also was significantly correlated with Aggressive Driving 1—$r(1{,}987) = .12$, $p < .001$—and Aggressive Driving 2—$r(1{,}987) = .12$, $p < .001$. The third content category contains descriptions related to speeding, such as large vehicles speeding or estimates of speed, most of which were "90+" (i.e., 90 mph or more, or over 145 km/h) or "100+" (over 161 km/h). This type of description was significantly correlated with Aggressive Driving 1—$r(1{,}987) = .14$, $p < .001$—and, intuitively, these descriptions were strongly correlated with the Speeding Alone category—$r(1{,}987) = .52$, $p < .001$.

The fourth category contained descriptions that were incidents of road rage. These were "harassing or threatening others verbally," "using rude language or gestures," "flashing high beams or headlights," "honking," "slamming on brakes in front," "preventing others from passing," "threatening others with a weapon" (e.g., knife, gun, throwing objects), "firing shots," "hitting vehicles with objects," "hitting other vehicles with vehicle," "chasing another vehicle," "trying to run someone down," and "trying to run someone off the road." It should be clear that all of these descriptions are considered road rage because they appear to be targeting a particular individual and are not incidents of aggressive driving in general. There was a robust correlation between these descriptions and the category Road Rage—$r(1{,}987) = .42$, $p < .001$. Road rage originally was just considered an "other" category but it was reclassified to Road Rage because most of the incidents in the category contained descriptions that were consistent with the stated definition of road rage. And finally, the last description category contained reports that were somewhat miscellaneous. These included "racing, playing chicken or other games," "motorcycle stunting," "trying to cause an accident," "almost hitting someone," "running red lights," and "hit-and-run" incidents. These descriptions also were significantly correlated with the Road Rage category because of the large proportion of road rage descriptions—$r(1{,}987) = .11$, $p < .001$.

SPATIAL ANALYSES OF CELL PHONE CALLS

The spatial analyses of the cellular telephone calls show that 33 percent of the calls are reporting incidents on Interstate 5, followed by Interstate 15, which generates about 22 percent of the calls, whereas Interstates 8 and 805 have about 12 and 11 percent, respectively (see Table 2 and Figure 2). The fact that over 70 percent of the calls are generated by these four freeways is not surprising because they are the major freeways, particularly Interstate 5, which is the oldest and longest (127 km, or 79 mi) and has the heaviest volumes [average daily traffic (ADT) of more than 160,000 vehicles per day at each interchange]. The remaining 30 percent of the calls come from all the other freeways and highways in San Diego County, and most of them (except CA-78) report less than 5 percent of the total incidents.

TABLE 2 Spatial Distribution of Calls

Freeways	Frequency	Percent
5	655	33.0
15	448	22.5
8	241	12.1
805	213	10.7
78	121	6.1
163	68	3.4
94	57	2.9
not a freeway	43	2.2
52	40	2.0
215 *	37	1.9
67	27	1.4
74*	10	.5
125	9	.5
76	4	.2
54	4	.2
79	3	.2
56	2	.1
905	2	.1
165	1	.1
212	1	.1
70	1	.1
Total	1987	100.0

* not in San Diego County but the calls were received by San Diego CHP Dispatch Office

ANALYSES OF AGGRESSIVE DRIVING BEHAVIORS REPORTED BY CALLERS

The purpose of this paper is to compare the frequency and patterns of aggressive driving behaviors reported by callers on the four major freeways (Interstates 5, 15, 8, and 805) that generate the highest number of calls (Figure 2). Figure 3 shows the freeway map for San Diego. As mentioned earlier, calls reported to CHP dispatchers for the months of April, June, and September were aggregated under the following categories: Aggressive Driving 1 (speeding and some other behaviors), Aggressive Driving 2 (weaving and cutting), Aggressive Driving 3 (tailgating), Speeding Alone, and Road Rage (Figure 1). In general, Aggressive Driving 2 and Aggressive Driving 1 were the most frequently reported. Speeding Alone was reported about 20 percent of the time with the majority of the callers reporting estimated speeds of over 161 km/h (100 mph). But the fact that 12 percent and 16 percent of the calls were reporting some hostile behaviors toward other drivers (Aggressive Driving 3 and Road Rage, respectively) is important. Figure 4 provides a breakdown of the types of driving behaviors observed in the four main freeways (5, 15, 8, and 805). The percentage breakdowns for the freeways closely correspond to the overall percentages but there are some differences. Interstates 8 and 805 have fewer Speeding Alone incidents than either Interstate 5 or Interstate 15. There are, however, proportionately more Road Rage and tailgating (Aggressive Driving 3) reported on Interstate 8 compared to the other types of behaviors.

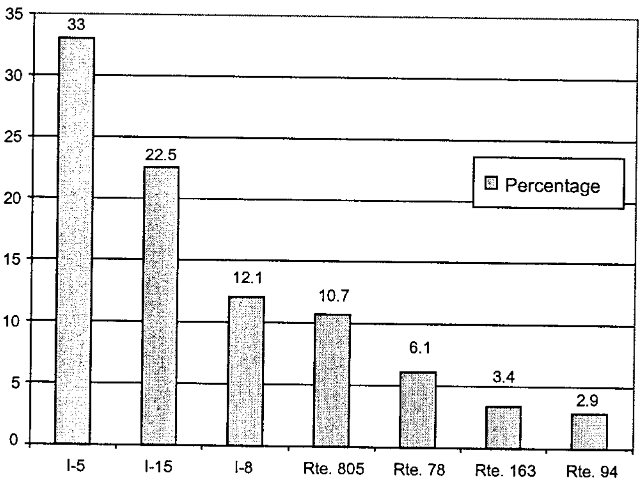

FIGURE 2 Frequency of calls by freeways.

COMPARISON OF EXPECTED AND OBSERVED VARIATIONS IN DRIVING BEHAVIORS FOR FOUR FREEWAYS

Chi-square tests were done to estimate if the reported incidents for each of the five categories—Aggressive Driving 1, 2, 3, Speeding Only, and Road Rage—would be equal to the expected number for each of the four freeways. The tests showed the following: Aggressive Driving 1 (speeding and some other offense) was much higher in I-5 and I-15—$\chi^2(3) = 82.8$, $p < .001$. Aggressive Driving 2 (incidents of weaving and cutting) was much higher than expected in I-5—$\chi^2(3) = 72.2, p < .001$. For Speeding Alone, the chi-square was significant—$\chi^2(3) = 98.4, p < .001$—because of a disproportionately large number of reports for I-5. The other behaviors, Aggressive Driving 3 and Road Rage, were either lower or almost equal to the expected number of calls.

EXPECTED VERSUS OBSERVED NUMBER OF INCIDENTS IN FOUR FREEWAYS BASED ON LENGTHS OF FREEWAYS

There is significant variation in the lengths of the four freeways that are being analyzed within San Diego County. The longest freeway within the county is Interstate 8 (124 km or 77 mi), followed by Interstate 5 (116 km or 72 mi), Interstate 15 (87 km or 54 mi), and Interstate 805 (47 km or 29 mi). Typically, chi-square tests use expected values by dividing the total number of observations by the number of groups (e.g., 1,987 observations by 4 groups). However, the length variation among the freeways of interest is an important factor when comparing these freeways. The disparities in length were taken into account in the chi-square tests that were done to assess whether the observed and estimated numbers of incidents reported were proportional to the lengths of the freeways. To do this, the percentage distribution for each of these freeways was derived. These percentages were used to arrive at the estimated number of incidents for all incidents together and for each category.

VARIATIONS IN TYPES OF INCIDENTS BY FREEWAYS

The chi-square test indicates that the number of incidents reported for each freeway differed significantly from the expected numbers even when the length of the freeway was taken into account—$\chi^2(3) = 280.6, p < .001$. Our analyses showed that Interstate 5 had

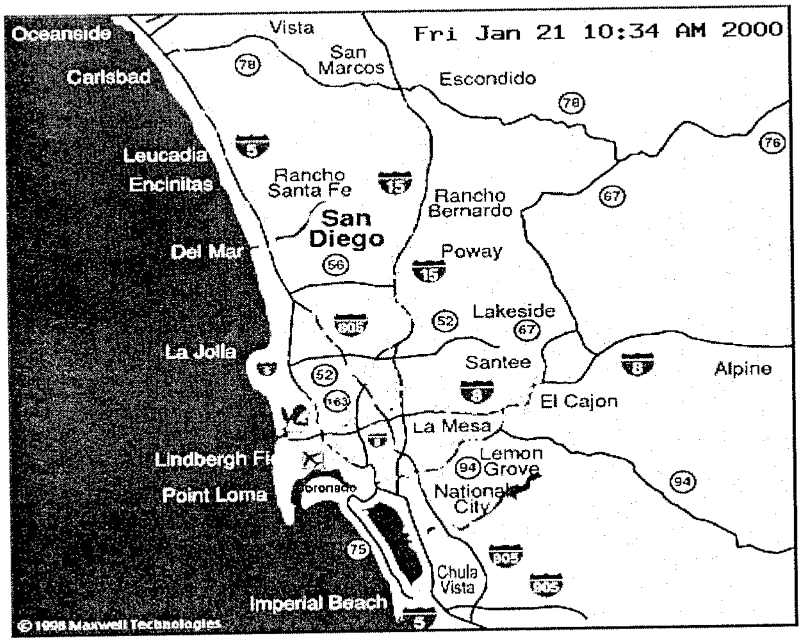

FIGURE 3 Freeway map of San Diego.

considerably more incidents when the lengths were considered. Interstates 15 and 805 also had higher numbers when length was taken into account. Interstate 8, however, had a lower number of incidents reported when length is taken into account.

For Aggressive Driving 1 incidents, the chi-square test indicated that observed values differed significantly from expected values based on length—$\chi^2(3) = 93.6$, $p < .001$. In particular, there were many more incidents reported for Interstate 5 than expected ($O = 177$, $E = 114$), slightly more for Interstate 15 ($O = 109$, $E = 91$), little difference for Interstate 805 ($O = 29$, $E = 22$), and less than expected for Interstate 8 ($O = 36$, $E = 71$).

This pattern of residuals was observed for all five classifications of driving, and chi-square tests indicated that for Aggressive Driving 2, Aggressive Driving 3, Speeding Alone, and Road Rage, observed values were significantly different from expected values based on length. These data suggest that taking length into account does not ameliorate the discrepancies in the proportion of total reported incidents for these four freeways.

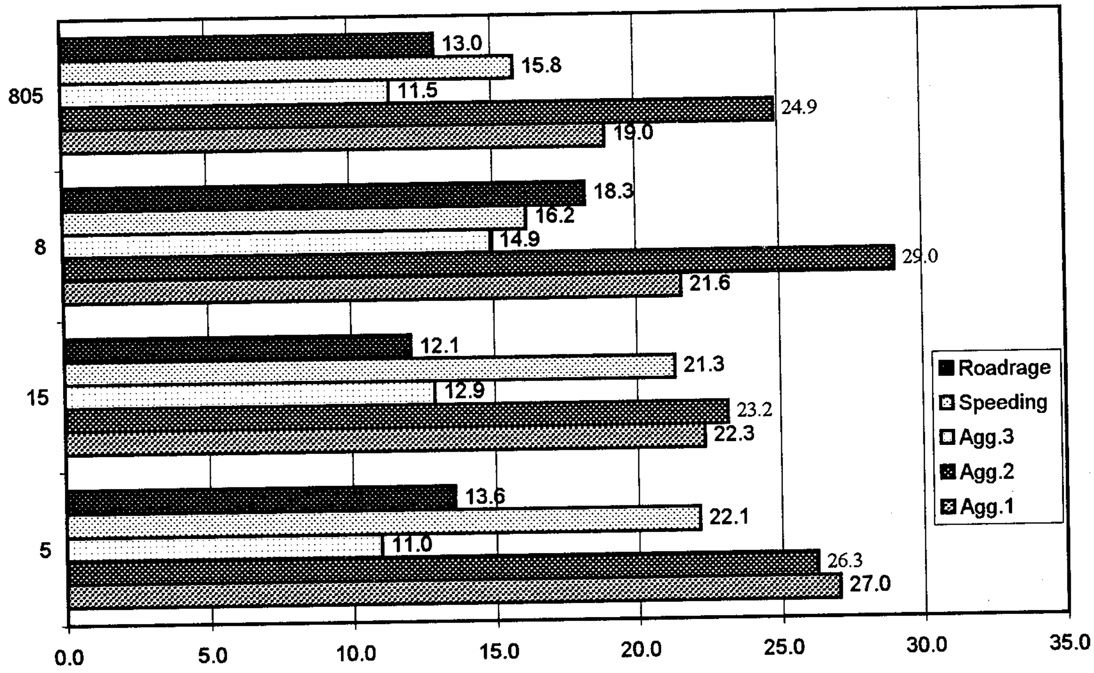

FIGURE 4 Breakdown of aggressive driving and road rage categories for Interstates 5, 15, 8, and 805.

It was felt that traffic volume on the freeway is an important factor to take into account when discussing the number of incidents reported. Therefore, other freeway data are included to assess the relationship among incidents, length, and traffic volume. Although the majority of this paper has focused on the four freeways, this analysis includes the cell phone reports from the 10 most frequently reporting freeways in San Diego County (see Table 2).

ADT data are available from the California Department of Transportation (Caltrans) in San Diego County. Averages over a year are reported for each interchange on the freeways. These data were used to compute an overall average volume for each interchange for the 10 freeways. Both volume—$r\ (10) = .69$, $p < .029$—and length—$r(10) = .77$, $p < .001$—were robustly correlated with the number of phone reports per freeway.

The above analysis explains why Interstate 8 has a lower than expected number of incidents. The urban section of Interstate 8, where the volumes at each interchange are more than 183,000, is only 27 km (17 mi); another 11 km (7 mi) has a volume of 60,000 vehicles per day for each interchange; and for the remaining length the volume drops sharply to 14,000 vehicles per day. For the same reason, Interstate 5 has more than expected incidents, as this long stretch of freeway has more than 160,000 vehicles per interchange.

VARIATION IN AGGRESSIVE DRIVING AND ROAD RAGE BEHAVIORS BY TIME OF YEAR

To estimate if there were any differences in the types of behaviors reported by the time of the year, a chi-square test was done for comparing June and September after combining Aggressive Driving 1, 2, and 3 and leaving Speeding Alone and Road Rage as separate categories (note: April was excluded because of the missing data). There were no differences in aggressive driving behaviors between June and September—$\chi^2(1) = 0.052$. For Speeding Alone, the chi-square test was not significant—$\chi^2(1) = 3.247$, $p = 0.072$—and for Road Rage, the chi-square was significant—$\chi^2(1) = 5.258$, $p = 0.022$.

VARIATION IN BEHAVIORS BY TIME OF DAY

To estimate whether the different types of aggressive behaviors categorized here varied by time of day, chi-square tests were done to assess the variations. Phone calls for Aggressive Driving 1 (speeding and some other behavior) were found to be higher between 9 a.m. and 9 p.m., with the highest number of calls reporting such incidents being from noon to 3 p.m. ($O = 111$, $E = 61.1$) and 3 to 6 p.m. ($O = 110$; $E = 61.1$)—$\chi^2(7) = 216$, $p < .001$. Reports of Aggressive Driving 2 (weaving and cutting) were quite high between 9 a.m. and 6 p.m., and the 3 to 6 p.m. time period ($O = 154$; $E = 67.1$) had the highest number of reported incidents, which corresponds with the peak hours of travel—$\chi^2(7) = 260$, $p < .001$. Aggressive Driving 3 (tailgating) was highest between 12 noon and 6 p.m.—$\chi^2(7) = 99.7$, $p < .001$. Speeding Alone incidents reported were higher than expected between 12 noon and 3 p.m., followed by 3 to 6 p.m. and 9 a.m. to 12 noon—$\chi^2(7) = 100.5$, $p < .001$. Road Rage incidents were reported more frequently during the 3 to 6 p.m. time period ($O = 90$; $E = 40$); the number of reports was marginally greater from noon to 3 p.m. and 6 to 9 p.m.—$\chi^2(7) = 143.6$, $p < .001$.

Chi-square tests were significant indicating that each freeway did exhibit differences in the driving behaviors based on time of day. The time period when aggressive driving, speeding, and road rage were reported most was 3 to 6 p.m. for all four freeways. Aggressive driving in general was reported more often between 9 a.m. and 6 p.m. (for convenience, all three types of aggressive driving categories were combined for this analysis). Interstates 5 and 15 had significant variations for aggressive driving by time of day—$\chi^2(7) = 192.3$, $p < .001$, and $\chi^2(7) = 111.1$, $p < .001$, respectively—with the highest reported for 3 to 6 p.m.

VARIATIONS IN BEHAVIORS BY DAY OF WEEK

The chi-square tests indicated that the number of calls varied by the day of the week for all incidents together and in each category (see Table 3). The number of calls was greater than expected on Fridays, followed by Wednesdays. Sunday had a lower than expected number of calls, followed by Monday and Saturday. For each separate category the trends were similar to the overall pattern with minor differences. Thursday generated a higher number of calls for Aggressive Driving 1 (speeding and something else). Aggressive Driving 2 (weaving and tailgating) was unusually high on Fridays.

CONCLUSIONS

This paper offers a spatial analysis (by major freeways) of aggressive driving behavior patterns that driver-callers report to CHP dispatchers. It also brings into focus the fact that the perception of endangerment due to aggressive driving and speeding is high. It is

TABLE 3 Residuals for Chi-Square Tests

Driving Category	Monday	Tuesday	Wednesday	Thursday	Friday	Saturday	Sunday	Expected
Aggressive 1	-13.9	.1	-10.9	16.1	21.1	-3.9	-8.9	**69.9**
Aggressive 2	-13.7	6.3	9.3	2.3	40.3	-7.7	-36.7	**76.7**
Aggressive 3	-2.4	3.6	-.4	7.6	8.6	-3.4	-13.4	**35.4**
Speeding Alone	-15.1	.9	14.9	-12.1	11.9	4.9	-5.1	**56.1**
Road Rage	-14.7	-.7	16.3	1.3	14.3	-5.7	-10.7	**45.7**
ALL INCIDENTS	-59.9	10.1	29.1	15.1	96.1	-15.9	-74.9	**283.9**

significant that at least 30 incidents are reported each day when only 10 percent of the people report such acts. A separate study done by Sarkar using employees in San Diego found that 1 out of 10 drivers called in aggressive behaviors.

Discussion of the frustration-aggression model by Dollard et al. (*8*) and Shinar's premise that congestion could be a contributing factor to aggression (*7*) can be partially proven by the authors' findings—that the type of behaviors that are reported vary and increase spatially and temporally. More research and study need to be conducted on this.

It is important to note that the information offered by the callers to the dispatchers is voluntary, making these data unique and useful. The fact that drivers define clearly when and where their driving conditions were being compromised by someone else can be very useful in defining aggressive driving and predicting the precursors to violent confrontations on freeways. The authors are planning to use these data to predict if certain sections of the freeways receive more calls than others.

The caller information used here to conduct the analyses exists in every city, and the San Diego Transportation Management Center (TMC) should be commended for taking the leadership in tabulating these data and providing the information to the California Institute of Transportation Safety for analysis. Similar endeavors are encouraged at other TMCs. Data such as those used in this paper are valuable to researchers and law enforcement and could be used in many ways, such as developing good public awareness and education campaigns. If similar data are compiled longitudinally for a certain number of years, then researchers and professionals could predict trends as well as determine spatial variations in unsafe driving patterns by time of day and day of week. The development of "smart highways" and the efficient use of law enforcement depend on a strong information base. The authors urge TMCs to work closely with local transportation safety research institutes to develop a useful database that would make it easier to understand, define, and predict spatial and temporal variations in aggressive driving.

ACKNOWLEDGMENTS

The authors would like to thank the California Office of Traffic Safety for sponsoring the Cool Operator program in San Diego County to increase awareness and educate drivers about aggressive driving. The information is analyzed in this paper to improve the education campaign in the county. The authors thank the Transportation Management Center of Caltrans for providing the data for analysis. They also would like to thank Kathleen Russell for her assistance with this paper. Special thanks is extended to Richard Compton, who presented a paper at the Aggressive Driving Conference in October 1998 in Los Angeles. Additionally, the authors would like to acknowledge Patricia Ellison-Potter for very insightful discussions on this subject in April 1999.

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Attention-Based Model of Driver Performance in Rear-End Collisions

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Several driver-performance factors contribute to rear-end collisions—driver inattention, perception-reaction time, and limitations of the human visual system. Although many evaluations have examined driver response to various rear-end collision avoidance systems (RECAS) display and algorithm alternatives, little research has been directed at creating a quantitative model of driver performance to evaluate these alternatives. Current considerations of driver behavior in developing warning algorithms tend to ignore the fundamental problem of driver inattention and assume a fixed driver reaction time with no further adjustment after the initial response. A more refined model of driver response to rear-end crash scenarios can identify more appropriate and timely information to be displayed to the driver. An attention-based rear-end collision avoidance model (ARCAM) is introduced that describes the driver's attention distribution, information extraction and judgment process, and the reaction process. ARCAM predicts the closed-loop nature of collision response performance and explains how the driver might use RECAS warnings.

Rear-end collision avoidance systems (RECAS) may help alleviate an important traffic safety problem. Front-to-rear-end crashes involving two or more vehicles currently represent approximately one-fourth of all collisions. Specifically, the National Safety Council reported that there were approximately 11.3 million motor vehicle crashes in 1995, of which 2.7 million were rear-end crashes (about 23.8 percent of the total) (*1*). According to the General Estimates System and Fatal Accident Reporting System, in 1992 there were approximately 1.4 million police-reported rear-end crashes. These rear-end crashes constituted approximately 23 percent of all police-reported crashes, but only about 4.7 percent of all fatalities. Beside the injuries and fatalities caused by rear-end crashes, rear-end crashes also cause approximately 157 million vehicle hours of delay annually, or approximately one-third of all crash-caused delays.

Several driver-performance factors contribute to rear-end collisions—driver inattention, perception-reaction time, and limitations in the human visual system. Driving an automobile is a complex task, one that requires the operator to scan the environment constantly and respond properly in order to maintain control, avoid obstacles, and interact safely with other vehicles. Knipling et al. estimated that driver inattention accounted for 64 percent of all police-reported rear-end crashes (*2*). All drivers experience some level of inattention while driving (e.g., talking to passengers, daydreaming, adjusting in-vehicle controls, or noticing extravehicle distractions). Inattention can be manifested in the various elements of driver behavior such as failing to attend to the roadway or not processing the information from the environment. As inattention is the primary cause of rear-end collisions, a model that examines the attentional aspects of the rear-end collision would be a valuable tool.

Over the past 10 years, the focus on technological solutions to the rear-end crash problem has intensified. Many prototype systems have been developed and tested to determine the best possible method for warning drivers of potential rear-end collisions. These systems have been developed and tested to identify algorithms and displays that will help drivers avoid rear-end collisions (*3*, *4*). A few have been marketed—primarily for commercial vehicle operations (Vorad, Nissan). These prototype and operational systems have employed a number of algorithms and displays.

Although many evaluations have examined driver response to various display and algorithm alternatives, little research has considered creating a quantitative model of driver performance to aid in these evaluations. Most systems have been designed using many simplifying assumptions regarding human performance. A fixed driver reaction time to the warning, constant braking at a given level, and a continuously inattentive driver are examples of these assumptions. Although these assumptions simplify the problem and allow for some analyses of the algorithms, they do not provide a comprehensive explanation of how the algorithm and driver interact (*5*). A more sophisticated attention-based quantitative model can provide more precise and accurate design guidance. This paper describes such a model: the attention-based rear-end collision avoidance model (ARCAM). ARCAM provides a flexible tool to examine the simplifying assumptions currently being made in RECAS algorithm development. Additionally, ARCAM will integrate the empirical data concerning driver attention and perception into the rear-end collision context.

THESIS

A quantitative model of the rear-end crash scenario will allow for the examination of a wide range of factors that affect the driver's ability to avoid collisions, including warning systems, without the time and expense required for field and simulator studies. The elements that define a rear-end collision situation include the driver as an information processor, the driver's vehicle and its related braking performance, and the lead vehicle's braking behavior. Figure 1 shows that this representation assumes that the effects of other vehicles are negligible. The inputs to the model are a desired index of cautiousness and lead vehicle behavior. The outputs of the model are the speeds and relative positions of the two vehicles.

A computational model of the driver can examine potential rear-end collision circumstances with and without RECAS to determine the safety benefit of RECAS. Current considerations of driver behavior in developing warning algorithms tend to assume a fixed driver reaction time with no further adjustment after the initial response (*3*).

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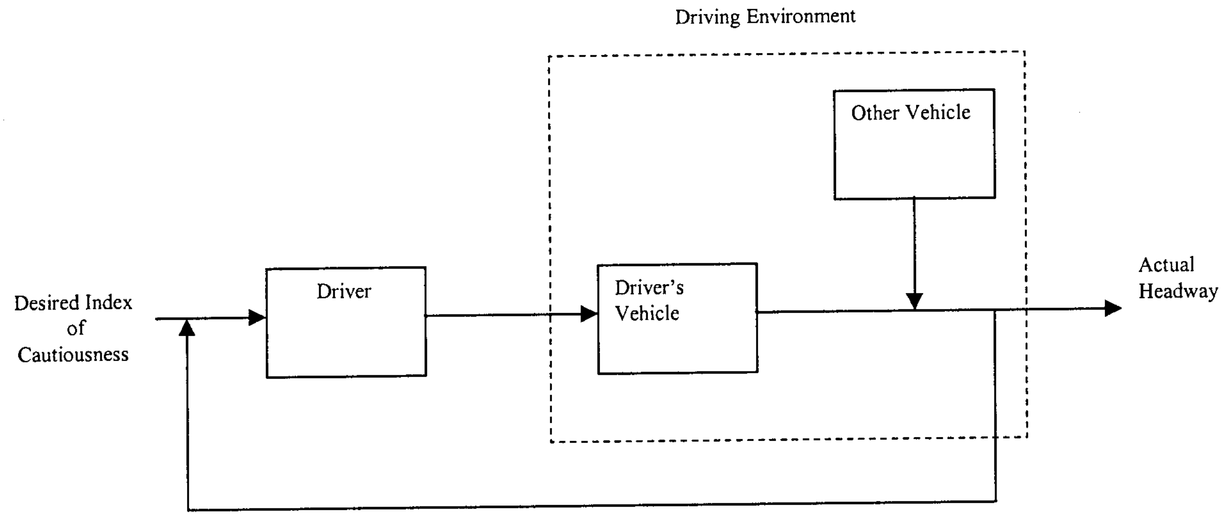

FIGURE 1 **Dynamic representation of a rear-end collision situation.**

A more refined model of driver response to rear-end crash scenarios can identify how these assumptions affect the joint driver–RECAS system and whether more appropriate and timely information can be displayed to the driver. This paper presents a conceptual model that outlines the structural requirements of predicting driver response to rear-end collision situations.

BASIS OF DRIVER MODEL

The driver portion of the model is of particular interest. Figure 2 shows an expanded view of the driver module, ARCAM. ARCAM is much more complex than a simple reaction time and step function response. Initially ARCAM will be constrained to longitudinal

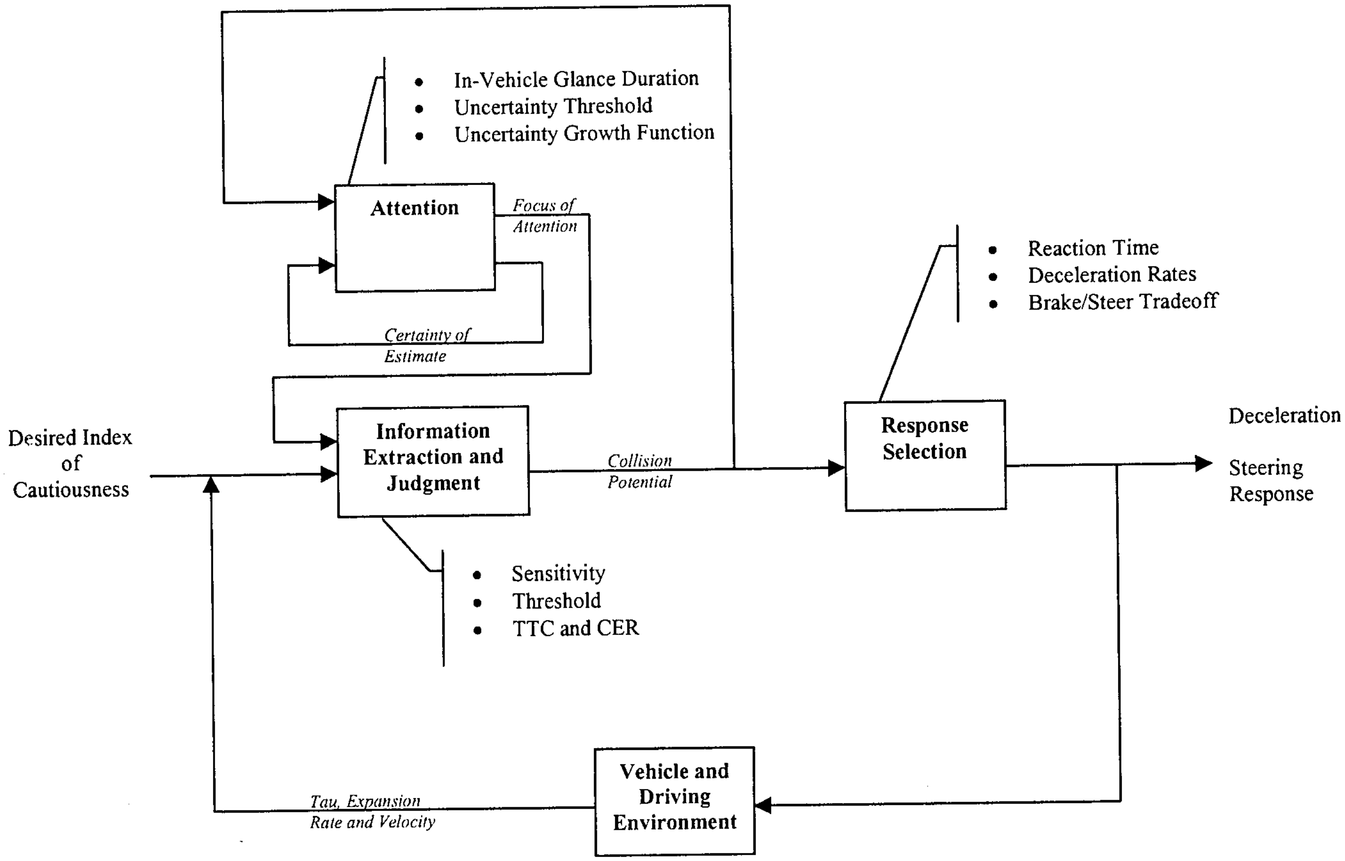

FIGURE 2 **Attention-based rear-end collision avoidance model.**

control; however, some aspects of lateral control will be briefly addressed. As ARCAM will not initially attempt to explain driver performance other than longitudinal control, the implementation of this theoretical model into a quantitative model is simplified compared to more general models of the driver that have been attempted in the past (*6*). By starting with a more manageable model, it can be implemented and incrementally expanded to include more situations. The driver's attention distribution, the information extraction and judgment process, and the reaction process are all incorporated in this model. The inputs to this model are desired index of cautiousness, tau, expansion rate, and velocity. The index of cautiousness, tau, and expansion rate will be discussed in the following sections. The outputs of the model are deceleration and steering response.

Attention

For the driver to react to a rear-end collision, his or her attention must, to some degree, focus on the lead vehicle. Typical driving does not require constant attention to the forward roadway; a surplus of visual scanning capacity exists that approaches 50 percent at times for driving (*7*). Because the driver's attention might not be focused on the forward view, he or she may not notice the visual cues that indicate a possible rear-end collision (*4*). Senders et al. predict that an observer will sample the environment at the rate information changes and that the glance length will be dependent upon the information in the sample (*8*). In general, they found that the duration of any given glance was between 0.3 and 0.5 s and that the sampling rate reflected uncertainty regarding the system state. A driver's attention to the roadway also depends on an uncertainty about the information contained in the last forward view. This uncertainty increases until it reaches an unacceptable level, at which time the driver will return attention to the forward view to decrease the uncertainty about the situation (*9*, *10*). The uncertainty grows as a function of the information density of the road, the velocity of the driver's vehicle, the rate of forgetting, and the time interval over which the road is not being attended (*9*, *11*). The driver's uncertainty about the environment also can be explained by the following simplified equation, where t is the time since the last sample and the constants define the situation (*10*):

$$\text{Standard deviation of memory position} = \alpha + \lambda \times t^{1.5} \qquad (1)$$

For the rear-end collision situation, uncertainty grows concerning the potential of a collision with the vehicle ahead. Collision potential is defined as the relationship between how much distance is required to stop and how much distance is available to stop. When the driver is unsure that the collision potential is safe, attention is shifted back to the roadway. The concept of collision potential is explained more thoroughly in the discussion of information extraction and judgment. The parameter α of the simplified uncertainty equation defines the initial uncertainty associated with the driver's estimate of collision potential. This parameter can be estimated by using known uncertainty in driver estimates of time-to-collision (TTC), the distance to the lead vehicle, and the distance required to stop. The parameter λ can be estimated by analyzing eye-glance behavior of drivers performing a secondary task that requires them to divert their eyes from the road for as long as they think it is safe. The duration and timing of glances as a function of headway and speed can be used to estimate this parameter. Once these constants have been estimated, this equation can be used to model how the driver looks toward and away from the driving environment.

The driver's attention distribution has significant effects on his or her ability to react to a possible collision situation. The driver's reaction time to the actions of the lead vehicle will be increased by the amount of time required to return his or her attention to the lead vehicle. This increase in reaction time includes both the time spent looking away from the road and the time required to transition attention back to the roadway. Pashler summarizes many studies of the time course of selective attention that examine how long it takes for a cue to initiate selective processing by location (*12*). The results of these studies suggest that the transition time for attention to the roadway might range between 100 and 250 ms.

This component of the model can guide RECAS design by identifying the benefit a warning can provide to a periodically distracted driver by redirecting attention to the roadway. This can be accomplished by comparing how long it would take the driver to return attention to the roadway with and without the warning.

In summary, the attention component of ARCAM converts collision potential and time since the last sampling of the roadway into a level of uncertainty that guides drivers to direct their attention to the road. It also identifies the delays associated with this process, including the time required to switch attention to the roadway.

Information Extraction and Judgment

The second component of the driver model describes the information extraction from the environment and the judgment of the need to brake. An early description of driver behavior provides a theoretical framework for explaining how drivers decide to decelerate (*13*). This theoretical framework describes the driver as attempting to move through the environment that is represented as a field of safe travel. This field is specified by visual information, and the driver moves along a path that avoids obstacles that would impede locomotion. This path follows the field of safe travel, which is a combination of all paths that the driver can take unimpeded. The field of safe travel has a positive "valence" with the center of the path having the highest positive valence, whereas obstacles have negative valences. The destination of the driver also has a large positive valence, which controls the overall course of the vehicle. The field of safe travel is not static and moves with the vehicle. It is independent of driver perceptions and describes the physical characteristics of the vehicle and the environment that govern safe travel. For longitudinal control, the field of safe travel extends to where the lead vehicle would be in the time taken for the driver to stop the vehicle. The driver uses a preferred normal deceleration as the basis for this determination. A good estimate of this normal braking level is 0.20 g (*14*).

The premise of the field theory of driving is that the driver will attempt to follow this field of safe travel, thus avoiding other vehicles and obstacles in the roadway. The driver does this through steering adjustments and velocity corrections. For steering adjustments, steering can be considered "a perceptually governed series of reactions by the driver of such a sort as to keep the car headed into the middle of the field of safe travel" (*15*, p. 122). The deceleration of the vehicle is controlled by the index of cautiousness (IC), which is the ratio between the field of safe travel (FST) and the minimum stopping distance (MSD). The inverse of the index of cautiousness is the collision potential (CP). This relationship is defined as

$$\text{IC} = \frac{1}{\text{CP}} = \frac{\text{FST}}{\text{MSD}} = \frac{\text{FST}}{-v^2/2a} \tag{2}$$

where V is the velocity of the driver's vehicle and a is the preferred acceleration for stopping. As the field of safe travel is reduced, the collision potential increases, and the driver reduces speed to keep the stopping distance less than the length of the field of safe travel.

To determine the field of safe travel and one's position in it, the driver periodically samples the forward view and makes judgments concerning the field and possible collisions. The attention module implies that no detection of dangerous situations can occur until the driver attends to the forward view in order to process the information (*16*, *17*). After attention is returned to the roadway, the driver must use perceptual cues to detect dangerous situations. There are two main perceptual cues that can be used in detecting collisions: tau (τ) and critical expansion rate (CER). Both τ and CER are employed in determining the field of safe travel and the collision potential.

CER is defined as the rate of change of the angular size of an object (*18*). The threshold for drivers' ability to detect relative motion (expansion rate) is 0.003 rad/s (*19*). Below this critical expansion rate, the driver is unable to determine that the range between the vehicles is being reduced. When this value is exceeded, the driver can detect a change in the field of safe travel and a potential collision situation.

When the driver can detect the relative motion between the vehicles, τ is used to aid in judging impending collisions. The ratio of angular size to the angular expansion rate defines τ. Tau has been used to describe how a person perceives and reacts to collision situations (*20*). In a small-angle situation, τ corresponds with time-to-collision. Tau is used to estimate collision potential by defining the extent of the field of safe travel:

$$\text{FST} = R + \left(V + \frac{R}{\text{TTC}}\right)t^* \tag{3}$$

where R is the range to the vehicle ahead and t^* is the time required for the driver's vehicle to brake to a stop. However, the driver's ability to estimate TTC is imprecise. This error in estimating TTC ranges from 1 s at low speeds to 0.4 s at higher speeds (*21*). This error accounts for some of the initial uncertainty about collision potential and could result in an increased reaction time or failure to respond to a collision situation.

Signal detection theory (SDT) translates the index of cautiousness into a decision to adjust velocity (*22*). SDT describes this process with two parameters, d' and β. The d' parameter reflects the precision of drivers' estimates of the index of cautiousness, and β reflects the criterion that, when crossed, triggers a decision. The criterion reflects the driver's degree of conservatism, whereas sensitivity is related to the severity of the collision situation (i.e., more severe collision situations have a greater chance of detecting the need to brake than less severe situations). The sensitivity and criterion for the model can be varied to examine many different types of drivers, that is, drivers with differing visual abilities and driving styles. When the index of cautiousness exceeds the driver's criterion, then the driver will begin to slow to avoid a collision. If the threshold has not been exceeded, then the driver will continue driving normally. SDT makes explicit the fact that sometimes drivers respond to conditions that do not warrant it, yet at other times responding too late or not at all.

This component of ARCAM can help identify situations in which RECAS can provide the greatest benefit to drivers. Specifically, combinations of headway, speed, and lead-vehicle deceleration that may be particularly difficult for drivers to estimate collision potential accurately can be identified.

In summary, the information extraction and judgment component of the model converts environmental information such as τ and CER into a decision concerning the need to decelerate and collision potential. It also identifies the delays associated with this component, which include the time required to extract the information from the environment.

Response Selection

The third component of the model describes the driver response based on the judgment made in the information extraction and judgment component. If a potential collision has been detected, the driver may respond by releasing the accelerator, applying the brakes, and steering the vehicle. The driver's response is influenced by the existing conditions and physical limitations of the vehicle (deceleration rates). If the driver responds early enough, the option of either steering or braking is available. But if the driver responds too late, the only option will be to steer to avoid the vehicle; however, this is not always possible due to the presence of other vehicles and roadside obstacles and terrain.

The braking portion of the response has not been easy to quantify (*23–26*). The exact mechanism used for modulating braking response has remained mostly undefined. Previous research suggests that braking depends on a driver's perception of optic flow (*23*) and the rate of change of range and range rate (*26*). The field theory of driving provides a useful foundation to define driver response (*13*). For each driver, there is a level of index of cautiousness (IC) that the driver prefers to maintain; this level of IC is the critical (IC_C) value for the driver. Driver response depends on situational severity, which can be defined relative to IC_C:

$$\text{Situational severity} = \text{CP} \times \text{IC}_C \tag{4}$$

When the decision has been made not to decelerate, the driver maintains speed by keeping the accelerator pedal depressed. When a decision to decelerate has been made and the situational severity is approximately 1, the driver releases the accelerator pedal but does not apply the brakes. When the decision to decelerate has been made and the situational severity is greater than 1, the driver applies the brakes and decelerates. The level of deceleration and speed of transition from accelerator to brake are determined based on preferred normal deceleration and the situational severity. Deceleration is continued until the collision potential has been reduced to an acceptable level—$\text{CP} \times \text{IC}_C < 1$.

Although there are a number of models of driver steering, the obstacle avoidance model may best explain driver steering in this situation (*27*). This model explains obstacle avoidance as lane change, control in the other lane, and return to the original lane. This model is based upon a steering response initiated by an error between the desired path of the vehicle and its current centerline. This model allows for steering to avoid the obstacle using a control theory mechanism and may be useful in predicting steering response to a slowing or stopped vehicle. However, this steering model must be integrated with the braking portion of driver response.

Most descriptions of drivers' response to RECAS assume a step-braking response. This element of the model will help determine how a closed-loop braking response affects the benefit of RECAS.

In summary, the response selection component of the model converts collision potential into deceleration. In addition, it specifies delays associated with moving from the accelerator to the brake and depressing the brake.

Model Outputs: Reaction Time and Response

Providing a framework for better understanding and predicting driver reaction time in rear-end collision situations is an important contribution of ARCAM. Driver information processing and motor control introduce delays in each component of ARCAM. Many studies have been conducted that examine the perception-reaction time (PRT), generating widely varying estimates. ARCAM may help reconcile these results so they can be applied to RECAS design. The PRT includes all delays associated with the model from information extraction through reaction. The time delay associated with each component of ARCAM suggests that for a braking response, the PRT is influenced by whether the driver is expecting the event or not, the specific perceptual characteristic of the situation, and the severity of the situation. When the driver is alerted to an event, the PRT will be less than if not alerted. In a study by Johannson and Rumar, it is suggested that when braking is anticipated, a correction factor of 1.35 s must be added to find the unalerted PRT (*28*). This 1.35-s correction factor was validated on Iowa driving simulator experiments in which the baseline reaction-time values were 2.34 to 2.53 s for an "unexpected" event (*29*). Based upon the model of the driver, this correction factor for reaction time may be attributed to a delay in attending to the road (attention module) relative to the alerted case.

A reexamination of the data obtained by McGehee et al. provides additional information about how a driver responds to a RECAS warning (*29*). The drivers' mean response to a RECAS warning, for a stopped lead vehicle, was 0.29 s to accelerator release, 0.90 s to brake application, and 2.32 s to maximum brake application. The mean time between brake application and maximum braking was 1.41 s for drivers with RECAS. Additionally, the 90th percentile time to brake application was 1.3 and 1.6 s for the two RECAS conditions examined in that study.

Another study that examined response to a lead-vehicle-moving scenario produced similar findings, but the mean response for accelerator release was 1.2 s instead of the 0.3 s found for the lead-vehicle-stopped scenario. This reaction time reflects a less severe lead-vehicle-moving scenario, thus allowing the driver more time to respond. Additionally, this study found that improvements in driver response were mainly the result of changes in initial accelerator release (McGehee, Lee, and Brown, unpublished data). This range of results is consistent with the predictions of ARCAM. Experimental situations will affect drivers' reaction time and response through the mechanisms of attention, perception, and motor control limits.

FINDINGS

ARCAM is a conceptual tool that can examine the rear-end collision situation and identify the implications for design and evaluation of RECAS. There are two main areas of interest in this regard: the validity of the conceptual model and the evaluation of RECAS warning effectiveness.

Validity of Conceptual Model

The closed-loop structure of ARCAM is an important contribution to its validity. Current algorithms and models assume that drivers do not adjust their response after making the initial decision. Data from recent studies examining RECAS show that drivers respond in a closed-loop fashion to rear-end collision situations. If the response to a rear-end collision were an open-loop process, it would be expected that the driver would make an initial reaction and then the response would remain unchanged; whereas, in a closed-loop process, the driver adjusts the response based upon new information. In a recent study, McGehee et al. found that 21 of 30 drivers made adjustments following the initial reaction (*29*). Figure 3 plots six variables for 7 s for one driver's response to a collision situation. The figure shows that the driver's first response is to brake. The driver then releases the brake somewhat and begins a steering maneuver; during this steering maneuver, the driver then increases brake application to avoid the collision. This response suggests that the driver is adjusting the response based upon changes in the driving environment.

Reaction-time data also provide support for the closed-loop nature of the response. Specifically, the data show that drivers adjust the brake pressure based upon the current state of the environment; they do not make a simple step-brake response when they begin braking. For example, the time between initial brake application and maximum braking is 1.4 s (*29*). This reflects a braking profile that is modulated by the driver's perception of the collision situation. This implies that the driver does indeed act as a closed-loop system, consistent with ARCAM.

The reexamination of the data in McGehee et al. provides additional validation of ARCAM (*29*). The data show that the driver does not immediately brake following the initial accelerator release; instead 0.6 s expires before the driver brakes. This delay reflects a process of information extraction and judgment. This characteristic of the model, validated with empirical data, is important because it shows that warnings may only return the driver's attention back to the roadway to obtain information rather than directing a response. The closed-loop nature of the driver's response to the RECAS warning, the delay between accelerator release and initial braking response, and the braking profile all provide validation for the conceptual model.

Effectiveness of RECAS Warnings

ARCAM has important implications for the design of RECAS. Specifically, the effectiveness of a RECAS warning depends on how drivers interpret the warning. One possibility is that the warning focuses the driver's attention to the roadway. Another possibility is that it causes the driver to immediately react. How an alert or a warning causes the driver to react has significant implications for the design of a system. For example, if the warning causes the driver to react immediately, the reaction time, from accelerator to brake, will be relatively small. However, if the warning causes the driver to process information from the environment, then that reaction time will be longer while the driver extracts information from the environment.

The model described in this paper contains several important features that support an accurate prediction of driver response. For

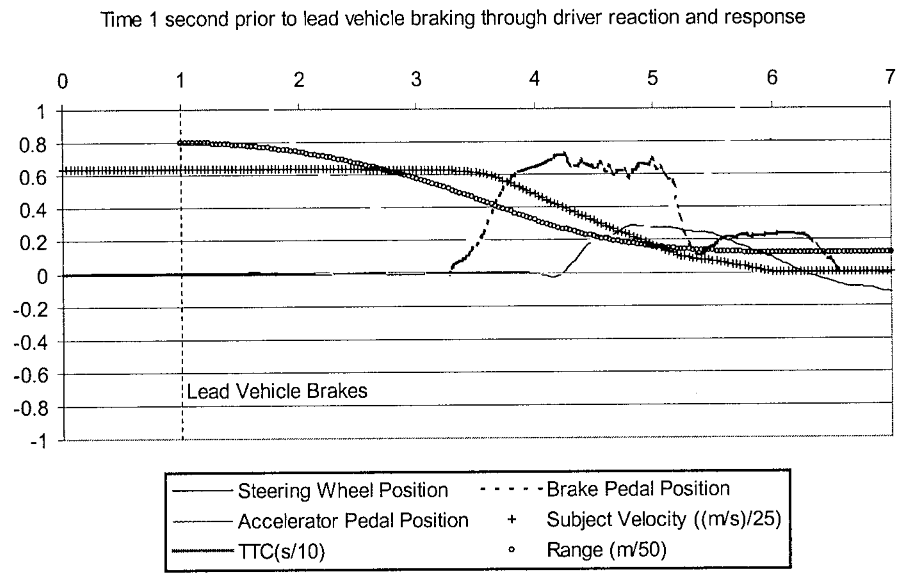

FIGURE 3 Closed-loop response to a rear-end collision situation.

example, the intermittent selective focus of attention and the uncertainty growth function describe a potential mechanism underlying inattention. These features provide a means of augmenting a RECAS warning algorithm to account for this inattention and determining the benefits that could be achieved. The information extraction and judgment process defines how τ and CER can be used to define the field of safe travel for the driver and the potential for colliding with the lead vehicle. This provides for identification of the circumstances under which drivers may misperceive the situation and RECAS will be most beneficial. The use of collision potential in directing the response selection process allows ARCAM to reflect the complex closed-loop braking profiles used by drivers. These complex deceleration profiles will allow for a more accurate prediction of the benefits of RECAS. These features provide a basis for ARCAM to improve RECAS warnings.

CONCLUSION

ARCAM brings together empirical findings from several studies to provide a solid basis for examining how the driver interacts with RECAS. Existing data validate the basic structure of ARCAM by showing that the driver operates in a closed-loop manner, adjusting the initial response as a result of subsequent observations. It also is clear that the RECAS warning causes the driver to extract information from the environment before reacting. These findings provide initial validation for the conceptual model of the driver that has been developed. The components of ARCAM provide a structure for interpreting conflicting reaction-time data and also provide several important recommendations for the design of warning algorithms and displays.

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Findings on the Approach Process Between Vehicles

Implications for Collision Warning

Mark A. Brackstone, Beshr Sultan, and Michael McDonald

Over the past 10 years there has been a growing body of research into modeling and describing driving behavior, particularly for situations that occur on motorways. This interest has arisen from the need to assess safety and capacity benefits that could be produced by changes to road design, operation, signage, and in-vehicle advanced transport telematics, such as collision warning (CW) or autonomous cruise control. For the most part these investigations have focused on "close" or "car" following, which describes the maintenance of a time- or distance-based following headway. However, often overlooked, and of equal importance, is the "approach" process, describing how a driver decelerates when approaching a slower vehicle. There are several competing theories of the behavioral basis underlying this process, including, for example, those based on time-to-collision or optic flow. There are, however, very few data against which such models can be assessed and systems designed. Presented are the results from an exploratory, instrumented vehicle study designed to assess approach mechanisms. The two key features of the process are explored: the circumstances under which driver deceleration is instigated, and the process governing the control of the deceleration itself. Finally, there is a brief assessment of the implications of these findings for the design of CW systems, in which realistic warnings may prove vital to their acceptance by the driving public.

Increasing pressure to alleviate congestion and reduce the frequency and severity of accidents has led over the past 10 years to increased investment in advanced transport telematics technologies. One particular subgroup of these systems, generally termed "advanced vehicle control and safety systems," is designed to advise motorway drivers about safe following distances and the existence of potentially dangerous closing situations (collision warning, or CW) (*1*). In some systems, intervention can occur by controlling the throttle or brake to achieve "safe" conditions (autonomous cruise control, or ACC) (2). An increased understanding of "normative" driver behavior clearly is essential to the design and assessment of such systems, for the following reasons:

- To allow the compilation of accurate driver models that may be used to assess the impact of such systems, either at an individual vehicle-vehicle level (*3*) or at a greater scale through microscopic simulation (*4*); and
- To allow the design of systems that are realistic, that is, ones that mimic true human responses while removing error through misperception or delay.

Although a substantial amount of research has been performed or is underway in the examination of the "following" process relevant to ACC (*5*), comparatively little has been published concerning the "approach" or closing process critical to the design of CW. A variety of studies is now underway into the quantification of the rear-end collision problem through epidemiological studies (*6*), and there is ample evidence in terms of accident figures to justify increased attention to this area (*7*). Additionally, the causative elements of accidents or "close calls" arising during approach have been well explored both qualitatively (*8*) and quantitatively, through investigations into driver visual search patterns (*9*) and misperceptions of relative motion cues (*10*). There are, however, few sources that have attempted to measure the process itself.

Additionally, a distinction must be drawn between measuring driver actions on approach (when the driver decided to instigate deceleration) and at the point at which the driver perceived the approach. The latter may be several seconds before the former, and the delay imposed between perception and action will involve physical movement times as well as a potential delay until the driver decides that the approach has become sufficiently "critical" to warrant action. Although many experiments have been performed according to the "perception paradigm," it is the action itself that is of interest to the authors, as it is this that any CW system should seek to replicate. It is, however, instructive to pursue the investigations using the perception variables in addition to those used in conventional engineering, as this may contribute to the formulation of a coherent model of behavior, and indeed the literature leads these authors to examine two basic measures with which the driver may relate.

The first indicator may be the optic flow θ_t, the rate of change of θ, the apparent visual angle of the vehicle ahead with respect to time (*t*). This is approximated as $\theta_t = -W.DV/DX^2$, with W the effective width of the lead vehicle, DX the distance between that vehicle and the observer, and DV the relative speed between them (a negative value indicating closing). Note that in this paper the optic flow is stated in units of milliradians per second (mr/s). It is quite logical that deceleration could not begin until it is possible for the driver to perceive this relative motion—that is, when θ_t exceeds a threshold, commonly held to be around 3 mr/s (*11*). Studies of this variable are well known and have been in place in driver behavioral models for several decades (*12–14*), and the approach has been adopted by Leutzbach and Wiedemann (*15*) and others as the basis for a series of simulation models used in traffic engineering and control.

The second and perhaps more obvious indicator of the urgency or criticality of the approach process is that of time-to-collision (TTC), which is the time after which a collision would occur if both vehicles were to continue at the same speed (*16*). This may be derived

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simply as TTC = *DX/DV*, or TTC = θ/θ_r. Research here has consistently shown that drivers have a tendency to underestimate TTC, at times by as much as 60 percent (*17*) [although other research has indicated that this may only be true when the driver is on a collision course (*18*)], and that additionally there may be a dependence on ground speed (*11*), initial observation distance (*19*), and closing speed (*20*).

Although a theoretical model has been proposed by Lee (*14*) concerning the relationship between the point at which the driver commences deceleration in terms of TTC ($\text{TTC}_{\text{start}}$) and the required magnitude of the average subsequent deceleration required to avoid a collision, few studies have attempted to quantify this or any other threshold that could be used in parameterizing this behavior. Of those that have, van der Horst examined drivers decelerating to a stop from various speeds on a test track, the drivers being instructed to wait until the last possible second before braking, and being split into two groups, each of which was allowed to brake only at certain levels (*21*). These findings indicated that at low speeds (8.3 m/s = 30 km/h, a high-approach speed from these authors' point of view), $\text{TTC}_{\text{start}}$ may be around 1.3 to 2.2 s, and subsequent behavior may be characterized by a TTC_{min}—the minimum value of TTC obtained—of around 0.3 to 0.7 s less. Van Winsum and Heino, using a driving simulator to examine behavior in car following at "low" speeds (40 to 60 km/h), found that the response of a following vehicle when faced with a decelerating lead vehicle was characterized by typical $\text{TTC}_{\text{start}}$ values of 5 to 16 s with a TTC_{min} of 2.5 to 5 s (*22*). Perhaps the most interesting study, however, is that of Spurr (*23*), who examined the time-series behavior of 15 drivers in an experiment similar to that undertaken by van der Horst. Although these individual deceleration traces seemed on inspection to be quite erratic, on reducing these to a dimensionless coordinate system (proportional to *DV*–duration of brake application versus percentage of brake application time elapsed), it was concluded that, on average, most drivers' responses could be characterized by a sudden reaction up to a maximum deceleration followed by a distinctive decay curve.

From the cited research, it is possible to conclude that although many indications exist concerning deceleration behavior during the approach process, few dedicated studies have been undertaken, particularly on real roads at typical speeds, leaving a substantial gap in our knowledge of an important driving behavioral process (from a safety standpoint at least). The study reported in this paper intends to provide some initial data and insights on which further experiments may be based. It specifically examines the circumstances under which driver deceleration is instigated, the process governing the control of the deceleration, and how this knowledge affects designs currently in place for collision warning systems.

METHOD

The experiments undertaken in this paper have been performed using an instrumented vehicle, that is, a vehicle equipped with distance- and speed-measuring sensors, which may be driven within the traffic stream as a platform from which to observe the behavior of a test driver or adjacent road users. The vehicle has been assembled over the past 2 years at TRG Southampton (*24*) and is equipped with the following:

- An optical speedometer, accurate to ±0.02 m/s at typical motorway speeds.
- A radar range finder, fitted to the front of the vehicle to measure the distance and relative speed between the test and lead vehicles. The unit has a measured accuracy of ±0.2 m in range and ±0.4 m/s in relative speed.
- A video-audio monitoring system allowing a permanent visual record of each experiment to be made—useful for an analysis of macroscopic features—apparent to the driver but not detectable to the sensors (e.g., lane, visual conditions, and lead vehicle type).

Information from each of the sensors is sent to a controller PC at a rate of 10 Hz and recorded in 5-min blocks. Once each experimental run has been finished, the logged data are directly transferred to a removable 1-Gb cartridge and taken for analysis, where dedicated processing software is used to compile time-series records of the behavior of the instrumented vehicle and a selected radar target (in this case, the vehicle directly ahead in the same lane).

Data for analysis in this series of experiments were collected using three university employees, unconnected with the research, ages 25 to 35, who drove regularly on the class of road used in this study. Each subject drove the test vehicle on laps of a 21-km test course on the two-lane dual carriageway A35 near Bournemouth in the United Kingdom for approximately 45 min. The drivers were instructed to drive at a "cruising" speed of their choice, in the nearside lane unless otherwise instructed, and that if their path were to become blocked by a slower vehicle, they were to decelerate as they saw fit and follow. The time of day chosen for the experiment (typically midmorning) was selected in order to minimize flow levels and, hence, allow a clearer interaction between the vehicles (minimization of the chance of the target vehicle changing lanes or other vehicles moving into the intervening gap during the approach). A familiarization period of approximately 30 min of each subject with the vehicle was allowed for the duration of the 35-km drive from the experimental base to the test site.

In total, 70 approach processes were observed, and in each case a time series representing ground speed, *DV*, and *DX* was isolated. Further examination of these traces was undertaken to ensure that the lead vehicle maintained an approximately constant speed during the approach process, in order to ensure that the behavior of the test drivers was solely affected by changes in *DX* and *DV* caused by their actions alone. To this end, each trace was examined, and those judged as being "unstable" (the lead speed varied by more than 2 m/s over the course of the series, nine in total) were removed from the analysis. Typical cases from this examination are given in Figures 1 and 2.

ANALYSIS OF APPROACH PROCESS

Start of Approach Process

The first question to be addressed is, "At what point and under what conditions do drivers start their approach process?" From the time series, it is possible to isolate distinct "action points" in which the drivers of the test vehicle start to decelerate, after which their acceleration becomes continuously negative, hence eliminating "throttle/brake switch-over noise" (*25*), the time between zeroing the accelerator and activating the brake. This is presented in Figure 3. As stated earlier, there are several candidate models that may describe this situation, and findings concerning their validity both overall (for all subjects combined) and individually are as follows.

Initial investigations sought to examine the relationship between *DX* and *DV* (see Figure 4), described by a linear relationship of the form *DX* = constant + gradient × *DV*, the coefficients of which are presented in Table 1. An alternative relationship between *DT* (time headway) and *DV* (see Figure 5) also was investigated, described by

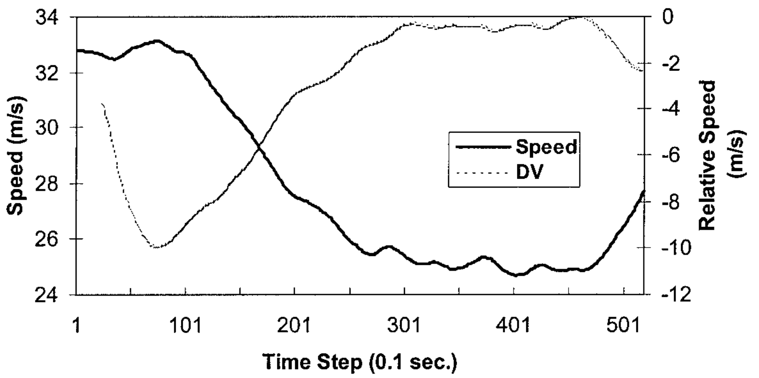

FIGURE 1 A stable approach condition in which the lead vehicle has a constant speed.

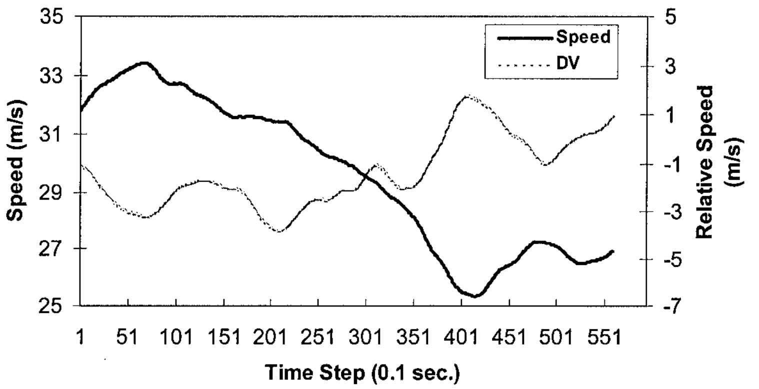

FIGURE 2 An unstable approach condition in which the lead vehicle has a varying speed.

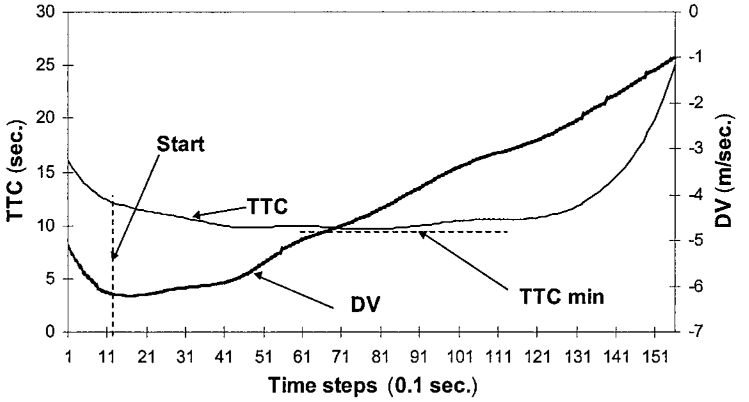

FIGURE 3 A typical approach profile.

a linear relationship of the form DT = constant + gradient × DV, the coefficients of which also are presented in Table 1. As can be seen, neither of these models provides a particularly good fit to the data.

It is clear, then, that no simple linear relationship can adequately describe the data sets, and therefore the values of the instantaneous optic flow at these points, θ_t, start, are examined. A strong lognormal distribution was found from the data with a group mean of 2.0 mr/s (through a Kolmogorov Smirnov test, KS = 0.80, see Table 2). Interestingly, these values are less than those suggested as minimal perception thresholds in the literature, which are of the order of 2.4 to 2.7 mr/s (*11*, *26*). It would seem highly likely that the subject may not have assessed the situation in terms of optic flow but also may have considered the overall dilation of the image over a period of time, the so-called Weber ratio, $\Delta\theta/\theta \sim 0.12$ (*10*). However, due to the nature of the experiment, a real-road trial, the elimination of this factor through occlusion is clearly impossible.

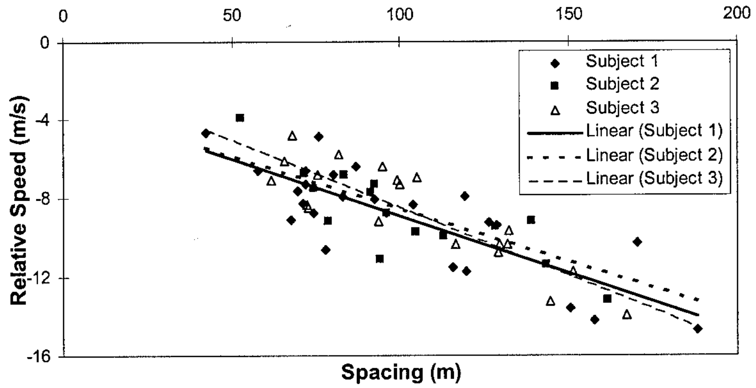

FIGURE 4 Separation against relative speed for the starting points of the approach process.

It is interesting to compare these values against those predicted by Leutzbach and Wiedemann, who implemented a normal distribution factor in their simulation model for the approach process to produce just such a spread between a minimum and maximum threshold, corresponding to 0.3 and 3.2 mr/s with an average 1.4 mr/s (*15*). This is illustrated in Figure 6, along with a new minimum threshold of 0.8 mr/s later suggested by Reiter (*27*). An examination of the dependence on *DX*, however, reveals that there is a strong reciprocal relationship between the threshold used and the intervehicle spacing present, indicating that a more appropriate threshold may indeed be one related to TTC, that is, a constant TTC_{start}. Indeed, an analysis of these points reveals that they are normally distributed around a group mean of 11.70 s (standard deviation 2.29 s) to a degree of significance of KS = 0.93 (Table 2). (Although it would be premature to comment on intersubject variability with such a low number of subjects, it is interesting to note that the distributions of all the parameters examined were found to be identical for each subject at the $p < 0.05$ confidence level.)

Control of Approach Process

The second issue to be addressed is how the driver decelerates to approach the lead vehicle smoothly once the approach process has begun. The initial step taken to examine this process was to plot the deceleration time profiles in dimensionless coordinates following Spurr (*23*); for an example, see Figure 7. In contrast to his conclusions, however, the authors find that there is a great deal of variation in the observed profiles, and in some cases the first peak of the profile is not the maximum value, with that occurring at a second or sometimes third peak. The degree of variation observed is indeed highly significant and at times may change from deceleration to acceleration. The reasons for this reversal in behavior will be discussed later. A significant effect is found, however, on examination of the values of TTC_{min} where a distinct lognormal grouping is found with a group mean of 8.41 s (KS = 0.63), demonstrated in Table 2. The value taken by TTC_{min} has an obvious relationship to the maximal deceleration (DC_{max}) observed during this time (the later a driver brakes, the harder he must decelerate). Indeed, DC_{max} is found to decrease almost linearly with TTC_{min} with an r^2 of ~ 0.6, where a lognormal distribution is again observed with a group mean of -0.87 m/s^2 (KS = 0.64), as shown in Table 2.

TABLE 1 Coefficient Table for Deceleration Action Points

		Fit parameter		
Model	Subject	Constant	Gradient	r^2
DV-DX	Subject 1	-3.19	-0.057	0.66
	Subject 2	-3.15	-0.0537	0.56
	Subject 3	-1.62	-0.068	0.70
	Overall	-2.71	-0.060	0.66
DT-DV	Subject 1	0.27	-0.31	0.64
	Subject 2	0.69	-0.30	0.47
	Subject 3	0.86	-0.27	0.63
	Overall	0.59	-0.29	0.58

IMPLICATIONS FOR COLLISION WARNING SYSTEMS

Despite a substantial body of work in the assessment of potential benefits of CW as an aid to headway observation (*28, 29*), there is little work available in the establishment of such systems for long-range warnings such as those that would be required by an inattentive driver during approach. The few references that are available, which are primarily reports on work performed by Japanese car manufacturers, reveal a number of interesting features, shown in Figures 8 and 9.

To begin with, if this paper's data are compared with a theoretical warning line (*30*) based on simple newtonian equations of motion and reaction times, it is seen that in the majority of cases, the test drivers would have crossed such a threshold, primarily on account of their willingness to use a greater level of deceleration than may otherwise have been predicted. Turning attention to empirical investigations, it is found that a variety of experiments have been undertaken. Fujita et al. conducted a collision avoidance test, measuring when drivers approaching a stationary obstacle altered their course in order to steer around it; and a warning line, which approximately delineated the closest conditions that a driver would attain for a given speed before responding, was fitted to these data points (*31*). Comparing

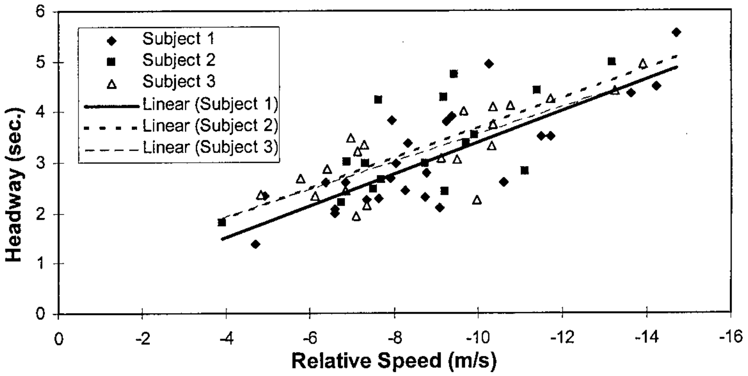

FIGURE 5 Relative speed against time headway for the starting points of the approach process.

this relationship with the present study's response points reveals a good match at lower approach speeds (≤ –10 m/s). However, the Fujita results would appear to be somewhat too "close" above these speeds, whereas this study's drivers already had started decelerating up to 20 to 40 m (~1.5 to 3 s) earlier.

Kuge and Ueno conducted an experiment very similar to the current one on a test track using a confederate lead vehicle and a range of specified approach speeds, finding in general an approximately linear relationship for the deceleration action point with comparatively little variation across the speeds tested—40 to 80 km/h ~11 to 22 m/s (*32*). The discrepancies between these findings and the current study may be due to the lower speeds and differences in experimental conditions (test track versus real road). Further verification of the overall magnitude of the current findings is given by Hasimoto et al., who, using five test drivers approaching a moving vehicle on a test track, found that deceleration commenced at a headway of 2.4 to 4.5 s for a *DV* of 10 to 40 km/h and at ground speeds of 40 to 70 km/h (*33*). Although no details are given on the dependency of these figures on *DV* or ground speed, this would be equivalent in the current experiments to a distance of 77 to 104 m. This provides a good match at the lower speeds, though it would appear to be a bit low at higher speeds.

TABLE 2 Statistics for the Distribution of Key Parameters Associated with the Approach Process

Parameter + Distrib. tested	Subject	Stats.		
		Mean	StDev.	KS[a]
$\theta_{t,start}$ (mr/s[b])	Subject 1	2.22	1.16	0.96
lognormal	Subject 2	1.84	0.72	0.91
	Subject 3	1.86	0.82	0.45
	Overall	2.00	0.95	0.80
TTC_{start}	Subject 1	11.20	2.48	0.88
normal	Subject 2	12.02	2.38	0.84
	Subject 3	12.00	2.03	0.88
	Overall	11.70	2.29	0.93
TTC_{min}	Subject 1	7.72	1.57	0.84
lognormal	Subject 2	7.82	1.89	0.95
	Subject 3	9.40	2.55	0.95
	Overall	8.41	2.01	0.63
DC_{max}	Subject 1	-0.89	0.32	0.55
lognormal	Subject 2	-0.82	0.34	0.71
	Subject 3	-0.88	0.37	0.99
	Overall	-0.87	0.34	0.64

[a] KS: Kolmororov Smirnov statistic.
[b] mr/s: milliradians per second.

A number of other formulations also are available, although in most cases experimental data are absent, at least in the published sources. For example, Watanabe et al. have put forward two relationships relating distance to approach and ground speed, with the condition for speeds over about 70 km/h, producing a linear relationship (*34*). Although suitable for closing speeds over about 10 m/s, they would seem to introduce decelerations too early below these speeds. (In some cases a warning would appear at 40 m, or about 9 s before the point at which the driver would start to brake.) To a certain extent this is due to the fact that the CW actuator system is not able to use braking as part of the deceleration process and is limited to throttle control and downshifting, and hence it must start decelerating earlier in some instances. Whether a driver would accept this limitation as a reason for a "premature" deceleration is another matter.

An alternative formulation is offered by McGehee (*35*) and evaluated as an aid to headway maintenance by Dingus et al. (*29*), in which a graduated series of warnings is offered to the driver consisting of colored bars and icons, the color of which is dependent on the closing situation (Figure 9). As can be seen, such a warning system may be quite valuable, particularly over closing speeds of around 10 m/s when the activation of the warning system alone may act to alert the driver that he has passed his usual deceleration point. Below such a closing speed, however, there may be both advantages and disadvantages to such a system. There are a number of points (*13*) in which the driver would have decelerated in the orange/amber zone, and the presence of this warning may eventually result in the driver decelerating earlier, resulting in a "safer approach." There are a large number of points in the green zone, however, and this may cause a problem in that a driver may not take such a warning in a

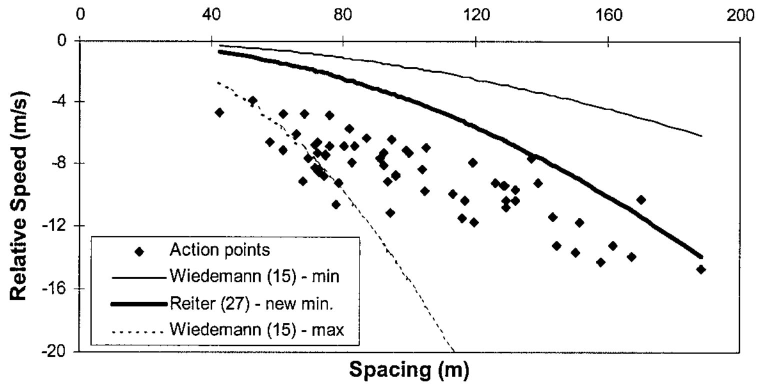

FIGURE 6 Approach process thresholds compared with the findings of Leutzbach and Wiedemann [*15*] and Reiter [*27*].

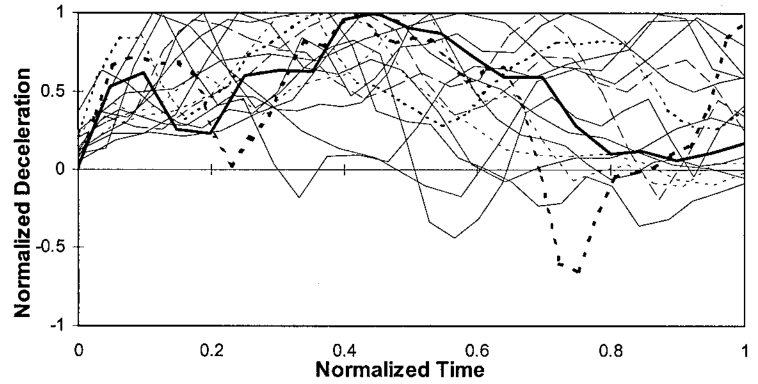

FIGURE 7 Normalized deceleration profiles for Subject 2, demonstrating the extreme variation present.

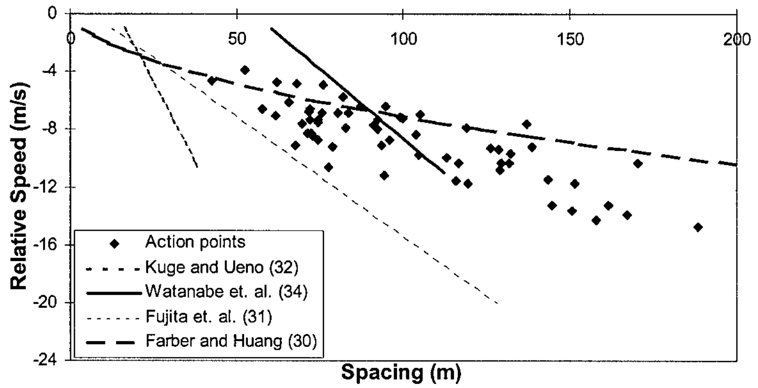

FIGURE 8 Comparison of deceleration initiation points with current CW thresholds.

positive way and modify his or her behavior but would instead view the system as being intrusive.

CONCLUSIONS

From these findings, it is possible to come to clear conclusions regarding the approach process on motorways, namely that it may be described by a process characterized by

- A set TTC_{start}, characterizing when drivers may start decelerating, which differs with each event and may be drawn from a normal distribution of mean 11.7 s; and
- A particular TTC_{min}, again differing for each event and drawn from a lognormal distribution with a mean of 8.4 s, characterizing the maximum criticality that is likely to be acceptable.

(It is clearly open to debate whether TTC_{min} is the true second characterizing measure in the process, as it is equally valid to state that

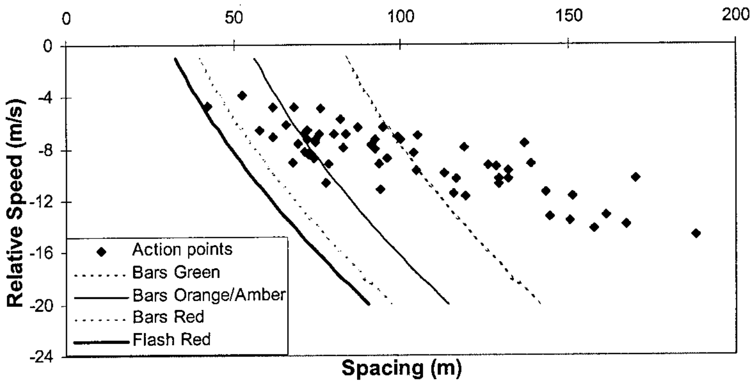

FIGURE 9 Comparison of deceleration initiation points with CW system from Dingus et al. (*29*).

the driver is decelerating at a subjectively judged comfortable value and that TTC_{min} is merely the result of this factor combined with the particular choice of TTC_{start} in each instance. For CW design, however, this is a moot point.)

Clearly, the experiment itself is not without weaknesses. Over and above the issue of sample size, it is possible to question the derivation of the start points, as these have been subjectively extracted from the time-series traces. A more exacting method should involve direct monitoring of brake/accelerator displacement and pressure. These criticisms aside, the authors believe that this experiment has significantly increased their understanding of the process concerned. It is tempting to undertake a more exhaustive analysis of the deceleration traces in an attempt to understand the relationship between the magnitude and temporal placements of each of the maximum and secondary peaks. However, a cursory examination of the traces in Figure 7 does not encourage such an investigation, and, indeed, attempts made by Spurr to find a more detailed relationship between braking magnitude and external conditions over time did not succeed (*23*). Additionally, although it is possible to examine the implications of the current data to a warning in a situation in which the lead vehicle brakes, the authors believe this would be misleading, with a large number of additional variables likely to be present that would impact behavior, such as anticipation and brake-light activation.

Comparison of these features with those that would be used as the basis of CW systems under development has revealed that although some provide suitably positioned warnings, others may alert the driver far too early. This has important implications for system effectiveness, as the driver may choose to deactivate the system if it is perceived to be providing unnecessary advice. These are important issues that must be further addressed before marketing of CW can begin.

It is the authors' belief that, although far from conclusive, their findings have given a good indication of the factors (and their magnitudes) that should be used in modeling this process. Work will continue in the next few years in increasing the statistical validity of the model formulated, deriving a suitable CW threshold, and, perhaps more importantly, relating the end of the closing process to the start of car following.

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Emergence of a Cognitive Car-Following Driver Model

Application to Rear-End Crashes with a Stopped Lead Vehicle

James A. Misener, H.-S. Jacob Tsao, Bongsob Song, and Aaron Steinfeld

Rear-end crashes are a major roadway safety problem, and the potential of crash countermeasures to address this has long been recognized. High-frequency or severe-consequence scenarios are focused on the general lead-vehicle-not-moving (LVNM) case and specific crash scenarios. Operating scenarios are identified, and frequencies are assessed. From these, a small number of prevalent LVNM crash scenarios are identified as the focus for subsequent model development and crash countermeasure efforts. These scenarios suggest nominal atmospheric, roadway, lighting, vehicle, and driver conditions in designing cost-effective safety features to avoid LVNM rear-end crashes. From this, emergent models for cognitive car following are developed, based on fusing current knowledge. This will serve as a foundation for further model development efforts as well as for future human-factors experiments.

It is widely acknowledged that the rear-end crash problem is ripe for potential crash countermeasure systems. Because up to one-quarter of all crashes involving two or more vehicles are rear-end collisions (*1*) and because automotive forward-sensing systems are becoming available, rear-end collision avoidance systems (CASs) could yield significant benefit, probably sooner than a CAS for other crash types. With this as a primary motivation, considerable research has been devoted in the past to the rear-end crash problem and from a variety of perspectives: to establish a case for rear-end collision warning systems (*1*), to further this case by estimating societal benefits of such systems (*2*), and also to critically examine warning system human-interface specifics such as frequency and timing (*3*). Along the way, a body of crash-causing statistics and scenarios has been generated (*4–6*), and it has been used in several analyses to assess the efficacy of rear-end crash countermeasures (*7, 8*). The state of knowledge acquired from this research is summarized quite well in Dingus (*9*). In a complimentary tack, automated rear-end CASs also have been examined. Different assumptions and designs have been reported with varying degrees of automated intervention (*10–12*), but a common thread is the baseline investigation of the magnitude of the problem, generated from several studies (*1, 4–6*).

This paper's focus is those rear-end crashes in which the lead vehicle is not moving or stopped prior to the crash. Such crashes have been referred to as lead-vehicle-not-moving (LVNM) rear-end crashes. (For convenience, LVNM rear-end crashes will be referred to simply as LVNM crashes.) To design vehicle features that provide significant safety gain against LVNM rear-end crashes, major crash scenarios must be identified and their frequency and severity assessed. Thus, this research identified a small number of highest-frequency LVNM crash scenarios based primarily on National Accident Sampling System (NASS) General Estimates System (GES) data. Although a significant portion of the LVNM crashes occurred under off-nominal conditions—for example, in darkness, on a wet surface, on curved roads, or with an impaired driver—the majority of LVNM crashes occurred under benign circumstances. This motivated the authors' approach of focusing on nominal driving conditions but ensuring the extensibility of the models to off-nominal conditions.

Identifying major LVNM crash scenarios alone is not sufficient for the purpose of identifying and developing advanced technologies to avoid LVNM crashes. Pertinent human perception and cognition need to be understood, and, specifically, the factors leading to deceleration decision making need to be identified. Simply put, designing safety features to assist the driver requires a clear understanding of relevant driver behavior. In the context of determining appropriate crash countermeasures for the highest-frequency LVNM scenarios, this points to the importance of accurate models for drivers' detection of a stopped vehicle ahead and deceleration decision making in such nominal conditions. Based on current knowledge about human cognitive processes and performance, the authors identified or developed several such models.

Their work differs from that reported above in two significant respects:

- The focus of this study is on the rear-end crash scenario, with the assumption that the researchers can understand—and eventually affect—crash countermeasures or roadway design changes within specific geometric configurations.
- To understand driver behavior for the purpose of developing vehicle features to assist the driver in avoiding LVNM crashes, this study develops cognitive driver-following models and deceleration decision-making models for drivers as they encounter a rear-end crash situation. They are embodied in closed-form mathematical models, with assumptions of the motivations and control objectives of drivers, which are intended to be implemented in an "intelligent vehicle" microsimulation (*13*).

In the next section, the crash-epidemiological database is reexamined with a renewed focus in understanding the highest-frequency rear-end crash scenario (and variants), along with accompanying categories and variables. The roles of some key variables in scenario construction are discussed in the following section, with an emphasis on their relevance to driver and vehicle characteristics. Then the

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subsequent section develops the underpinnings of a driver car-following model to analyze specific rear-end collision scenarios. Finally, concluding remarks, including a discussion of future work, are given in the last section.

DEFINING SCOPE: SCENARIOS AND FACTORS OF REAR-END CRASHES

Rear-End Crash Scenarios

The immediate focus is on LVNM crashes because of the high proportion of such crashes reported in the latest available (1997) NASS GES (10,009 LVNM crashes from a sample of 55,562 represented crashes) (*14*). The authors chose not to address the companion severity and likelihood components in determining LVNM crash scenarios. They also recognize that an LVNM crash may involve three or more vehicles and, actually, multiple LVNM vehicles. Only the initial rear-end collision is considered because crash countermeasures are presumed to be most effective in warning and control up to the crash. Nevertheless, postcrash control to avoid secondary crashes also may be possible, as shown in Chan and Tan (*15*).

To ensure a complete and rigorous analysis of crash data in identifying highest-frequency LVNM crash scenarios, the authors examined all possible building blocks or variables for scenario construction that can be reconstructed and analyzed with the 1994 and 1997 NASS GES databases. The analysis was guided by the results reported in Knipling et al. based on 1990 NASS GES data (*16*). In fact, the vast majority of their observations and analysis results remains valid through the years and has been used in the current analysis when appropriate. The current definitions differ only in that Knipling et al. use the term *lead-vehicle stationary* instead of this study's LVNM. (In an LVNM crash, the struck vehicle may have just slowed down to a complete stop before being struck or may have been stationary for a longer period of time. The data item "Accident Type" in the GES does not distinguish the two. Other data items may be used to infer the precrash activity of the struck vehicle, but only vaguely.)

The four most frequent LVNM scenarios are listed in Table 1, with totals and frequencies based on the 10,009 LVNM crashes reported from 1997 GES data given in parentheses. The rationale behind selecting these four scenarios will be discussed. Note that nearly 75 percent of all LNVM crashes fall within the first two scenarios. For this reason, this paper will further focus on "near intersection" and "midblock" nonfreeway scenarios.

Rear-End Crash Factors

The 1997 GES was systematically examined to identify crash scenarios. The objective was to focus on key variables to efficiently sort the important causal variables of crashes, along with correlations. In this manner, the authors arrived at categories and the importance of

TABLE 1 Four Most Frequent LVNM Scenarios (*14*)

SCENARIO 1: "NEAR INTERSECTION"	SCENARIO 2: "MIDBLOCK"	SCENARIO 3: "FREEWAY"	SCENARIO 4: "NON-INTERSECTION JUCTION"
The struck vehicle stopped at or near an intersection. (4,274; 43%)	The struck vehicle stopped due to traffic congestion or at the end of a long queue of vehicles waiting to pass through an intersection. (3080; 31%)	The struck vehicle stopped on a freeway. (1828; 18%)	The struck vehicle stopped at a non-intersection junction, e.g., a junction between a regular roadway and a driveway, an alleyway, or a ramp, or an unknown type of junction. (827; 8%)
• *Scenario 1.1:* stopped at or near a signal (2,539; 25%) • *Scenario 1.2:* stopped at or near a stop sign (542; 5%) • *Scenario 1.3:* stopped at an intersection with no signals or signs in the travel direction (but possibly and even likely with signals or signs in the crossing directions) (111; 11%)	(A more precise description of this scenario is that the struck vehicle stopped on a non-freeway travel lane, but was not proximate to any junction, e.g., an intersection, a ramp, a driveway, an alleyway, railroad crossing, etc. The current title of the scenario is actually an inference made based upon this more precise description.)	• *Scenario 3.1:* on an urban freeway (881; 9%) • *Scenario 3.2:* on a rural freeway (231; 2%) • *Scenario 3.3:* on an urban/rural freeway (716; 7%)[a]	

[a] The freeways on which the crashes occurred run through both urban and rural areas in the primary sampling unit (the basic unit of geographical area for accident reporting). The GES infers this based on the police accident reports, which in general report only the freeway identity and the location on the freeway but not whether the accident scene is located on an urban or rural section of the freeway.

scenario-descriptive variables, as well as those that center about the vehicle and the driver actions. The approach consists of the following three steps.

Step 1: Obtain Comprehensive Listing of Possible Crash-Causing Variables

To ensure a complete and rigorous examination of all possible scenarios, the authors began with a comprehensive list of variables and the associated variable values. Not only were factors contributing to LVNM accidents considered but also possible discriminators for technology requirements. For example, the study considered the possibility that a striking vehicle changed lanes from a lane with slower traffic only to find (too late) a vehicle having stopped in the destination lane. Also considered was the availability of data in developing the list. A "stutter stop" originally was considered but was removed from consideration because of a lack of data. The variables are listed in Table 2 by category.

Step 2: Focus on Key Variables

To avoid dimensional explosion, the authors next focused on one individual variable at a time and examined the (marginal) frequencies of different values. For example, they examined roadway surface (dry, wet, snow, etc.) and calculated the absolute and relative frequencies of LVNMs occurring on these types of surfaces.

Quickly removed from the next stage of consideration were all those values of an individual variable or even an entire category of variables that accounted for a very small percentage of all LVNM crashes. As an example, the "disabled (stalled) or parked vehicle in travel lane" value was removed from further consideration because this occurred in less than 1 percent of all LVNM accidents. Also eliminated was "Driver Impairment" (e.g., alcohol, drug, drowsiness) from further consideration because this category of variables accounted for less than 5 percent of LVNM accidents. Other such variables removed from further consideration in this step include "Crash Trajectory—immediately after lane change" and "Mechanical Failure" (of striking vehicle).

Other variables also have been excluded from explicit consideration in constructing the small number of highest-frequency crash scenarios. "Driver Age" is not considered because the goal is to develop technologies to assist drivers of all ages, although its distribution is much skewed and very informative. "Speed Limit" and "Speed of Striking Vehicle Prior to Collision" are not explicitly considered because the goal is to develop technologies to assist the driver at a wide range of speeds. "Vehicle Type" is excluded for similar reasons. Also, because of the focus on frequency, "Damage" is excluded, although it, by itself, could be a criterion for a "high value" scenario.

TABLE 2 Key LVNM Crash Variables

CATEGORY 1: STRUCK LVNM VEHICLE	
Variable 1.1: Reason For Stopping	
	• stalled or parked in travel lane (e.g., double parked) • traffic signal • traffic sign • prior to turning at intersections without signals or signs in the travel direction • stopped at the end of a long queue behind a signal or sign • traffic congestion • parked on the shoulder or by the curb • stutter stop
CATEGORY 2: CONTRIBUTING FACTORS	
Variable 2.1: Roadway Configuration	
	• type (urban highway, city streets, etc.) • intersection (signalized or not) • curve • grade
Variable 2.2: Roadway Surface Conditions	
Variable 2.3: Visibility	
	• lighting conditions • atmospheric conditions
Variable 2.4: Speed Limit	
CATEGORY 3: STRIKING VEHICLE	
Variable 3.1: Driver Impairment	
	• drinking • physical/mental impairment, e.g., drowsiness • distraction, e.g., phone, radio, passenger, etc.
Variable 3.2: Driver Age	
Variable 3.3: Crash Trajectory	
	• same lane • immediately after lane change
Variable 3.4: Speed Of Striking Vehicle Prior To Collision	
Variable 3.5: Mechanical Failure	
CATEGORY 4: VEHICLE-DESCRIPTIVE	
Variable 4.1 Vehicle Types (Struck and Striking)	
Variable 4.2 Damage (Severity)	

Hence, only a few variables survived this one-variable or marginal distribution analysis. Since the focus was on frequency, rather than likelihood, the authors temporarily removed from consideration variables such as roadway curvature, roadway grade, roadway surface conditions, lighting condition, and atmospheric condition in defining scenarios. However, they revived their consideration to check for possible strong correlations between the selected scenarios and these variables.

This process led to the explicit consideration of only those variables related to "Reason for Stopping" and nominal "Roadway Configuration," all of which appear in one or more of the four scenarios defined in Table 1.

Based on 1994 and 1997 GES data, the authors estimated the marginal distributions of the individual values of the variables listed in Table 1. As mentioned earlier, many, but certainly not all, of these distributions have been estimated and charted by Knipling et al. (*16*) based on the 1990 GES data, and the current findings regarding these do not deviate significantly from theirs. Note that Knipling et al. focused on descriptive statistics whereas the current study's goal goes beyond that and to actually constructing highest-frequency scenarios for LVNM countermeasure development, based on the previous and the current additional descriptive statistics. Because of the difference in goals and the continued validity of the earlier findings (based on 1990 data) for the 1994 and 1997 data, the focus will be on those additional descriptive statistics that were not addressed in Knipling et al. and on scenario construction. The statistics provided in Table 1 are examples of such additional descriptive statistics.

Step 3: Analyze Key Variables and Their Interaction, Followed by Checking for Strong Correlation Between Key Variables and Other Variables

Based on the analysis outlined in Steps 1 and 2, the variable combinations were narrowed down to those specified in the scenarios defined in Table 1. After having reached the scenarios, the authors checked for possible correlations between the selected scenarios and the variables or values that were temporarily removed from consideration for scenario development but still contributed significant percentages in the LVNM accidents—for example, wet or other slippery roadway surface conditions, a curved roadway, a grade or hill crest, or darkness. No such strong correlations were found to exist. It was determined, for example, that 75 percent of the LVNMs occurred during daylight and that the rest occurred during either "dark and lighted" or "dark and unlighted" conditions. Although the daylight accidents clearly are much more frequent than their "dark" counterparts, the latter may actually have much higher occurrence likelihoods when the volume of traffic traveling in daylight or darkness also is considered. (The same can be said about roadway surface conditions, roadway curvature, roadway grade, and so forth.)

However, because of the preponderance of daytime crashes, the authors chose to focus on this kind of nominal but "high value" scenario. Furthermore, although combining multiple adverse conditions—for example, the combination of darkness, wet roadway surface, curved road, hillcrest, and driver impairment—may increase the likelihood of an LVNM crash, the probability of these conditions occurring simultaneously is low, and hence the corresponding scenario tends not to be a high-frequency one.

In short, because of dimensional explosion, not all the possible combinations of variable values were considered. However, through examination of the marginal distributions of the individual variables and a large number of selected possible correlations among some of the variables, the authors were able to discern the important variables from the unimportant variables. In other words, the Pareto phenomenon occurs, in which a small number of variables uniquely characterize the vast majority of the LVNM accidents.

The absence of off-nominal factors in the four highest-frequency crash scenarios led to a focus on the "fundamentals." This is a prudent approach, anyway, because countering nonnominal factors tends to be more complex than dealing with nominal conditions. Despite the focus on nominal conditions, models were developed that already address, or can be extended to cover, nonnominal conditions. Through the models and their validation and calibration, a combination of human-driver and scenario-modeling parameters can be identified and LVNM crash countermeasures developed. As will become clearer later, the models may be useful not only for dealing with off-nominal conditions but also for preventing rear-end crashes in lead-vehicle-moving (LVM) scenarios.

DISCUSSION OF KEY VARIABLES

In order to determine the cognitive factors that lead to a car-following driver model for rear-end crashes and microsimulation-based studies based on this model, the taxonomy of key variables discussed earlier should serve as a foundation—and also could be further embellished. That is, of the four listed categories—"struck LVNM vehicle," "contributing factors," "striking vehicle," and "vehicle-descriptive"—only the third, striking vehicle, pertains directly to the driver; the others pertain to the description of the scenario. It still is important to consider variations to the scenario, as better highway or vehicle designs can yield insight to the contributing-factors and vehicle-descriptive categories.

However, the striking-vehicle category is of primary importance to any subsequent analysis, and the variables within that category require more detailed discussion, which follows. Some of the other key variables also are discussed. The emphasis on "high value" scenarios led to the focus on nominal conditions.

Driver Impairment

Approximately 3 percent of LVNM crashes reported in the 1990 GES involved charges of driving under the influence (DUI) of alcohol or drugs. Less than 5 percent of the LVNMs reported in either the 1994 or 1997 GES involved driver impairment. This will be discounted as the frequency of occurrence is low vis-à-vís the study's "high value" countermeasures and analyses approach.

It has been shown that drivers occasionally will look away with short glances (*17*). If the distracting task requires a longer time, they typically will utilize multiple 1- to 1.5-s glances rather than one long fixation. Thus, in normal, otherwise unimpaired driving, a distraction latency of up to 1.5 s could be added.

Driver Age

According to the 1990 GES data, drivers between the ages of 15 and 19 were involved in 594.4 rear-end crashes per 100 million vehicle miles traveled, whereas all other drivers were involved in only 569.8 rear-end crashes (*16*). Attributes such as higher risk taking among younger populations, and compensatory low-risk behavior and experience by older drivers, outweigh the younger drivers' ability to react faster in collision-imminent situations.

Crash Trajectory

Within the GES database, there is a "Corrective Action Attempted" data field that "describes the actions taken by the driver of this vehicle in response to the impending danger." The nonhighway cases with this field were examined in Wiacek and Najm (*5*), showing that for the top two LVNM rear-end scenarios, the majority of the drivers made no action prior to impact (78.4 percent and 68.6 percent for each scenario). A small percentage braked only (15.5 percent and 25.7 percent), while less than 4 percent steered only or braked and steered. Moreover, the 1990 GES data show that 87 percent of the striking vehicles in an LVNM crash were "going straight," with 13 percent of them turning. The turning-left movement was almost three times as likely to result in a rear-end crash as turning right. The fact that most drivers do not swerve is corroborated by Hatterick and Bathurst—of the 265 rear-end crashes they examined, the most frequent maneuver was to steer straight and brake (*18*).

In Yoo et al., a simulator collision-warning study is described, in which there was a subset of eight unwarned, unalerted subjects who encountered a lead vehicle cutting in from a parked position on the side of the road (*19*). Only one of the subjects swerved to miss the lead vehicle; the other seven crashed and did not swerve. All subjects applied the brakes during the incident. Finally, in Adams, drivers' initial response to an obstacle is to brake (*20*). Once beginning the braking action, some drivers also added a swerve component. It is unclear when such steering actions occur or at what angle magnitude. However, Adams also reports on clinical studies showing a relatively high incidence of steering maneuver reactions (*20*). One possible reason is that most of the studies cited were conducted with simulators and test tracks, thus leading to low-traffic scenarios with limited obstacles on the side of the road. This low-risk environment may have made swerving more acceptable to drivers.

Thus, as an overall observation, it is probably safe to assume that most drivers who rear-end an LVNM either make no action or brake. It seems that a small percentage incorporates a steering component.

Speed of Striking Vehicle Prior to Collision

In the GES, travel speed is estimated by the police. Drivers' or witnesses' estimates in the "narrative" section of the police accident report are supposedly not used but are still likely to influence police estimates. Since approximately 14 percent of the LVNM cases in 1990 resulted in a charge of speeding and 27 percent for other charges, including 3 percent for alcohol or drugs, a driver might lie lest he or she would be charged with speeding. Still, in 70 percent of the 1990 LVNM crashes, the precrash travel speed was unknown. Among those in which the travel speed was reported, the median was 35 km/h (22 mph), and 2.5 percent had a precrash speed of 88.5 km/h (55 mph) or higher. The median speed of 35 km/h (22 mph) is consistent with the typical two nonhighway LVNM scenarios.

Mechanical Failure

Mechanical failures accounted for a minute percentage of LVNM crashes and were eliminated from further consideration in this study.

Other Variables

Roadway Surface Conditions

According to our analysis of 1994 GES LVNM data, 73 percent of LVNM crashes occurred on dry roadway surfaces, with 76 percent of interstate crashes on dry roadway surfaces and 71 percent on city streets where signals or signs were present. Hence, the "high value" focus of any rear-end-crash countermeasure effectiveness analysis would be on dry roadway surfaces first, but other surface conditions also should be considered in due course.

Visibility and Lighting Conditions

The 1990 GES data suggest that 76.5 percent of LVNM crashes occurred during daylight. According to our analysis of 1994 GES data, 78 percent occurred during daylight, 13 percent during dark-but-lighted conditions, and 5 percent during dark and unlighted conditions. On interstate highways, 76 percent occurred during daylight, 12 percent during dark-but-lighted conditions, and 7 percent during dark and unlighted conditions. On city streets where signals or signs are present, 76 percent occurred during daylight, 17 percent during dark-but-lighted conditions, and 4 percent during dark and unlighted conditions. In all cases, dawn and dusk were insignificant (for LVNM crashes only). Therefore, the "high value" focus should be on daylight.

Braking

Because of the preponderance of light-duty vehicles, they will be our primary—but not exclusive—focus. In the *Task C3(1) Interim Report*, braking distributions were derived from vehicle stopping-distance data published in *Consumer Reports* and applied to sales figures from the *Automotive News Market Data Book* (*21*). The distribution contains 2 years of domestic unit sales, 1994–95, with data on maximum braking rates covering approximately 85.5 percent of the 29,870,481 vehicles sold in the United States during those 2 years. To build these distributions of car and light truck braking rates corresponding to dry and wet pavement conditions, the brake stopping distances were paired with the corresponding market class and unit sales data, then converted to deceleration rates. The mean and the standard deviation for the dry pavement test were 0.867 g and 0.059 g, respectively. Derating factors could be applied to these data to obtain an emergency braking distribution. It would take into account the decreased braking capability of vehicles due to anticipated "wear and tear" and the fact that typical drivers are not able or are not trying to stop their vehicles as quickly as test drivers.

It has been difficult to gather data about the braking profile of drivers in crash-imminent situations and on appropriate derating factors. However, non-emergency comfortable braking rates from the surrounding traffic, especially in the 35-km/h (22-mph) nonhighway traffic scenarios, can be taken from Lloyd et al., in which deceleration rates of drivers approaching stop signs are measured for speeds of 5 to 18 m/s (*22*). The mean and standard deviation of the deceleration rates of the drivers tested were found to be 0.2 g and 0.04 g, respectively.

CAR-FOLLOWING DRIVER MODEL FOR REAR-END CRASHES

This section describes models developed in order to understand the human cognitive processes and deceleration decision making, to identify possible weaknesses of a human driver, and to explore how technological countermeasures may improve the driver's performance—all in the context of preventing LVNM crashes. As mentioned earlier, despite the focus on nominal conditions, these models already address or can be extended to cover off-nominal conditions. In fact, they are useful not only for dealing with off-nominal conditions but also for preventing rear-end crashes in which the lead vehicle is moving.

Driver responses to a rear-end collision warning system will be different from those for unassisted drivers. This study's modeling scheme first will utilize driver response-time distributions to describe driver responses both with and without warnings.

A driver's response to a forward stimulus (e.g., brake lights) is broken into two subunits. Response time is the sum of the reaction time (the time from the appearance of the stimulus to the removal of the foot from the accelerator pedal) and the movement time (the time to move the foot from the accelerator pedal to the brake pedal). Additionally, two elements of perception should be considered in human vision- and cognition-based detection models: acquisition (defined for these purposes as proximal obstacle or vehicle detection probability P_d at range x) and tracking (defined for these purposes as deceleration x' relative to the driver). After a brief description of nomenclature, we will propose several acquisition models and longitudinal tracking models.

Brief Description of Nomenclature Used for Driver Response Time

Response-time classifications are described as follows:

- Alerted: the driver is aware, ready, and expecting to brake.
- Surprised: the driver is in a neutral driving state and is responding with some degree of urgency to a surprising stimulus.
- Unalerted: the driver is in a neutral driving state and is responding to an unsurprising stimulus.

The following potential modifier also is defined:

- Distracted: The driver is not looking at the road prior to his or her response. This latency typically will only be paired with "surprised" or "unalerted."

The definition listed for "alerted" is similar to that used by Olson and Sivak (*23*). The drivers were told the purpose of the test and were asked to repeat the test under alerted conditions. In the alerted condition, the drivers were asked to respond as quickly as possible upon sighting the obstacle. This distribution therefore would be classified as alerted.

The mean unalerted response-time distribution to standard brake lamps in traffic was reported in Sivak and Flannagan (*24*); the time for in-traffic responses to brake signals from standard brake lamps is 1.25 s, with a standard deviation of about 0.46 s. Also, from earlier in this paper, these response-time classifications can further be modified by a distraction latency (typically 1 to 1.5 s). Since a driver who is expecting to brake (alerted) will probably not look away, this modifier is seen as only being used with surprised and unalerted (depending on how surprised the driver is upon detecting the stimulus).

Since the model will not include perceptual impairments due to curves, low visibility, and driver impairment (i.e., DUI), perceptual information processing failure by the driver needs to be represented through the driver response-time distribution. It is probably safe to assume that the drivers who typically enter dangerous LVNM scenarios have some sort of misperception of the locations, speeds, and/or accelerations involved in the event. Such drivers will be modeled by the slow tail of the distribution since the extreme response times (e.g., beyond three sigma) are probably a result of such misperceptions.

Driver Response-Time Distribution Without Warning

This distribution describes a population that has a reduced level of alertness since there will be no advance warning of the LVNM. Therefore, the most logical response-time classification to use for this case is surprised. This selection is further reinforced by the fact that data on surprised response times were collected from drivers who were not exposed to collision warning systems (*23*).

Driver Response-Time Distributions With Warning

A warning display will result in a modified response-time distribution. For example, an in-dash display will require the driver to refocus on a shorter focal distance, which can be captured in the response time. Due to the supplementary prompting of the warning, this distribution also should describe a population that has an elevated level of alertness.

Because it is a reasonable bound for the warned LVNM scenario, the previously mentioned alerted response-time mean and standard deviation will be used (*23*). With a salient crash-warning signal (visual, audible, tactile, and/or haptic), it is presumed that the mean response time of the following driver would be less than the surprised mean, but not as low as the alerted mean.

To additionally address the change in focal distance between the exterior road scene and an interior visual warning, it is assumed that a driver will quickly and accurately glance (saccadic eye movement) to an interior display (i.e., the driver is familiar with the location of the display). The model human processor technique will be used as bounds (*25*): eye movement = (70 ~ 700) ms. [This is a raw value; it does not include the impact of driving. Actual saccadic eye-movement times (travel plus fixation time) can vary considerably depending on the task and the skill of the observer. In Russo, 70 ms is listed as the minimum time and 230 ms as typical time (*26*). The largest time given by Busswell for eye movements in reading is 660 ms (for first-grade children) (*27*), which Card et al. rounded to 700 ms (*25*).]

Acquisition (Detection) Models and Sensitivity to Inclement Weather

Detection probability at LVNM crash warning distances of 100 to 150 m of an alerted, nondistracted driver usually is assumed to be near 1.0 (*28*), but the more interesting case is inclement weather. Even though poor visibility conditions are not regarded as the "high value" case, they are shown in Table 2 to be an important contributing factor, and their effect will be quantitatively illustrated.

Bailey-Rand Contrast and Similar Models

The Bailey-Rand (BR) model incorporates, in a compact manner, the first-order effects of luminance contrast. To do so, it assumes that targets are static and can be represented by circles with varying contrasts to an appreciably uniform (and therefore uncluttered) background (*29*, *30*). Given these simplifications, the prediction of the detection probability as a function of range x, $P_d(x)$, is relatively straightforward:

$$P_d = \frac{1}{2} \pm \frac{1}{2}\left\{1 - \exp\left[-4.2\left(\frac{C_R}{C_T} - 1\right)^2\right]\right\}^{1/2}$$
$$+ \text{ when } \frac{C_R}{C_T} \geq 1,$$
$$- \text{ when } \frac{C_R}{C_T} < 1, \qquad (1)$$

where

$$C_T = 10^{-2}10^{\left[\frac{1}{\log[3440\,(D/x)+0.5]}\right]}, \quad \text{and} \qquad (2)$$

$$C_R = \frac{C_0}{1 + SGR\left[\exp\left(3.912\,\frac{x}{V}\right) - 1\right]} \qquad (3)$$

where C_T is the human detection threshold, and D/x is an angular resolution term that may be expressed in terms of line pairs/target (when viewed through a vision enhancement device), cycles/mrad, or some other appropriate measure of spatial frequency. Also, C_R is the apparent contrast and is expressed as a function of C_0, the physical target contrast with the local surround; SGR is the sky-to-ground luminance ratio; the parameter D is the diameter of the equivalent-area target circle; and x is the detection range.

The BR model also includes a target visibility V factor, or the maximum range to a target with $C_R = 1$, where C_R is diminished no more than 2 percent. Atmospheric phenomenology—specifically, the magnitude of weather obscuration affecting P_d—can be represented in V by pairing it with a Beer-Lambert or Koschmeider's Law multiplier:

$$T(\lambda) = e^{-ax} \qquad (4)$$

where $T(\lambda)$ is the transmittance, and a is the precipitation volume extinction coefficient (km^{-1}). Expressions for a are available in the form br^c and values for b and c for a variety of natural and manmade obscurants, and also as a function of density, for example, rain rate (*31*).

Limitations of the BR model primarily include the aforementioned assumption of static, circular targets. However, it has been successfully applied in U.S. Department of Defense applications (*30*), on noncircular targets and on natural backgrounds with considerably more clutter than many highway scenes. In this case, the LVNM target is not static relative to the approaching vehicle's velocity. Moreover, it is certainly not circular, nor the surround clutter-free or devoid of spatial or glare cues. There is also no explicit driver search model in the BR formulation; rather, each 0.33-s BR glimpse is assumed to be independent, which is reasonable if it is expected that with the presence of an LVNM collision warning signal, the driver will contain any alerted search within the lane directly ahead. [Note that a viable alternative would be the PCDETECT model (*32*), which takes into account driver age and glare, but the BR is used at this point for its simplicity, as it clearly highlights the importance of understanding and modeling target, background, and weather characteristics toward distal vehicle detection. It serves to illustrate the effects of atmospheric conditions and how this can be quantitatively characterized.]

In applying the BR model to the LVNM case, the following parameter values are substituted into Equation 1:

- In determining C_T, $D = 2.26$ m (4 m^2 target).
- In determining C_R,

$$C_0 = \frac{L_0 - L_b}{L_b} = \frac{R_0 - R_b}{R_b} = \frac{0.5 - 0.15}{0.15} = 2.3 \qquad (5)$$

The L_0 and L_b quantities are target and background luminance, respectively. Given the same insolation, they equate to first order to R_0 and R_b, the target and background reflectances. Substituting readily available values for R_0 and R_b yields a value for C_0 (*31*).

- $SGR = 1.4$, a typical value for clear skies and desert conditions (*31*). Values for desert-floor reflectivity should be near those for asphalt reflectivity (*33*), and the environment is nearly clutter-free, similar to unobscured road surfaces. Variations due to SGR typically are due to different sky conditions (e.g., clear versus diffuse) and terrestrial surface reflectivities (e.g., snow versus desert versus forest canopy). The range of SGR values is 0.2 (clear sky, snow surface) to 25 (diffuse sky, forest-canopy surface).

Using the BR input values for the ranges considered ($x = 90 - 160$ m), C_T (90 m) = 0.033, and $C_R/C_T > 1$. For a singular 0.33-s glimpse, $P_d = 1.0$ at a typical $V = 10\,000$ m (*31*). This confirms intuition: a visually unimpaired and alerted human performs well in an unobscured, direct line-of-sight detection task over LVNM detection ranges.

Longitudinal Tracking Model

A cognitive car-following model is developed as a tool to understand and study "unfolding" rear-end crashes, that is, precursor actions of either following or stopped vehicles that lead to an LFNM crash event. In Hoffmann and Mortimer, a perception model of range and range rate based on a "looming" effect of the car in front is proposed (*34*). In the model, the looming angular target size and its rate of increase (or decrease) are described. According to the model, at distances such that $d\omega/dt < 0.003$ rad/s, drivers are unable to discern differences in relative speed. However, at values above this threshold (i.e., at shorter distances), drivers scale perceived speed in a practically linear relationship with respect to a visual angle (ω), at just-noticeable increments of $\delta\omega/\omega = 0.12$. This can be expressed as

$$\dot{R} = -\frac{R^2\dot{\omega}}{d} \qquad (6)$$

where

$\dot{R}$ = the perceived range rate between the driver and the forward vehicle or obstacle,
R = the distance between the vehicles,
$\dot{\omega}$ = the rate of visual change, and
d = the forward vehicle or obstacle diameter.

This model has been modified with a cognitive description of the driving objective and control behavior by observing that when a driver visually perceives that the range rate is equal to zero, he or she maintains a comfortable time gap to the car in front as his or her tactical (i.e., near-term) driving objective.

A comfortable time gap is derived from the individual headway choice studied in Blackwell and McCready (*29*). In that study, a time gap is defined as

$$T_g = \frac{R}{v} \tag{7}$$

where v is the current speed of the following car. According to observed time gaps, the mean time-gap values were categorized to at least four kinds of psychologically distinct zones: danger, critical, comfortable, and pursuit. The limits of time gap for these zones are 0.6, 1.1, and 1.7 s, respectively. For example, a driver is in the comfortable zone when the time gap is between 1.1 and 1.7 s. These are based on a relatively small sample, and by Japanese social norms; nonetheless, they serve as important elements (whose values could be adjusted later) in this study's subsequent models.

Another approach, given in Ohta, is based on time-to-collision (TTC) (*35*). TTC is defined from simple kinematics as

$$\text{TTC} = -\frac{R}{\dot{R}} \tag{8}$$

In the literature, several studies on estimates of TTC are reported (*36–38*). In these studies, TTC to a stationary object such as LVNM is consistently underestimated.

According to the hypothesis suggested in van der Horst, both the decision to start braking and the control of braking are based on the estimated TTC available from the optic-flow field (*39*). In experiments with 12 male student drivers who were instructed to leave braking until the last possible moment, TTC values ranged from 2.1 to 2.9 s for normal, non-emergency braking and from 1.2 to 1.9 s for hard braking.

From the relations just described, Figure 1 is an illustration of the fused model including the driver's perception and cognitive feelings in car-following behavior, in which each zone is based on time headway when the current velocity is 26.5 m/s (60 mph). Zones I, II, III, and V are where the driver cannot detect the range rate directly based on Equation 6. To provide a clear graphical representation of these zones, a limited range of speed is included in Figure 1. The range of speed shown in the figure is particularly relevant for rear-end crashes with the lead vehicle moving, but the fused model is intended for both LVNM crashes and LVM crashes.

Since the range perception model of a driver is considered, the range threshold is ±4.452 m when the current speed is 26.5 m/s and the time gap is 1.4 s, as shown in the figure. According to the range-rate perception model in van der Horst (*39*), Zones IV, VI, and VII (with Zone VII—and Zone V—also the danger zone to an LVNM) are in the approaching region, where the range rate is negative and perceptible to a driver. Conversely, Zone VIII is the separating zone. Zones IV, VI, and VII are categorized by the TTC of the driver when a stationary vehicle is detected. Since normal braking is applied when the actual TTC is between 2.1 and 2.9 s, the Zone VI area can be generated for the driver to start the normal braking.

Based on Figure 1, a driver will minimize the time leading up to Zone II, that is, the comfort zone, and maximize the time within

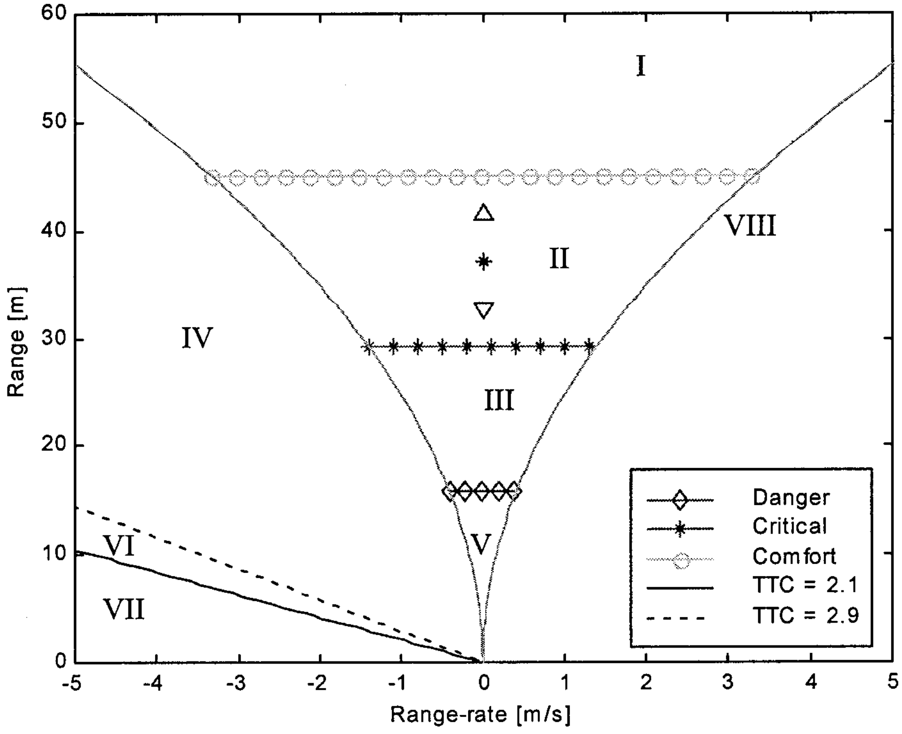

FIGURE 1 Regional model of driver car-following or braking behavior.

Zone II. Since the control objective for following a car is to be in Zone II, the control behavior will reflect this. For instance, suppose that a male driver is located in Zone IV with a range less than the upper limit of Zone II. Since the driver has a perception of closing (range rate), he begins to reduce velocity for the state to traverse one of Zones II, III, or V. Once the driver enters Zone II, he feels comfortable, and he will maintain current throttle pedal position. However, if the driver enters Zone V, he will brake to avoid a rear-end crash. Otherwise, he will choose one tactical behavior between changing a lane and following a leading car, based on road environment such as the positions of the vehicles in the adjacent lane. Consequently, LVNM—and for that matter, many LVM—traffic scenarios can be explained and analyzed through the driver perception zones in Figure 1.

Range rate is an important factor with respect to safety and comfort, also recognized by Fancher and Baraket who have formulated a car-following decision model based on the perception model discussed (*40*). Their model defines state space in terms of regions of the range versus range-rate phase graph. It features a comfortable following zone and a driver control objective to fall within that zone. In comparison, this paper's model also uses the previously mentioned perception model but has relatively many zones, each with its own control law, depending on whether the time gap is larger or smaller than comfortable and whether the range rate is positive or negative. There are also separate regions for braking and hard braking, which are defined by TTC values. Since the time gap is related only to the range and speed, the range rate therefore is used to define the car-following objective.

FUTURE WORK

The authors have identified a small number of predominant LVNM crash scenarios on which they based their driver model development efforts. Further model development efforts will be conducted insofar as "tuning" the microscopic LVNM and LVM car-following mathematical formulations of perception and motivation with available car-following data. Because in situ observations of LVNM crashes are rare, this tuning likely will be in the form of experimental work with California PATH Program vehicles. Moreover, these models can be extended easily to nonnominal situations, for example, detection in low-visibility conditions.

The authors next will focus their work on microsimulation-based analyses of the "highest value" rear-end crash scenarios, to include the rear-end crash car-following model described here, along with existing detailed models of the roadway environment and vehicle dynamics (*13*). Their ultimate objective will be to accurately describe and understand LVNM to the extent that they consequently can quantitatively understand the dynamics of potential crash countermeasures or roadway design changes.

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Paper No. 00-1474

Response to Simulated Traffic Signals Using Light-Emitting Diode and Incandescent Sources

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Simulated light-emitting diode (LED) traffic signals of different luminances were evaluated relative to incandescent signals of the same nominal color and at the luminances required by the specifications of the Institute of Transportation Engineers. Measurements were made of the reaction times to onset and the number of missed signals for red, yellow, and green incandescent and LED signals. Measurements also were made of subjects' ability to correctly identify signal colors and of their subjective brightness and conspicuity ratings. All measurements were made under simulated daytime conditions. There were no significant differences in mean reaction time, percentage of missed signals, color identification, or subjective brightness and conspicuity ratings between simulated incandescent and LED signals of the same nominal color and luminance. Higher luminances were needed for the yellow and green signal colors to ensure that they produced the same reaction time, the same percentage of missed signals, and the same rated brightness and conspicuity as a red signal at a given luminance. Equations fitted to the reaction time data, the missed signals data, and the brightness and conspicuity ratings for the LED signals can be used to make quantitative predictions of the consequences of proposed changes in signal luminance for reaction time, brightness, and conspicuity.

In North America, the Institute of Transportation Engineers (ITE) sets photometric specifications for traffic signals (see Table 1) (*1*). Typically, traffic signal modules use incandescent lamps and colored filters to produce red, yellow, and green signals. However, in 1998 the ITE published an interim specification for light-emitting diode (LED) modules, which specified luminous intensities for LED modules at 85 percent of those for modules using incandescent lamps (*2*). The results from the following experimental work could be used by decision makers for considering the consequences of adopting or revising the interim LED specification. Using an apparatus that simulated 200-mm LED and incandescent signals seen from 100 m under daytime conditions, the authors measured

- The reaction time to signal onset,
- The number of missed signals,
- The number of signals correctly identified by color, and
- Subjective ratings of brightness and conspicuity.

Reaction time is important because the onset of a signal (in particular, a red signal) should cue a driver to take appropriate action upon approaching an intersection (slowing down, stopping, or continuing at the same speed). Of course, detecting the onset of a signal at all is important and missed signals must be minimized. The correct identification of signal colors and subjective impressions of signals when approaching them help ensure safe traffic flow through intersections. This paper summarizes research to investigate responses to simulated traffic signals under daytime conditions. A detailed description of this research is available (*3*).

BACKGROUND

The failure to see a traffic signal can be catastrophic, so several studies have been conducted to determine the minimum luminous intensities required of traffic signals. Most researchers consider 100 m as the minimum distance at which traffic signals need to be clearly seen (*4, 5*). Cole and Brown investigated response times and the number of missed signals for red 200-mm signals (*6*). Normal-sighted and "protan" subjects viewed a schematic road scene. The luminance of the scene simulating the sky was about 5000 cd/m^2 and a signal was placed about 3° left of and 1.5° above the average direction of view. Reaction times and missed signals were measured when subjects looked directly at the signal and when they performed a tracking task. In general, as signal luminance decreased, reaction times lengthened and the probability of missing the signal increased. Protan subjects also had longer reaction times and more misses, as would be expected from their decreased sensitivity to long-wavelength ("red") light. Cole and Brown concluded that red signals in daytime conditions required a luminance of 5000 to 8000 cd/m^2 (*6*).

Fisher and Cole recommended that the intensities of yellow and green signals be higher than red signals (*7*). They recommended that the ratio of the luminous intensities for green to red signals be 1.33, and for yellow to red signals, 3.0. These recommendations were repeated by the Commission Internationale de l'Éclairage (*8*). The reason for the higher luminous intensity recommendations may be related to the perceived saturation of the colors used in conventional incandescent signals. In general, the red signal appears more saturated than the yellow and green signals, and the perceived brightness of a signal light increases for more saturated lights (*9*). LEDs have narrow spectral power distributions resulting in more highly saturated colors than incandescent signals, so questions have arisen recently about the required intensities of LED traffic signals relative to incandescent signals.

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TABLE 1 ITE Recommendations for Round 200-mm Traffic Signals and Associated Luminances (*1, 2*)

Signal color	Luminous intensity for incandescent signals (cd)	Average luminance for incandescent signals (cd/m²)	Luminous intensity for LED signals (cd)	Average luminance for LED signals (cd/m²)
Red	157	5000	133	4250
Yellow	726	23,121	617	19,652
Green	314	10,000	267	8,500

METHOD

Apparatus

The approach used to evaluate simulated traffic signals is similar to that employed by Cole and Brown (*6*). Subjects sat at a narrow desk 2 m from a 2.4-m by 2.4-m vertical wall (see Figure 1). The wall was painted white (reflectance = 0.87) above a horizon line located 1.1 m above floor level. Below the horizon line the wall was painted gray (reflectance = 0.17). The wall simulated a driver's view of the sky and ground along a straight road in flat country. Sulfur flood lamps with diffusers illuminated the wall uniformly so that the white background near the center of the wall had a luminance of about 5000 cd/m². The correlated color temperature of the flood lamps was approximately 3850 K, with a broad spectral power distribution.

In the center of the wall on the horizon line, a small meter (4.8 cm tall and 1.9 cm wide) was positioned, containing a horizontal pointer that could be moved by turning a knob at the subject's desk. This meter enables the subject to perform a tracking task. A random voltage was applied to the meter so that the needle slowly drifted randomly up and down unless the subject used the knob to keep the needle stationary. The background of the meter was painted red with a green band; subjects were instructed to keep the needle positioned over the green band during the experiment.

At 2.5° above and 2.5° to each side of the tracking task were two 4-mm-diameter apertures that simulated 200-mm traffic signals viewed from 100 m (or 300-mm signals viewed from 150 m). Visible through each aperture was the interior of a small integrating sphere containing red, yellow, and green LEDs matching ITE color specifications (*1*). The spheres were used to ensure that the signal luminance remained constant if subjects moved their heads slightly while performing the experiment. The spheres also contained another aperture through which a beam of light from an incandescent lamp could be passed. The red and yellow LED signals were very close in color to the red and yellow incandescent signals. The green LED signal appeared more saturated than the green incandescent signal, but both green signals fell within ITE color specifications (*1*). The luminance of the LED signals could be varied by changing the current through the LEDs, and the luminance of the incandescent signals could be changed via neutral density filters located between the incandescent lamps and the spheres. The neutral density filters and red, green, and yellow colored filters were mounted in computer-controlled filter wheels.

LEDs and incandescent lamps have differing onset times, with incandescent lamps taking 100 to 200 ms to reach full light output and LEDs reaching full light output in much shorter times. In order to eliminate this difference as a confounding variable in the experiment, electromechanical shutters with opening times of 3.5 ms were mounted in front of the sphere apertures, and the LEDs and incandescent lamps were switched on before the shutter opened.

A control panel containing the knob for controlling the tracking task and a switch for the reaction time was located at the subject's desk. Subjects were instructed to perform the tracking task with the knob, and to hold down the switch until they detected the signal onset, at which time they should release it. In this way, simple reaction time to the signal onset was measured. Both the left and right apertures were presented simultaneously and had the same color and luminance during each trial. An override was built into the apparatus so that if the needle in the tracking task was not positioned over the green area of the display, the presentation of the next stimulus would be delayed. This helped to ensure that subjects looked at the tracking task rather than the signal apertures. Subjects wore headphones that played white noise to mask sounds produced by the opening of the shutter.

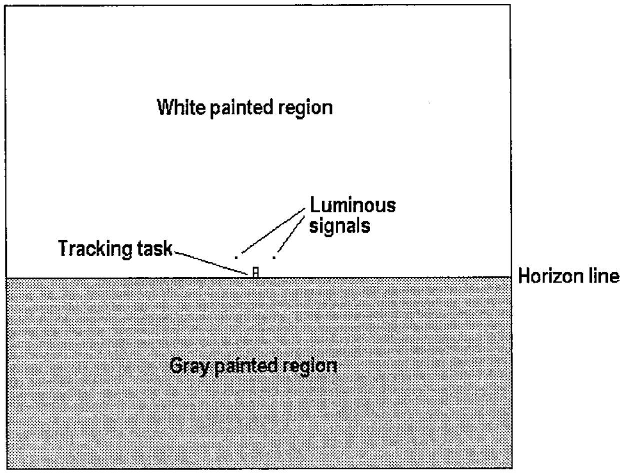

FIGURE 1 View of the vertical wall from the subject's desk.

Reaction Time and Missed Signal Measurements

To measure reaction time and missed signals, subjects performed the tracking task and held down the switch. At random intervals between 2 and 5 s, the simulated signals were presented and subjects would release the switch upon detection, and then re-press it for the next trial. The reaction time was measured as the time interval between the onset of the stimulus and the release of the switch. If the subject did not release the switch within 1 s after the onset of the stimulus, the signal lights were extinguished and the trial was counted as a miss. If the subject released the switch within 200 ms of the onset, that trial was repeated, because 200 ms is the minimum possible visual reaction time, determined by human physiology (*10*). This process was repeated for 10 successive presentations of the same luminance and signal color. Each combination of light source, luminance, and color was presented in random order in sets of 10 during each experimental session. Ten subjects (five males, five females) who had normal color vision, visual acuity of at least 20/25, and were between the ages of 25 and 35 participated in the reaction time and missed signals experiment. Each subject completed five sessions. Table 2 shows the nominal luminances used for each type of light source in a single session. The means of actual luminance measurements of all conditions were within 7.5 percent of the nominal luminances. Subsequently, 6 of the 10 subjects completed reaction time and missed signal trials at lower luminances between 1000 and 5000 cd/m^2. All of these data were combined for subsequent analysis.

The luminances in Table 2 were chosen with several criteria in mind:

- The incandescent stimuli should match the luminance of signals meeting the ITE recommendations (Table 1);
- One of the LED stimuli for each color also should have the ITE luminance;
- The luminance range for the LED signals should be wide enough to produce a clear increase in reaction time at the lowest luminances;
- The LED stimuli should have at least one luminance that is the same for all three colors; and
- The LED stimuli should include luminances corresponding to the average luminances recommended for traffic signals in Europe (red, yellow, and green = 12 732 cd/m^2, corresponding to European Performance Level 3) and Japan (red, yellow, and green = 7639 cd/m^2).

For the green signals, some of the LED conditions (marked with an asterisk in Table 2) actually used the incandescent source rather than a green LED, with the incandescent illumination filtered to produce a more saturated color similar to that emitted by the green LED. This was necessary in order to achieve luminances higher than 5000 cd/m^2 for the green signal using the integrating spheres in the apparatus.

TABLE 2 Light Sources Used in This Study and Their Nominal Luminances

Light source	Nominal luminance (cd/m^2)
LED – Red	12,732
LED – Red	7639
LED – Red	5000
LED – Red	3408
LED – Red	2000
LED – Red	1500[§]
LED – Red	1000
Incandescent – Red	5000
LED – Yellow	21,000
LED – Yellow	15,829
LED – Yellow	12,732
LED – Yellow	7639
LED – Yellow	5000
LED – Yellow	3000[§]
LED – Yellow	2000[§]
LED – Yellow	1500[§]
LED – Yellow	1000
Incandescent - Yellow	23,121
Incandescent – Green*	12,732
Incandescent – Green*	10,000
Incandescent – Green*	7639
Incandescent – Green*	6845
LED – Green	4500
LED – Green	3000[§]
LED – Green	2000[§]
LED – Green	1500[§]
LED – Green	1000
Incandescent – Green	10,000

[§] Additional luminances used during the subsequent reaction time and missed signals experiment.

*Incandescent source filtered to provide similar color to green LED.

Color Identification, Brightness, and Conspicuity Measurements

Measurements of perceived color and subjective ratings were made in a separate experiment, using the same combinations of light source, color, and luminance as in Table 2. While subjects performed the tracking task, the right signal was presented peripherally, as described earlier, for 1 s. After the presentation, subjects named the color of the signal and rated its brightness and conspicuity on 10-point scales with the ends labeled "very dark/very bright" and "invisible/very conspicuous." Thirty subjects (14 male, 16 female) between the ages of 22 and 54 participated in this experiment.

RESULTS

Reaction Times

For three LED signal luminances (1000, 7639, and 12 732 cd/m^2) at which all three colors were presented, a within-subjects analysis of variance was performed to determine the effect of luminance and color on reaction time. Both luminance ($F_{2,18} = 32.2, p < 0.001$) and color ($F_{2,18} = 20.4, p < 0.001$) had a statistically significant effect on reaction time. The interaction between luminance and color also was significant ($F_{4,36} = 10.0$, $p < 0.01$). As expected, increasing luminance resulted in shorter reaction times. Additionally, the red signals resulted in the shortest reaction times and green the longest.

For each session, and for each combination of source type, luminance, and color, the median of the 10 reaction times within each trial was calculated. (The median is less sensitive to extreme values than the mean.) Then, the mean of the five median values was calculated, as well as the associated standard deviation. The mean reaction times for the LED signals were fitted to an equation of the form

$$Y = aL^n + Z \tag{1}$$

where

Y = mean reaction time in milliseconds,
L = signal luminance in cd/m^2,
Z = minimum possible reaction time (and was set to 200 ms), and
a, n = fitting constants.

Equations of this type commonly have been fitted to reaction-time data (*10–14*) and are consistent with the latency of the visual system's response to stimuli of different luminous intensities (*15*). The values of the fitting constants, the goodness of fit (r^2) to the data, and the mean reaction time at the ITE luminances (*1*) for each subject are shown in Table 3. The fitted curves for each subject and for each signal color were normalized to a value of 100 at the luminance corresponding to the ITE recommendation for that color (*1*). Then the y-values of the normalized curves for each subject and color were calculated for a stepped series of luminances, and the mean y-value and associated standard deviation were calculated for each color for the subjects as a group. The results for each color are plotted in Figures 2, 3, and 4. These functions are a tool that

TABLE 3 Fitting Constants and Goodness of Fit for Mean Reaction Times for Each Subject and Each Color

LED color	Subject	a	n	r^2	Reaction time at ITE (*1*) luminance (ms)
Green	A	3483	-0.383	0.97	302
Green	B	4847	-0.326	0.69	441
Green	C	22,835	-0.512	0.86	404
Green	D	1423	-0.187	0.73	454
Green	E	2969	-0.253	0.97	489
Green	F	340,955	-0.860	0.99	324
Green	G	10030	-0.393	0.92	469
Green	H	6769	-0.374	0.71	406
Green	I	404,720	-0.933	0.92	275
Green	J	6918	-0.405	0.91	366
Yellow	A	3057	-0.358	0.88	284
Yellow	B	8655	-0.401	0.92	354
Yellow	C	14,111	-0.501	0.80	292
Yellow	D	1202	-0.175	0.92	407
Yellow	E	1457	-0.165	0.85	478
Yellow	F	102,413	-0.711	0.98	281
Yellow	G	3499	-0.291	0.93	388
Yellow	H	1996	-0.245	0.90	370
Yellow	I	479,726	-0.984	0.82	224
Yellow	J	5306	-0.386	0.83	310
Red	A	1940	-0.350	0.88	298
Red	B	7014	-0.411	0.91	412
Red	C	1161	-0.231	0.88	362
Red	D	381	-0.047	0.10	455
Red	E	1779	-0.201	0.73	521
Red	F	231,158	-0.878	0.94	331
Red	G	1030	-0.160	0.87	464
Red	H	1216	-0.201	0.94	419
Red	I	25,370	-0.640	0.59	309
Red	J	1141	-0.226	0.84	366

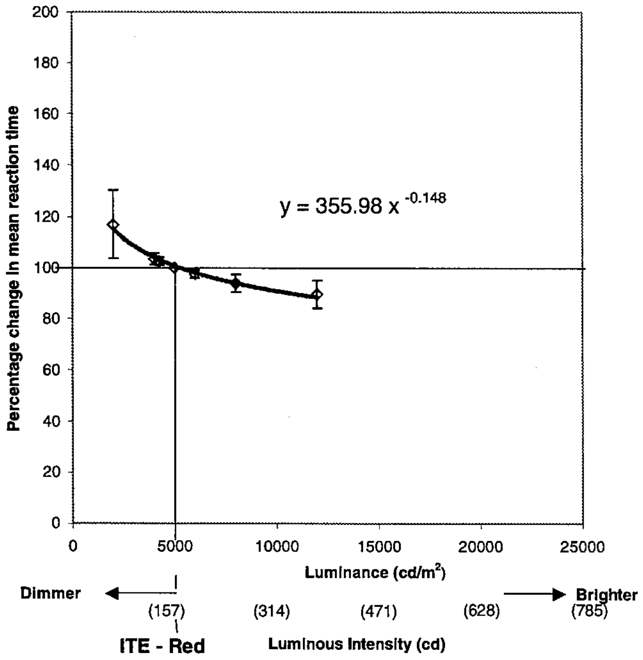

FIGURE 2 Percentage change in mean reaction time for the red LED signal; 100 percent reaction time is at a luminance of 5000 cd/m².

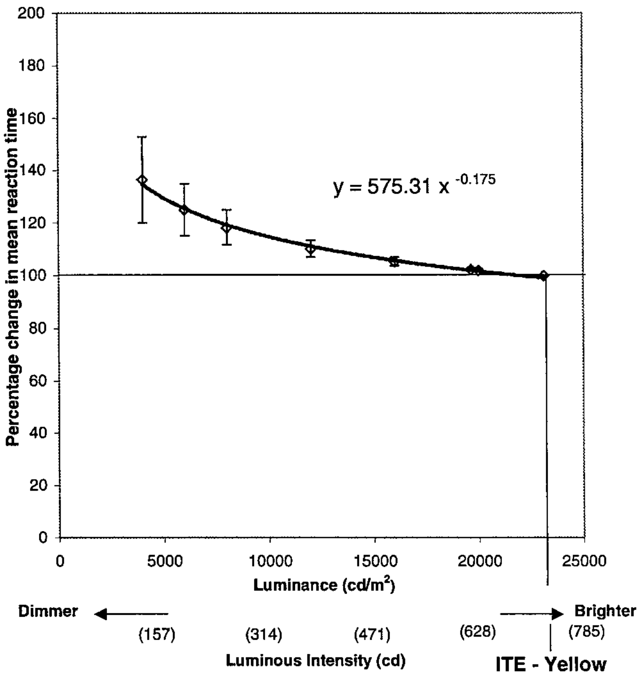

FIGURE 3 Percentage change in mean reaction time for the yellow LED signal; 100 percent reaction time is at a luminance of 23 121 cd/m².

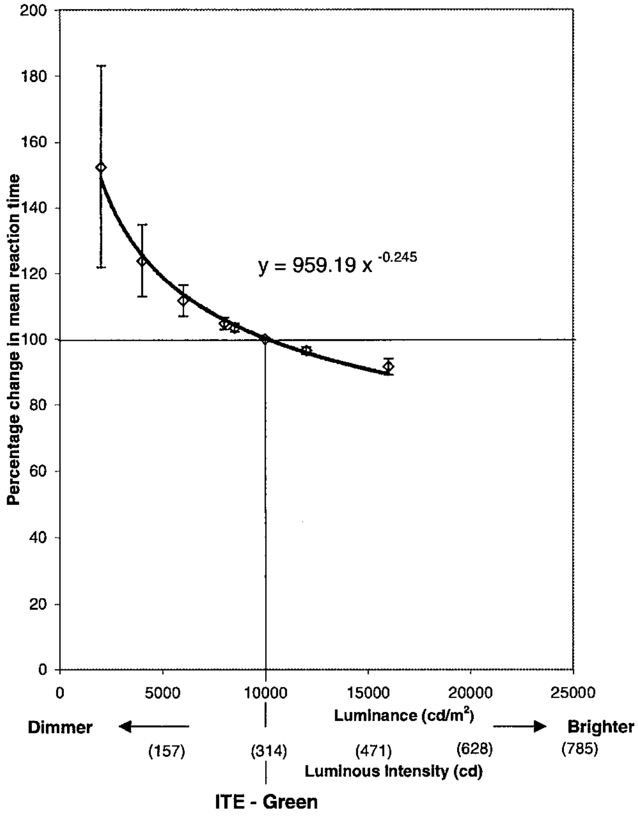

FIGURE 4 Percentage change in mean reaction time for the green LED signal; 100 percent reaction time is at a luminance of 10 000 cd/m².

can be used to predict the percentage change in reaction time for a departure in signal luminance from the ITE recommendation.

Missed Signals

The mean percentages of missed signals for each LED signal color are plotted in Figure 5 as a function of luminance. The percentage of missed signals clearly increases with decreasing signal luminance, and this trend appears to be more pronounced for the green LED signal than for the yellow or red signals. At the ITE luminances for each color (*1*), subjects missed 0.7 percent of the red signals, 0.0 percent of the yellow signals, and 1.0 percent of the green signals. At 2000 cd/m², there are clear differences among the colors in terms of the percentage of signals missed (green, 26 percent; yellow, 7 percent; red, 2 percent).

Color Identification

For each combination of source, luminance, and color in the second experiment, Table 4 lists the percentage of colors correctly identified by the 30 subjects as a group. It is clear that correct color identification is high, despite the fact that subjects did not view the signals directly, but rather peripherally. The resolution of the data in Table 4 is 3.3 percent, and there were no statistically significant differences in color identification between incandescent and LED signals at the ITE-recommended luminances (*1*). Of the 10 misidentifications of the green signal, 9 times it was thought to be yellow and once (at 1000 cd/m²) to be red. Of the 9 misidentifications of the red signal, all 9 were thought to be yellow, and of the 16 misidentifications of the yellow signal, all 16 were thought to be red.

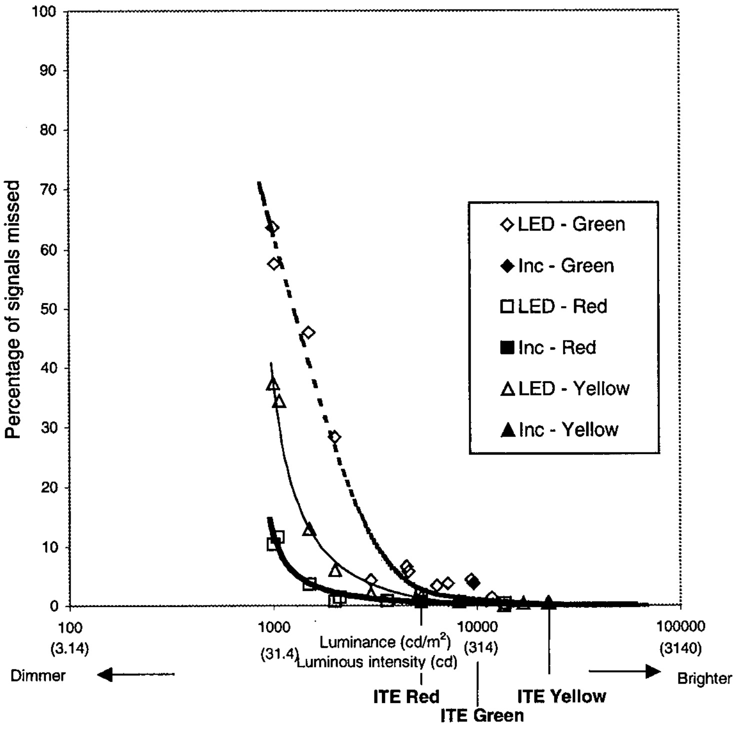

FIGURE 5 Percentage of signals missed by all subjects for each signal color and luminance.

TABLE 4 Percentage of Signals of Each Light Source, Color, and Luminance Correctly Identified

Light source	Nominal luminance (cd/m^2)	Percent correctly identified
LED – Red	12,732	100.0%
LED – Red	7639	93.3%
LED – Red	5000	93.3%
LED – Red	3408	96.7%
LED – Red	2000	96.7%
LED – Red	1000	93.3%
Incandescent - Red	5000	96.7%
LED – Yellow	21,000	100.0%
LED – Yellow	15,829	90.0%
LED – Yellow	12,732	96.7%
LED – Yellow	7639	93.3%
LED – Yellow	5000	83.3%
LED – Yellow	1000	83.3%
Incandescent – Yellow	23,121	100.0%
Incandescent – Green*	12,732	100.0%
Incandescent – Green*	10,000	93.3%
Incandescent – Green*	7639	100.0%
Incandescent – Green*	6845	93.3%
LED - Green	4500	90.0%
LED - Green	1000	93.3%
Incandescent – Green	10,000	96.7%

*Incandescent source filtered to provide similar color to green LED.

NOTE: The resolution of the data is 3.3 percent.

Brightness and Conspicuity Ratings

Figures 6 and 7 show the mean brightness and conspicuity ratings, respectively, for each combination of light source, luminance, and color. As expected from the visual science literature (*9*, *15*), brightness shows a linear relationship to the logarithm of the luminance of the signal, and the brightnesses of the red signals were higher than for the yellow and green signals. A very similar relationship holds for ratings of conspicuity, most likely because the uniform background used in the experiment meant that conspicuity was a simple matter of its brightness. Also shown in Figures 6 and 7 are the best-fitting logarithmic functions to the brightness and conspicuity ratings for the LED signals only. Table 5 shows the constants for these functions of the form

$$Y = A \ln(L) + B \qquad (2)$$

where

Y = mean rating of brightness or conspicuity (ranging from 1 to 10),
L = luminance of the signal in cd/m^2, and
A and B = fitting constants.

DISCUSSION OF RESULTS

Differences Between Incandescent and LED Signals of Same Luminance

Using matched-pair t-tests, the reaction times for the incandescent signals were compared to the reaction times for the LED signals at the recommended ITE luminances (*1*). The difference between the mean reaction times was not statistically significant for any of the colors. With the same analysis used, there were also no statistically significant differences ($p > 0.05$) between the LED and incandescent signals in terms of missed signals, color identification, or their brightness and conspicuity ratings. The signals were presented using an electromechanical shutter that resulted in equal onset times for each source. LEDs have shorter onset times than incandescent lamps and under certain conditions result in shorter reaction times (*16*). The work described here did not measure this effect.

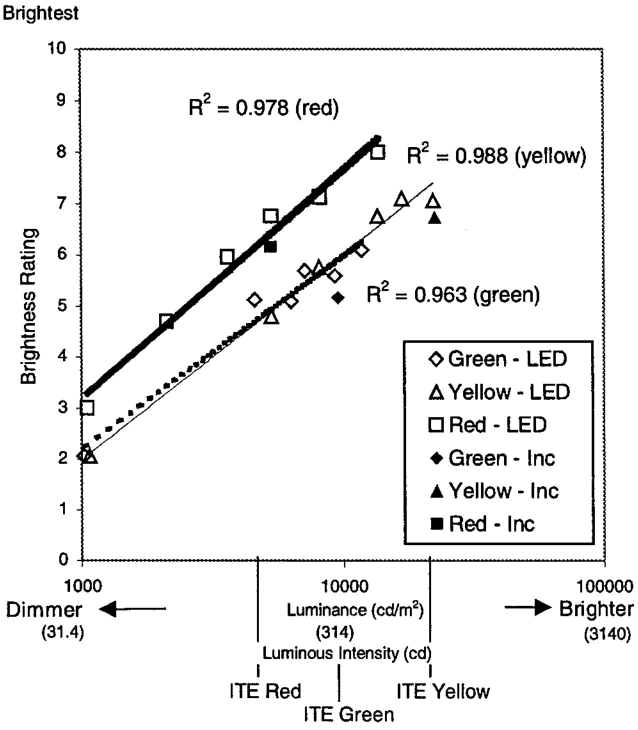

FIGURE 6 Mean brightness ratings for each color and luminance combination plotted against luminance. The lines are fitted through the mean ratings for the LED signals only.

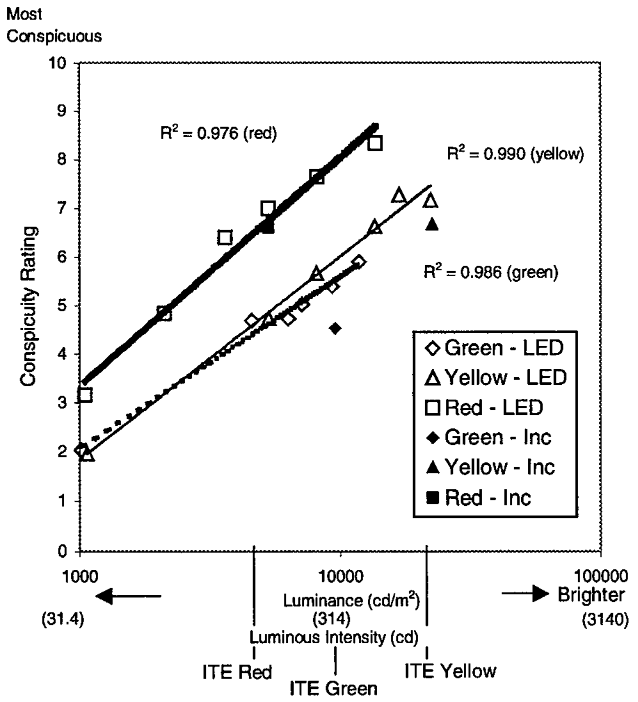

FIGURE 7 Mean conspicuity ratings for each color and luminance combination plotted against luminance. The lines are fitted through the mean ratings for the LED signals only.

Differences Among Signal Colors

Red LED traffic-signal modules have been used in the field for several years with considerable success (*17*). This could be taken as evidence that reaction time to and brightness and conspicuity of red LED signals that conform to ITE recommendations are satisfactory in practice. The mean luminances of yellow and green LED signals that have the same mean reaction time as the red LED signal with a luminance of 5000 cd/m² are approximately 10 000 and 13 000 cd/m², respectively, using the fitting equations described in Table 3. With the functions from Figure 5 used, the mean luminances of yellow and green LED signals needed in order to have the same number of missed signals as the red LED signal at 5000 cd/m² are 7000 and 14 000 cd/m², respectively. In comparison, the mean luminances of yellow and green LED signals that have the same brightness rating as the red LED signal with a luminance of 5000 cd/m² are approximately 12 000 cd/m² for both colors, and the mean luminances of yellow and green LED signals that have the same conspicuity rating as the red LED signal with a luminance of 5000 cd/m² are approximately 14 000 and 20 000 cd/m², respectively.

TABLE 5 Fitting Constants and Goodness of Fit for Brightness and Conspicuity Ratings

LED Color	a	b	r^2
Brightness			
Red	1.94	-10.18	0.98
Yellow	1.75	-10.10	0.99
Green	1.64	-9.12	0.96
Conspicuity			
Red	2.04	-10.72	0.98
Yellow	1.81	-10.68	0.99
Green	1.53	-8.52	0.99

This difference among colors (with red signals resulting in faster reaction times, fewer missed signals, and higher ratings of brightness and conspicuity) is consistent with the approach used by the ITE in its recommendations (*1, 2*), and it also is consistent with previous vision research investigating response to colored stimuli against bright backgrounds (*18–20*). This finding appears to disagree with specifications such as those proposed in Europe and Japan, which specify equal luminous intensity for each signal color.

Effects of Decreasing Signal Luminance

As previously discussed, the ITE-recommended interim signal luminances for LED signal modules (*2*) are 15 percent lower than the recommendations for incandescent signals (*1*), possibly because previous generations of LED signal modules were not able to meet the standard recommendations. Table 6 shows the percentage changes in reaction time and missed signals and changes in predicted ratings of brightness and conspicuity that would be a consequence of reducing the luminance of LED signals from the incandescent ITE-recommended luminances (*1*) to the interim LED values (*2*). It is hoped that similar exercises using these results can contribute to a well-informed discussion of any proposed changes to traffic signal standards worldwide.

CAVEATS

The results in this paper were obtained under a specific set of conditions, representing daytime conditions in clear terrain, and do not address, for example, nighttime viewing conditions or viewing signals against a complex background of competing signals, signs, and other stimuli. It seems likely that reaction times would be shorter and perhaps less dependent on color in clear nighttime conditions (*12, 19, 21*) and that discomfort ratings might be higher if glare is perceived. The subjects participating in this study were relatively young, and it is likely that higher luminances would be needed for the detection of signals by older subjects. Finally, this work eliminated onset time as a variable when measuring response; differences between LED and incandescent onset times might result in different reaction times (*16*). These caveats emphasize the importance of understanding the response to signals under different conditions, especially nighttime conditions, and by older subjects before making specific minimum or maximum performance recommendations for signal luminances.

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TABLE 6 Predicted Changes in Mean Reaction Time, Missed Signals, Rated Brightness, and Rated Conspicuity as Consequence of Reducing Luminance of LED Signals by 15% as in Interim ITE Specification (*2*)

Measure	Red LED	Yellow LED	Green LED
Percentage change in reaction time	+2.4%	+2.9%	+4.1%
Percentage change in missed signals	from 0.7% to 0.8%	no change	from 1.0% to 1.2%
Change in rated brightness (1=very dark, 10=very bright)	from 6.34 to 6.03	from 7.48 to 7.20	from 5.98 to 5.72
Change in rated conspicuity (1=invisible, 10=very conspicuous)	from 6.66 to 6.32	from 7.51 to 7.21	from 5.57 to 5.32

or drafts; and to Daniel Dyer, Robert Lingard, Richard Pysar, and Martin Overington for their work on the apparatus. Finally, the authors acknowledge all of the subjects who participated in this research. Without them, this project could not have been brought to fruition.

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Behavioral Adaptation, Safety, and Intelligent Transportation Systems

Alison Smiley

It is intrinsic to human nature to modify behavior to suit new conditions. How drivers are likely to change the way they drive if their vehicles are equipped with intelligent transportation system (ITS) devices is considered. It is clear from the antilock braking system experience that improvements in safety cannot be predicted on the basis of proof-of-concept studies alone, in which one simply looks at changes in performance of the task being aided, whether that is braking, navigation, or detection of hazards. One also must look at changes in other aspects of the driving task and at the type of driving being done to determine the likely effect on safety. In particular, one should assume that there may be trade-offs of mobility for safety, that is, more driving in more difficult conditions and at higher speeds leading to more crashes. Further, one should expect drivers to attempt to increase productivity while driving, given reduced driving task demand. The prolific use of cellular phones is evidence of this behavior. Research is needed on driver mental models of ITS devices, to ensure that drivers understand how they function. The best design from a mechanistic point of view may not be the most effective for drivers.

In the next 5 to 10 years, intelligent transportation system (ITS) devices will change the driving task dramatically. Vision enhancement, collision warning, and navigation systems will become standard devices. The aim of these devices is to improve safety. However, they all will change the nature of the driving task, inevitably leading to driver adaptation. That adaptation may have safety consequences.

PERVASIVENESS OF ADAPTATION

Adaptation is defined by the Oxford Dictionary as "the process of modifying to suit new conditions." The concept of behavioral adaptation is sometimes confused with a controversial theory known as "risk homeostasis." This theory, promulgated most notably by Wilde (*1*, *2*), claims that drivers have a target level of risk, and that safety countermeasures that reduce risk stimulate increased risk taking on the part of drivers so that a state of equilibrium or homeostasis is maintained. According to Evans' book *Traffic Safety and the Driver*, this theory has been debated at length and debunked by numerous traffic safety scientists (*3*). Evans points to the huge differences in risk of a crash per kilometer on U.S. urban interstates versus on rural arterial roads, as well as changes in crash risk per kilometer over the past decades, as evidence that risk homeostasis does not occur.

Risk homeostasis focuses on risk taking as being the motivating force behind driver behavior. In contrast, it is the intelligent reallocation of attention and effort that is seen as the motivating force for behavioral adaptation. Unlike the theory of risk homeostasis, there is no expectation that behavioral adaptation will result in constant crash rates. There is an expectation that, depending on the impact of the countermeasure on the driving task, trade-offs such as mobility for safety may be made, with the result that crash rates may not be reduced to the level that would have been anticipated, had there been no change in behavior.

When we drive we face constantly changing conditions to which we must adapt. This adaptation occurs on many levels. It occurs in response to both temporary and permanent changes in driver condition. Short-term adaptations occur as we are pressed for time and take a chance of running a red light. Long-term adaptations occur as we age. Older drivers slow by a few kilometers per hour on average and allow longer headways (*4*, *5*).

Adaptation occurs in response to the driving task. Mourant and Rockwell show the dramatic narrowing of eye fixations when drivers are closely following another vehicle (*6*). Rockwell found that eye-glance durations related to car radio operation were reduced by 20 percent in heavy traffic as compared to light traffic (*7*).

Adaptations occur in response to the roadway environment. A change in traffic signalization to provide an all-red clearance interval will increase the numbers of drivers who enter the intersection in the caution period. Increasing the lane width, widening the shoulder, and resurfacing the roadway all result in higher speeds (*8*).

Adaptations also occur in response to changes in the vehicle. Many changes have occurred in the past, prior to ITS, that likely resulted in various adaptations. It may well be that the installation of turn signals inside the vehicle increased the likelihood of drivers signaling, especially in inclement weather. Automatic transmissions may have speeded up the learning process for novice drivers who no longer had to deal with shifting gears while controlling vehicle speed and lane position. (The Young Drivers of Canada standard course is 18 lessons for those learning on standard and 13 for those learning on automatic transmissions.) Power-assisted brakes must have allowed drivers to approach situations requiring a stop at higher speeds. Improved car handling is thought to be one of the elements behind continual increases in average speed over the past 20 years.

Adaptation is intrinsically human. It is one of our most valuable characteristics and the reason that a human presence is desirable to monitor even the most highly automated systems—to deal with the unexpected. Adaptation is a manifestation of intelligent behavior.

When seen in this context, the often-used definition of behavioral adaptation as "those behaviors which may occur following the introduction of changes . . . which are not consistent with the initial purpose of the change" (*8*) seems limiting. Assuming the purpose of the change is to improve safety, the implication seems to be that adaptation is both negative and unforeseen by the designers.

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Yet, one cannot expect drivers to maintain the same strategy and pay the same attention to a task when assistance is provided. When a task is aided, the intelligent response is to reallocate attention and to change one's decisions so as to benefit from the aid. However, it is frequently the case that engineers who develop in-vehicle devices assume that drivers will not change their behavior. For example, when antilock brakes were introduced, predictions about their impact on safety were based on the assumption that only stopping distance and directional control during braking would change—speed and headways would not be affected (more on this later).

Why do engineers make such assumptions? According to Hauer, it is likely that the reason lies in the fact that engineers are trained to deal with the characteristics of inanimate matter such as loads, flows, stress, strain, and that "Once the physics of the situation and the properties of the materials are understood, we can predict fairly well 'what will happen if' and make the corresponding design choices." (*9*) In contrast to inanimate matter, drivers adapt, and speed and headway choices and reaction times cannot be considered to be invariant quantities that remain the same once the roadway or the vehicle has changed. That adaptation will occur is predictable—we should be more surprised by its absence.

UNFULFILLED PREDICTIONS: ANTILOCK BRAKING SYSTEM

A prime example of unfulfilled predictions because of adaptation is the antilock braking system (ABS). Early studies of ABS were proof-of-concept studies, in which drivers drove at a set speed and then braked. Not surprisingly, braking distances were found to decrease on wet surfaces. Moreover, directional control was maintained during braking on wet or dry surfaces. Based on such studies, optimistic predictions were made. For example, according to Langwieder, "the universal adoption of ABS in Germany would result in a 10–15 percent reduction in accidents involving heavy damages and/or injuries" (*10*).

Later studies considered the possibility of adaptation. A test track study showed that when drivers could choose their speed, they traveled slightly faster after practicing with ABS on wet surfaces, with the result that the emergency stopping distance was no different than with standard brakes (*11*).

Other researchers made naturalistic observations of 213 taxi drivers en route to an airport (*12*). This sample of drivers was chosen since they were likely to be pressed for time, leading to adaptive changes. Measures were taken of speed, lane keeping, headway, and seat-belt use. Questionnaires then were given out at the airport to taxi drivers to establish whether their vehicles were equipped with ABS or airbags or both, and to determine various demographic characteristics. These were used in a regression analysis to ensure that the effects seen were truly related to ABS or airbags. With ABS, drivers were found to adopt significantly shorter time headways. With airbags, there was no change found in measured behavior.

These were the performance effects. How was safety affected? An extensive study was carried out by the Highway Loss Data Institute (*13*). A comparison of claim frequency and size was made between 1991 models without ABS, and 1992 models with ABS, based on a total of 840,408 insured vehicle years. No significant differences were found in either claim frequency (8 per 100 vehicles) or size (average of $2,215 per 1991 model claim versus $2,293 per 1992 claim). Researchers then examined a subsample from the northern states in the winter but still found no significant differences.

Based on the performance studies, and on this crash rate study, it appears that drivers with ABS adapted by trading off safety for mobility, to the extent that there was no safety benefit—a far cry from the predicted 10 to 15 percent based on proof-of-concept studies.

DRIVER TRADE-OFFS AFFECTING STRATEGY

That the type of adaptation that does occur is frequently in the direction of less safety and more mobility should not be surprising. It is unfortunately the case that safety and mobility are frequently, though not always, inversely correlated. An improvement in mobility—higher speeds or easier lane changing—may result in a decrease in safety. Mobility improvements provide an immediate payoff—drivers get to their destinations faster. Safety improvements are far more intangible—a change in the risk of a certain type of accident from one every 100 years to one every 150 years. It is hardly surprising that drivers often choose greater mobility. The payoff is certain and immediate.

Although the safety/mobility trade-off is well known [see, for example, the extensive Organization for Economic Co-operation and Development report (*8*)], there is a second type of trade-off that influences driver strategy that may be important but has not yet been discussed in the literature. It is likely to be of particular importance for ITS devices, many of which will reduce driver workload. As drivers receive assistance with navigation, with monitoring the road ahead for hazards, and with keeping safe headways, the opportunity arises for other, nondriving-related, activities to occur in the vehicle. This was foreseen in an advertisement 10 years ago in which BMW showed a driver's-eye view of the German autobahn, with the caption "The New Office!" We live in an age when people try to accomplish more in less time. The proliferation of drivers using cellular phones, whether for business or pleasure, is evidence of the desire to be more productive while driving (*14*). With more driving assistance from ITS devices, this trend can be expected to continue.

ITS AND ADAPTIVE EFFECTS

As in-vehicle systems change the nature of driving, they affect the choices made by drivers. At the highest level, the strategic level, they are likely to affect the decision to drive. Vision enhancement systems may make drivers feel more comfortable about driving in poor visibility. Collision warning systems may encourage a fatigued driver to keep going when he might otherwise have stopped. A navigation system may encourage tourists to explore more widely than they might have otherwise.

In-vehicle systems also will affect the choices made at the tactical level, that is, while driving. Anyone who has driven a vehicle with brakes in need of maintenance knows that one becomes more cautious, driving more slowly and with greater headways. It is hardly surprising that drivers equipped with antilock brakes do the reverse.

In the following sections, various studies of ITS are reviewed, in terms of the degree to which driver adaptation, at both the strategic and tactical levels, was considered.

Adaptive Cruise Control Systems

A study of adaptive cruise control (ACC) by Fancher et al. is similar to the early studies of ABS in that it is a proof-of-concept (*15*). The effect of ACC was compared to that of standard cruise control and no cruise control in an on-road test. Velocity and headway were measured. Not surprisingly, the results indicated that the ACC system conferred a substantial margin of safety compared to the manual and the cruise control modes. Driving was smoother and instances of short headways less frequent.

This study demonstrates that ACC functions as designed, but within very strict limitations. It does not address the larger question of how drivers will change their strategy as a result of having ACC. This is not to criticize this particular study, only to point out that proof-of-concept is only the first stage of evaluation. Several studies are needed, and at different stages of implementation (*16*).

There is a need to examine changes in behavior that may result from reducing driver workload. For example, on a strategic level, drivers may do more driving or drive for longer periods with ACC. They may be more inclined to drive in high-density traffic, to drive when tired, and to spend more time attending to nondriving tasks inside the vehicle. This may lead to a reallocation of attention, so that less attention is given to the road ahead and more to in-vehicle tasks. The result may be poorer detection of hazards (with the exception of the moving vehicle ahead). A hazard of particular concern with ACC is a stopped vehicle ahead. Currently these systems only respond to moving vehicles—this is to avoid, for example, the vehicle slowing inappropriately on a curve in response to a fixed object on the roadside directly ahead of the vehicle. This means that the system will not respond to a stopped vehicle—such as one at the end of a queue. Because of drivers' poor perception of closing velocity, such stopped vehicles are particularly hazardous and especially so if the driver has become dependent on the system to detect and respond to unsafe headways. A lack of attention to the road ahead because of dependence on ACC may contribute to crashes into such stopped hazards. The final impact on safety will depend on the trade-off among fewer crashes due to drivers being late in recognizing a reduced headway, more crashes due to inappropriate dependence on the system to detect stopped vehicles, and more crashes due to greater exposure.

Vision Enhancement Systems

Vision enhancement systems (VES) are intended to assist drivers in detecting hazards, particularly pedestrians and animals, under low-visibility conditions. These systems improve visibility of a central area of the road scene through the use of infrared detection. Bossi et al. examined potential adaptive effects at dusk and at night using such a system in a driving simulator (*17*). At night, there is a greater discrepancy between visibility of the central field enhanced by VES and the peripheral field of view. In a simulator study, they showed that at night, but not at dusk, VES reduces target detection and discrimination for peripheral targets outside the central field enhanced through VES. No significant effect of VES on reaction time was found.

This study examined an important aspect of adaptation—the change in focus of attention induced by the system. The safety result may be a decreased likelihood of crashes involving hazards on or near the road but an increased likelihood of crashes involving hazards entering the road.

Another concern is that with better detection of hazards, drivers may be inclined to drive faster, with negative consequences for safety. Studies in Finland found that improving delineation on roads by using post-mounted reflectors on roads with substandard geometrics resulted in an inappropriate increase in speeds and higher rates of nighttime collisions (*18*). VES may well have the same result.

On a strategic level, as with ACC, VES may result in more driving in poor visibility, particularly for older drivers. The positive effect is that mobility will be increased—whether the net safety effect also is positive remains to be seen.

Navigation Systems

Navigation systems have received much attention from researchers with regard to effects on performance (*19*). Most studies have considered adaptations at the tactical level. For example, Antin et al. examined visual search behavior for drivers using an ETAK navigator, as opposed to drivers using a map or following a memorized route (*20*). The ETAK system displayed a map and allowed the driver to choose the map scale by using a zoom feature. The system was autonomous and operated by "dead-reckoning." Study results showed that on the memorized route, 85 percent of glances were ahead, at the road. With a map, this was reduced to 78 percent, and with the ETAK navigator, only 57 percent of glances were at the road.

When subjects used the navigator, 33 percent of glances were toward the display, as compared to only 7 percent toward the paper map. Although subjects were permitted to read the map while they drove, they chose to spend more time studying the map before starting to drive (1.55-min study time versus 0.75-min study time for the navigator) and less time using it while driving. Other studies of navigation systems find similar results (*21*, *22*). Moreover, these studies find that the visual search of older drivers is particularly affected. Glance times are longer and glances more frequent than is the case for younger drivers.

These results certainly raise a concern about safety. However, one cannot be sure of the effect without knowing much more about where drivers are looking. Rockwell's early studies of driver eye movements suggest a fair amount of spare capacity (*7*). While driving on highways with no traffic ahead, about two-thirds of driver fixations were on targets other than road markings, signs, and other vehicles (*7*). However, today's roads are busier. Furthermore, one does not know what spare capacity is available in today's urban situations in which navigation systems will be referred to most often—it is likely to be considerably less.

To date, visual demand associated with navigation systems has been measured using video cameras that allow researchers to separate glances at the navigation display from those at the mirrors and those on the road scene ahead. However, greater resolution would be required to determine what spare visual capacity exists as well as to see what happens when a navigation system is in use. Particularly needed is to know how far ahead the driver is looking and how appropriately he or she monitors the traffic around the vehicle, both with and without a navigation system. For example, the closer a vehicle in front is, the more frequently it should be glanced at. A vehicle exiting a driveway should be monitored more frequently if its speed indicates it may cross the driver's path.

A particular concern is vulnerable road users. Drivers pay greatest attention to objects likely to cause them the most harm. Drivers allow larger gaps when crossing in front of trucks as opposed to cars. One study showed that drivers at a T-junction turning right spent much more time looking left toward oncoming vehicles than right toward pedestrians or bicyclists who were about to cross the driver's path (*23*). If drivers neglect the road ahead, they may be more likely to neglect those that are more vulnerable, such as pedestrians and cyclists, and concentrate on the immediate threat of other vehicles to themselves.

Although there are grounds for concerns about safety, there is also reason to believe that drivers make adaptations in allocation of visual attention that are appropriate to the traffic demand. For example, Bhise and Rockwell examined driver sign-reading behavior in low- and high-density traffic (*24*). Glance durations in high-density traffic were approximately half those found for low-density traffic. Reeves and Stevens found that drivers using a map-based navigation system in an on-road study had glance durations 30 percent less than those found in a simulator study in which the traffic demands were lower (*25*).

An on-road study using the ETAK navigator examined the influence of traffic density on attention to the display (*26*). Subjects used the system to drive in unfamiliar areas that varied greatly with respect to traffic density. Video recordings were made of eye-scan patterns for light traffic, heavy traffic, and traffic in which an incident (potential conflict with other vehicles or pedestrians) occurred. The attentional demand of various roadway sections was rated and compared to driver eye-scan patterns. As attentional demand increased, the probability of a glance to the roadway center increased and the probability of a glance to the navigational display decreased. In addition, the length of glances to the roadway center increased for high-density as compared to low-density traffic and for incidents as compared to high-density traffic. The authors concluded that their results showed that drivers adapt their visual resources to account for increases in roadway demand, and they reduce their attention to the navigational display.

These data suggest that most drivers will tailor their glances to in-vehicle displays or tasks to the driving workload. However, it is necessary to examine changes in detection of on-road hazards to be sure that safety is not compromised.

Such an approach was taken by Walker et al. who used the FHWA driving simulator to compare driver detection performance, as well as vehicle control, for various types of navigation systems (*27*). These included maps, auditory messages, and visual displays. The detection task involved watching dashboard instrument gauges. The task difficulty was varied by the type of other traffic that was present, the roadway width, the degree of wind gusts, and the difficulty of a monitoring task.

Lane position variability was not affected by display modality or complexity. However, subjects appeared to cope with greater display complexity and greater task difficulty by dropping their speed and by reducing the attention paid to the gauge monitoring task. The speed on straight sections was not affected by the navigational device used. Speed effects were only found just before and just after turns.

The gauge monitoring task was performed most poorly for the paper-map group and next most poorly for the complex visual display. This latter finding was mainly attributable to the performance of the older subjects. Overall, subjects missed 16 percent of the signals presented. Older subjects using the map display or the paper map missed large numbers of signals (approximately 40 and 50 percent, respectively). Other types of visual and auditory devices (with the exception of the paper map) were associated with much lower miss rates.

Although this study did examine the effects of changes in the focus of visual attention on monitoring, the task used was an in-vehicle monitoring task. The more critical monitoring task in driving is for on-road hazards. The effect of navigation systems on such detection remains to be studied.

There has been little research addressing changes in performance at the strategic level for any ITS device. One experiment that did address this demonstrates some interesting adaptive effects of a navigation system (*28*). The results showed that unintentional (lost) users of neighborhood streets benefited more from car navigation information and revised their route more easily than those using simple or detailed maps. Users of car navigation systems appeared to learn to worry less about the consequences of getting lost and therefore intentionally traveled relatively more on neighborhood streets to avoid congested arterial streets. These authors concluded that widespread use of route guidance systems and traffic congestion information will increase neighborhood congestion unless countermeasures are taken.

In addition, adaptive effects were found with respect to the development of a mental model of the area. The group provided with the most route information recalled the fewest landmarks at every level of route experience. The authors suggest that the car navigation system substitutes for cognitive mapping of the route.

Further research is required on both the strategic and tactical changes resulting from the use of navigation systems to determine the likely safety effect. At the strategic level, there may be more driving by unfamiliar drivers. At the tactical level, there may be less attention to the road ahead, resulting in poorer detection of hazards. The overall safety effect will depend on the impact of greater exposure of unfamiliar drivers as well as the trade-off between reduced attention required to the road ahead due to the navigation task and greater attentional demand inside the vehicle.

Collision Avoidance Systems

As has been illustrated here, if the task is changed, drivers will modify their behavior. The task of designers and researchers is to ensure that the design encourages optimal modification. This is done by considering the likely changes in strategy and by modifying the design to ensure the resulting behavior is appropriate to the design goal of increased safety.

A good example of this approach is a study by Janssen et al. (*29*). Performance was measured for three types of collision avoidance systems (CAS):

- Driver's braking distance shown by a horizontal red line projected onto the windshield using a head-up display (HUD);
- Time-to-collision (TTC) plus pedal—4-s TTC trigger criterion with the CAS applying accelerator counterforce; and
- TTC plus 1 s plus pedal—the preceding CAS with an additional trigger criterion of 1-s simple headway, either criterion being sufficient.

These three systems were compared to a control condition as drivers drove a simulator. Vehicles ahead were presented with an initial headway of 7 s and a relative closing speed of 10 to 40 km/h. In a quarter of scenarios this vehicle braked after initial appearance. Frequent but irregular oncoming traffic made passing difficult. The average speed and the percentage of time that intervehicle headway was less than 1 s were measured.

The results showed that only the CAS consisting of TTC plus pedal counterforce provided a safety benefit. It reduced the percentage of time that the headway was less than 1 s, without increasing average speed. In the degraded visibility conditions, the HUD that showed braking distance significantly decreased driver safety by increasing short headways relative to no CAS.

Based on a purely mechanistic analysis, one would expect the third system to be better than the second. However, the results showed that adding a simple 1-s headway trigger criterion to TTC plus pedal significantly worsened driver safety by increasing the proportion of short (<1 s) headways and the average speed. This may have been because with two distinct criteria, drivers found it more difficult to understand how the CAS was operating. It is sobering to remember that one of the first accidents with ABS involved a police officer in a high-speed chase who removed his foot when he felt the unfamiliar vibration of the ABS brake. The driver's understanding or mental model of how the device operates is an important issue that has received little attention to date.

SUMMARY AND CONCLUSIONS

It is intrinsic to human nature to modify behavior to suit new conditions. A consideration of "intelligent behavior" and a review of a sample of ITS studies strongly suggest that one should assume that adaptation will occur when the driving task is changed. It is clear from the ABS experience that safety cannot be predicted on the basis of proof-of-concept studies alone. One cannot simply look at changes in performance of the task being aided, whether that is braking, navigation, or detection of hazards. One has to look at changes in other aspects of the driving task and at the type of driving being done.

In particular, one should assume that there may be trade-offs of mobility for safety, that is, more driving in more difficult conditions and at higher speeds leading to more crashes. Furthermore, one should expect drivers to attempt to increase productivity while driving, given reduced driving task demand. The prolific use of cellular phones is evidence of this behavior.

Research is needed on driver mental models of ITS devices, to ensure that drivers understand how they function. The best design from a mechanistic point of view may not be the most effective for operators.

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