



SAfety VEhicles using adaptive  
Interface Technology  
(Task 2b)

Visual Demand of Curves and Fog-Limited Sight Distance  
and Its Relationship to Brake Response Time

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## 2.0 PROGRAM OVERVIEW

Driver distraction is a major contributing factor to automobile crashes. National Highway Traffic Safety Administration (NHTSA) has estimated that approximately 25% of crashes are attributed to driver distraction and inattention (Wang, Knipling, & Goodman, 1996). The issue of driver distraction may become worse in the next few years because more electronic devices (e.g., cell phones, navigation systems, wireless Internet and email devices) are brought into vehicles that can potentially create more distraction. In response to this situation, the John A. Volpe National Transportation Systems Center (VNTSC), in support of NHTSA's Office of Vehicle Safety Research, awarded a contract to Delphi Electronics & Safety to develop, demonstrate, and evaluate the potential safety benefits of adaptive interface technologies that manage the information from various in-vehicle systems based on real-time monitoring of the roadway conditions and the driver's capabilities. The contract, known as Safety VEHICLE(s) using adaptive Interface Technology (SAVE-IT), is designed to mitigate distraction with effective countermeasures and enhance the effectiveness of safety warning systems.

The SAVE-IT program serves several important objectives. Perhaps the most important objective is demonstrating a viable proof of concept that is capable of reducing distraction-related crashes and enhancing the effectiveness of safety warning systems. Program success is dependent on integrated closed-loop principles that, not only include sophisticated telematics, mobile office, entertainment and safety warning systems, but also incorporate the state of the driver. This revolutionary closed-loop vehicle environment will be achieved by measuring the driver's state, assessing the situational threat, prioritizing information presentation, providing adaptive countermeasures to minimize distraction, and optimizing advanced collision warning.

To achieve the objective, Delphi Electronics & Safety has assembled a comprehensive team including researchers and engineers from the University of Iowa, University of Michigan Transportation Research Institute (UMTRI), General Motors, Ford Motor Company, and Seeing Machines, Inc. The SAVE-IT program is divided into two phases shown in Figure i. Phase I spans one year (March 2003--March 2004) and consists of nine human factors tasks (Tasks 1-9) and one technology development task (Task 10) for determination of diagnostic measures of driver distraction and workload, architecture concept development, technology development, and Phase II planning. Each of the Phase I tasks is further divided into two sub-tasks. In the first sub-tasks (Tasks 1, 2A-10A), the literature is reviewed, major findings are summarized, and research needs are identified. In the second sub-tasks (Tasks 1, 2B-10B), experiments will be performed and data will be analyzed to identify diagnostic measures of distraction and workload and determine effective and driver-friendly countermeasures. Phase II will span approximately two years (October 2004--October 2006) and consist of a continuation of seven Phase I tasks (Tasks 2C--8C) and five additional tasks (Tasks 11-15) for algorithm and guideline development, data fusion, integrated countermeasure development, vehicle demonstration, and evaluation of benefits.

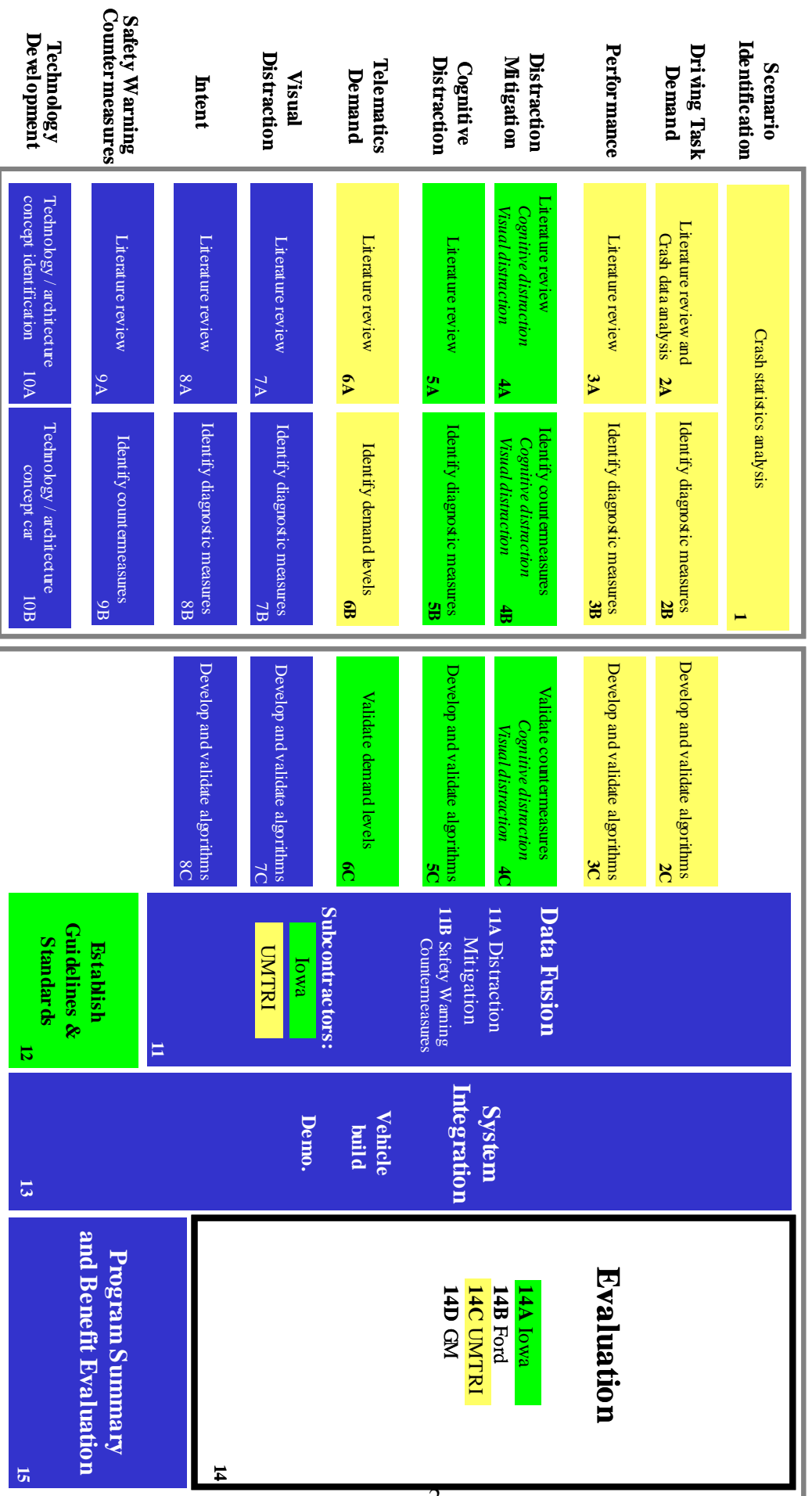


Figure i: SAVE-IT tasks

It is worthwhile to note the SAVE-IT tasks in Figure i are inter-related. They have been chosen to provide necessary human factors data for a two-pronged approach to address the driver distraction and adaptive safety warning countermeasure problems. The first prong (Safety Warning Countermeasures sub-system) uses driver distraction, intent, and driving task demand information to adaptively adjust safety warning systems such as forward collision warning (FCW) systems in order to enhance system effectiveness and user acceptance. Task 1 is designed to determine which safety warning system(s) should be deployed in the SAVE-IT system. Safety warning systems will require the use of warnings about immediate traffic threats without an annoying rate of false alarms and nuisance alerts. Both false alarms and nuisance alerts will be reduced by system intelligence that integrates driver state, intent, and driving task demand information that is obtained from Tasks 2 (Driving Task Demand), 3 (Performance), 5 (Cognitive Distraction), 7 (Visual Distraction), and 8 (Intent).

The safety warning system will adapt to the needs of the driver. When a driver is cognitively and visually attending to the lead vehicle, for example, the warning thresholds can be altered to delay the onset of the FCW alarm or reduce the intrusiveness of the alerting stimuli. When a driver intends to pass a slow-moving lead vehicle and the passing lane is open, the auditory stimulus might be suppressed in order to reduce the alert annoyance of a FCW system. Decreasing the number of false positives may reduce the tendency for drivers to disregard safety system warnings. Task 9 (Safety Warning Countermeasures) will investigate how driver state and intent information can be used to adapt safety warning systems to enhance their effectiveness and user acceptance. Tasks 10 (Technology Development), 11 (Data Fusion), 12 (Establish Guidelines and Standards), 13 (System Integration), 14 (Evaluation), and 15 (Program Summary and Benefit Evaluation) will incorporate the research results gleaned from the other tasks to demonstrate the concept of adaptive safety warning systems and evaluate and document the effectiveness, user acceptance, driver understandability, and benefits and weaknesses of the adaptive systems. It should be pointed out that the SAVE-IT system is a relatively early step in bringing the driver into the loop and therefore, system weaknesses will be evaluated, in addition to the observed benefits.

The second prong of the SAVE-IT program (Distraction Mitigation sub-system) will develop adaptive interface technologies to minimize driver distraction to mitigate against a global increase in risk due to inadequate attention allocation to the driving task. Two examples of the distraction mitigation system include the delivery of a gentle warning and the lockout of certain telematics functions when the driver is more distracted than what the current driving environment allows. A major focus of the SAVE-IT program is the comparison of various mitigation methods in terms of their effectiveness, driver understandability, and user acceptance. It is important that the mitigation system does not introduce additional distraction or driver frustration. Because the lockout method has been shown to be problematic in the aviation domain and will likely cause similar problems for drivers, it should be carefully studied before implementation. If this method is not shown to be beneficial, it will not be implemented.

The distraction mitigation system will process the environmental demand (Task 2: Driving Task Demand), the level of driver distraction [Tasks 3 (Performance), 5 (Cognitive Distraction), 7 (Visual Distraction)], the intent of the driver (Task 8: Intent), and the telematics distraction potential (Task 6: Telematics Demand) to determine which functions should be advised against under a particular circumstance. Non-driving task information and functions will be prioritized based on how crucial the information is at a specific time relative to the level of driving task demand. Task 4 will investigate distraction mitigation strategies and methods that are very well accepted by the users (i.e., with a high level of user acceptance) and understandable to the drivers. Tasks 10 (Technology Development), 11 (Data Fusion), 12 (Establish Guidelines and Standards), 13 (System Integration), 14 (Evaluation), and 15 (Program Summary and Benefit Evaluation) will incorporate the research results gleaned from the other tasks to demonstrate the concept of using adaptive interface technologies in distraction mitigation and evaluate and document the effectiveness, driver understandability, user acceptance, and benefits and potential weaknesses of these technologies.

In particular, driving task demand and driver state (including driver distraction and impairment) form the major dimensions of a driver safety system. It has been argued that crashes are frequently caused by drivers paying insufficient attention when an unexpected event occurs, requiring a novel (non-automatic) response. As displayed in Figure ii, attention to the driving task may be depleted by driver impairment (due to drowsiness, substance use, or a low level of arousal) leading to diminished attentional resources, or allocation to non-driving tasks<sup>1</sup>. Because NHTSA is currently sponsoring other impairment-related studies, the assessment of driver impairment is not included in the SAVE-IT program at the present time. One assumption is that safe driving requires that attention be commensurate with the driving demand or unpredictability of the environment. Low demand situations (e.g., straight country road with no traffic at daytime) may require less attention because the driver can usually predict what will happen in the next few seconds while the driver is attending elsewhere. Conversely, high demand (e.g., multi-lane winding road with erratic traffic) situations may require more attention because during any time attention is diverted away, there is a high probability that a novel response may be required. It is likely that most intuitively drivers take the driving-task demand into account when deciding whether or not to engage in a non-driving task. Although this assumption is likely to be valid in a general sense, a counter argument is that problems may also arise when the situation appears to be relatively benign and drivers overestimate the predictability of the environment. Driving

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<sup>1</sup> The distinction between driving and non-driving tasks may become blurred sometimes. For example, reading street signs and numbers is necessary for determining the correct course of driving, but may momentarily divert visual attention away from the forward road and degrade a driver's responses to unpredictable danger evolving in the driving path. In the SAVE-IT program, any off-road glances, including those for reading street signs, will be assessed in terms of visual distraction and the information about distraction will be fed into adaptive safety warning countermeasures and distraction mitigation sub-systems.

environments that appear to be predictable may therefore leave drivers less prepared to respond when an unexpected threat does arise.

A safety system that mitigates the use of in-vehicle information and entertainment system (telematics) must balance both attention allocated to the driving task that will be assessed in Tasks 3 (Performance), 5 (Cognitive Distraction), and 7 (Visual Distraction) and attention demanded by the environment that will be assessed in Task 2 (Driving Task Demand). The goal of the distraction mitigation system should be to keep the level of attention allocated to the driving task above the attentional requirements demanded by the current driving environment. For example, as shown in Figure ii, “routine” driving may suffice during low or moderate driving task demand, slightly distracted driving may be adequate during low driving task demand, but high driving task demand requires attentive driving.

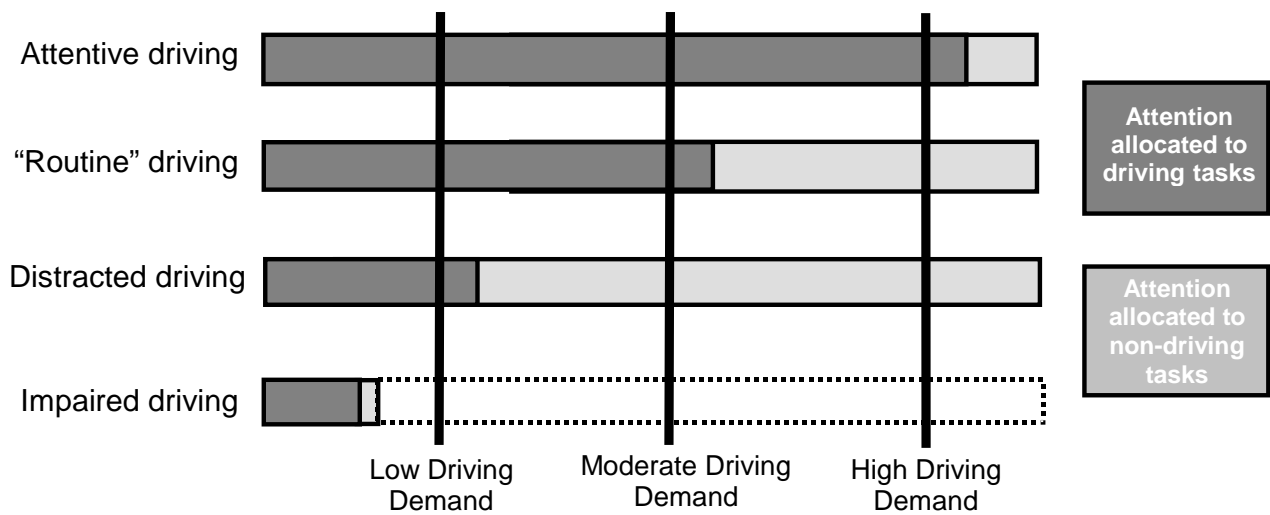


Figure ii. Attention allocation to driving and non-driving tasks

It is important to note that the SAVE-IT system addresses both high-demand and low-demand situations. With respect to the first prong (Safety Warning Countermeasures sub-system), the safety warning systems (e.g., the FCW system) will always be active, regardless of the demand. Sensors will always be assessing the driving environment and driver state. If traffic threats are detected, warnings will be issued that are commensurate with the real time attentiveness of the driver, even under low-demand situations. With respect to the second prong (Distraction Mitigation sub-system), driver state including driver distraction and intent will be continuously assessed under all circumstances. Warnings may be issued and telematics functions may be screened out under both high-demand and low-demand situations, although the threshold for distraction mitigation may be different for these situations.



It should be pointed out that drivers tend to adapt their driving, including distraction behavior and maintenance of speed and headway, based on driving (e.g., traffic and weather) and non-driving conditions (e.g., availability of telematics services), either consciously or unconsciously. For example, drivers may shed non-driving tasks (e.g., ending a cell phone conversation) when driving under unfavorable traffic and weather conditions. It is critical to understand this "driver adaptation" phenomenon. In principle, the "system adaptation" in the SAVE-IT program (i.e., adaptive safety warning countermeasures and adaptive distraction mitigation sub-systems) should be carefully implemented to ensure a fit between the two types of adaptation: "system adaptation" and "driver adaptation". One potential problem in a system that is inappropriately implemented is that the system and the driver may be reacting to each other in an unstable manner. If the system adaptation is on a shorter time scale than the driver adaptation, the driver may become confused and frustrated. Therefore, it is important to take the time scale into account. System adaptation should fit the driver's mental model in order to ensure driver understandability and user acceptance. Because of individual difference, it may also be important to tailor the system to individual drivers in order to maximize driver understandability and user acceptance. Due to resource constraints, however, a nominal driver model will be adopted in the initial SAVE-IT system. Driver profiling, machine learning of driver behavior, individual difference-based system tailoring may be investigated in future research programs.

## Communication and Commonalities Among Tasks and Sites

In the SAVE-IT program, a "divide-and-conquer" approach has been taken. The program is first divided into different tasks so that a particular research question can be studied in a particular task. The research findings from the various tasks are then brought together to enable us to develop and evaluate integrated systems. Therefore, a sensible balance of commonality and diversity is crucial to the program success. Diversity is reflected by the fact that every task is designed to address a unique question to achieve a particular objective. As a matter of fact, no tasks are redundant or unnecessary. Diversity is clearly demonstrated in the respective task reports. Also documented in the task reports is the creativity of different task owners in attacking different research problems.

Task commonality is very important to the integration of the research results from the various tasks into a coherent system and is reflected in terms of the common methods across the various tasks. Because of the large number of tasks (a total of 15 tasks depicted in Figure i) and the participation of multiple sites (Delphi Electronics & Safety, University of Iowa, UMTRI, Ford Motor Company, and General Motors), close coordination and commonality among the tasks and sites are key to program success. Coordination mechanisms, task and site commonalities have been built into the program and are reinforced with the bi-weekly teleconference meetings and regular email and telephone communications. It should be pointed out that little time was wasted in meetings. Indeed, some bi-weekly meetings were brief when decisions can be made quickly, or canceled when issues can be resolved before the meetings. The level of coordination and commonality among multiple sites and tasks is un-precedented

and has greatly contributed to program success. A selection of commonalities is described below.

#### Commonalities Among Driving Simulators and Eye Tracking Systems In Phase I

Although the Phase I tasks are performed at three sites (Delphi Electronics & Safety, University of Iowa, and UMTRI), the same driving simulator software, Drive Safety™ (formerly called GlobalSim™) from Drive Safety Inc., and the same eye tracking system, FaceLab™ from Seeing Machines, Inc. are used in Phase I tasks at all sites. The performance variables (e.g., steering angle, lane position, headway) and eye gaze measures (e.g., gaze coordinate) are defined in the same manner across tasks.

Common Dependent Variables An important activity of the driving task is tactical maneuvering such as speed and lane choice, navigation, and hazard monitoring. A key component of tactical maneuvering is responding to unpredictable and probabilistic events (e.g., lead vehicle braking, vehicles cutting in front) in a timely fashion. Timely responses are critical for collision avoidance. If a driver is distracted, attention is diverted from tactical maneuvering and vehicle control, and consequently, reaction time (RT) to probabilistic events increases. Because of the tight coupling between reaction time and attention allocation, RT is a useful metric for operationally defining the concept of driver distraction. Furthermore, brake RT can be readily measured in a driving simulator and is widely used as input to algorithms, such as the forward collision warning algorithm (Task 9: Safety Warning Countermeasures). In other words, RT is directly related to driver safety. Because of these reasons, RT to probabilistic events is chosen as a primary, "ground-truth" dependent variable in Tasks 2 (Driving Task Demand), 5 (Cognitive Distraction), 6 (Telematics Demand), 7 (Visual Distraction), and 9 (Safety Warning Countermeasures).

Because RT may not account for all of the variance in driver behavior, other measures such as steering entropy (Boer, 2001), headway, lane position and variance (e.g., standard deviation of lane position or SDLP), lane departures, and eye glance behavior (e.g., glance duration and frequency) are also be considered. Together these measures will provide a comprehensive picture about driver distraction, demand, and workload.

Common Driving Scenarios For the tasks that measure the brake RT, the "lead vehicle following" scenario is used. Because human factors and psychological research has indicated that RT may be influenced by many factors (e.g., headway), care has been taken to ensure a certain level of uniformity across different tasks. For instance, a common lead vehicle (a white passenger car) was used. The lead vehicle may brake infrequently (no more than 1 braking per minute) and at an unpredictable moment. The vehicle braking was non-imminent in all experiments (e.g., a low value of deceleration), except in Task 9 (Safety Warning Countermeasures) that requires an imminent braking. In addition, the lead vehicle speed and the time headway between the lead vehicle and the host vehicle are commonized across tasks to a large extent.

Subject Demographics It has been shown in the past that driver ages influence driving performance, user acceptance, and driver understandability. Because the age

effect is not the focus of the SAVE-IT program, it is not possible to include all driver ages in every task with the budgetary and resource constraints. Rather than using different subject ages in different tasks, however, driver ages are commonized across tasks. Three age groups are defined: younger group (18-25 years old), middle group (35-55 years old), and older group (65-75 years old). Because not all age groups can be used in all tasks, one age group (the middle group) is chosen as the common age group that is used in every task. One reason for this choice is that drivers of 35-55 years old are the likely initial buyers and users of vehicles with advanced technologies such as the SAVE-IT systems. Although the age effect is not the focus of the program, it is examined in some tasks. In those tasks, multiple age groups were used.

The number of subjects per condition per task is based on the particular experimental design and condition, the effect size shown in the literature, and resource constraints. In order to ensure a reasonable level of uniformity across tasks and confidence in the research results, a minimum of eight subjects is used for each and every condition. The typical number of subjects is considerably larger than the minimum, frequently between 10-20.

Other Commonalities In addition to the commonalities across all tasks and all sites, there are additional common features between two or three tasks. For example, the simulator roadway environment and scripting events (e.g., the TCL scripts used in the driving simulator for the headway control and braking event onset) may be shared between experiments, the same distraction (non-driving) tasks may be used in different experiments, and the same research methods and models (e.g., Hidden Markov Model) may be deployed in various tasks. These commonalities afford the consistency among the tasks that is needed to develop and demonstrate a coherent SAVE-IT system.

## The Content and Structure of the Report

The report submitted herein is a final report for Task 2 that documents the research progress to date (March 2003-March 2004) in Phase I. In this report, the major results from the literature review are summarized to determine the research needs for the present study, the experimental methods and resultant data are described, diagnostic measures and preliminary algorithms are identified, and human factors recommendations are offered.

## 2.1 INTRODUCTION

### 2.1.1 Why develop a workload manager?

As competition in the market place grows and product quality improves, it is becoming increasingly difficult for automotive manufacturers to distinguish their products from those of their competitors. This is particularly true for the conventional aspects that people consider when buying a motor vehicle such as price, fuel economy, reliability, and so forth. Therefore, manufacturers are looking at providing features in their products that distinguish their products from the competition.

Telematics, in-vehicle information and communications systems for drivers, is one collection of features of interest. Common telematics features include navigation, cell phones, collision avoidance systems, parking assist systems, and so forth. Although telematics can greatly enhance the comfort, convenience, and safety of driving, there is concern that some tasks, when performed with some systems, can pose unacceptable risks to drivers. For that reason, there has been discussion of, for example, banning cell phone use while driving.

For other systems, such as navigation, there are limitations on tasks to keep these tasks from interfering too much with driving. For example, SAE Recommended Practice J2364 (the "15-Second Rule"), states that no navigation task, when tested statically (parked), should take longer than 15 seconds to complete (Society of Automotive Engineers, 2003a,b). In fact, when driving, the task will take longer than 15 seconds, but the static procedure has been chosen for ease of implementation. Further, J2364 has an alternative procedure that involves visual occlusion. See the Recommended Practice for details. A huge advantage of J2364 is that compliance (that is, task times) can be estimated using SAE Recommended Practice J2365 (Society of Automotive Engineers, 2002)

Complementing SAE J2364 are other procedures that have been developed by the Alliance of Automobile Manufacturers and by the International Standards Organization (ISO).

Another approach that might either complement or supplement such rules is to employ a workload manager (Michon, 1993; Green, 2000; Hoedemaeker, de Ridder, and Janssen, 2002; Remboski, Gardner, Wheatley, Hurwitz, MacTavish, and Gardner, 2000). This device will continually measure the workload of the driving task, and knowing the task demands and potentially the driver's capabilities, decide which particular tasks could be executed at what time. For example, in heavy traffic in a rainstorm, the system might automatically direct all incoming cell phone calls to an answering machine. At other times, the system might prevent drivers from entering street addresses, but allow them to complete a generally easier task, such as selecting points of interest.

### 2.1.2 Why focus on rear-end crashes?

This report is part of a major, federally-funded project to develop a workload manager prototype to reduce distraction-related crashes. In reviewing that literature (Wang, Knipling, and Goodman, 1996; Stutts, Reinfurt, Staplin, and Rodgman, 2001; Eby and Kostyniuk, 2003), an important point emerged that crashes in which distraction is a causal factor are statistically different from other crashes. Table 2.1 presents data by crash type across such conditions as sleepy, distracted, looked but did not see, unknown, and attentive.

Table 2.1. Crashes by Type

Crash type Row % Column %	Sleepy	<b>Distracted</b>	Looked but did not see	Unknown	Attentive	<b>Total</b>
Single vehicle	58 66.2	18.1 <b>41.2</b>	0.2 0.7	3.8 20.6	44.1 <b>45.9</b>	100.0 <b>30.0</b>
Rear- end/Lead vehicle moving	12.7@ 27.9	21.3 <b>9.6</b>	3.4@ 2.0	48.3 6.4	14.3 <b>2.9</b>	100.0 <b>5.9</b>
Rear-end/LV stopped	*	23.9 <b>21.9</b>	11.4 13.8	52.6 14.1	11. <b>4.9</b>	100.0 <b>12.1</b>
Intersection/ Cross path	*	7.0 <b>18.1</b>	17.9 63.6	528 39.8	22.3 26.6	100.0 <b>34.3</b>
Lane change/ Merge	*	5.6 1.6	7.2 6.7	41.8 3.4	35.3 4.6	100.0 <b>3.8</b>
Head-on	1.0 1.7	7.0 2.2	8.1 3.5	46.4 4.3	37.5 5.0	100.0 <b>4.2</b>
Other	*	7.3 5.4	9.7 9.7	535 11.4	28.9 9.7	100.0 <b>9.7</b>
Total Crashes	2.6 100.0	13.2 100.0	9.7 100.0	45.6 100.0	28.8 100.0	100.0 <b>100.0</b>

@=5-9 cases

\*=too few for a stable estimate

Source: Wang, Knipling, and Goodman (1996)

Note: Within each cell, there are two values representing the row and column percents respectively. For example, referring to the single vehicle distracted cell, in 18.1% of all vehicle crashes, drivers were distracted. Of all distracted crashes, 41.2% involve single vehicles.

Notice that rear end collisions, both into moving and stopped vehicles are relatively much more common when drivers are distracted than when they are attentive. It was this and other data that led to this project focusing on rear-end crash scenarios.

### 2.1.3 Why Examine Visual Demand?

Given this finding, what measure of performance should be assessed in experiments to support workload manager development? Previous research presents many possibilities (Gawron, 2000, Brookhuis and De Waard, 2001; Kantowitz and Simsek, 2001). However, in this case, the accepted proposal submitted by the prime contractor for this project, Delphi, focused on brake response time. Indeed, the more complicated the driving situation, longer it should take drivers to respond.

Although response time can be easy to measure, collecting enough response times within a 2-hour test session in an experiment is a problem and the project resources were insufficient to conduct numerous experiments. A two-hour limit is about the maximum for a subject, and it is highly desirable to examine differences within subjects while not requiring more than one session. With multi-session experiments, there are problems with subjects failing to return, with variable time periods between sessions due to subject schedules, and with other factors that make them generally undesirable.

In a typical 2-hour experiment, about 10-15 minutes are needed for the introduction, 5-10 minutes for the initial practice drive to become familiar with the simulator, and 5-10 minutes for debriefing, final comments, and payment. Thus, only about 90 minutes are available for experimentation. Of that time, another 10-20 minutes are needed for baseline driving. In telematics studies, drivers are usually first trained in using a device. Then baseline (parked) device use data is collected, followed by dual task (while driving) use data as well as data for just driving. Thus, depending on the number of conditions examined (for example, several levels of driving workload), the time available for testing in the most complex condition (for example, dual task in high workload) is only 20 – 40 minutes, depending on the number of conditions explored.

For discussion, assume the mean of that range is 30 minutes. How many braking response times can be collected in 30 minutes? To make the braking events somewhat unpredictable (and indicative of real driving situations), having no more than 1 event per minute seems reasonable, with some variation of the interval between braking events. This suggests a maximum of 30 events of interest per experiment.

Having some replication within subjects is highly desired. For discussion, assume the minimum is two. This leads to 15 (30/2) unique combinations per subject. For example, a 3 x 5 design might be used, which places huge limitations on the number of factors and combinations that might be explored. Thus, using response time measures directly, a large number of experiments would be required to comprehensively examine the factors of interest.

There is at least one other approach. Response time to a lead vehicle braking should depend on the visual demand of the driving situation. The more information in the scene a driver needs to consider, the more time the driver requires to respond to a lead vehicle braking. One might think of other scene information (vehicles other than the lead vehicle, complex road geometry, signs, etc.) as distracting the driver from attending

to the lead vehicle. Furthermore, difficulty in extracting scene information (for example, due to limited visibility) also increases the demand of the driving situation and accordingly, response time.

There are many ways visual demand can be measured, though the favored measure here relies on visual occlusion. Though no one knows for sure how much of the driving task is visual (Sivak, 1996), there is agreement that driving is primarily a visual task and that measuring the visual component of driving captures much of the workload.

The idea behind the visual occlusion method is that one must see in order to drive. In its simplest form, subjects close their eyes whenever they can and the fraction of time their eyes are open indicates visual demand. See Wooldridge, Bauer, Green, and Fitzpatrick (2000) and van der Horst (2001) for contemporary on-the-road studies using this method and Senders, Kristofferson, Levison, Dietrich, and Ward (1966, 1967a, b) and Senders and Ward (1968) for some of the original applications of this method to driving. However, for the purpose of this project, obtaining permission for such methods would have been extremely difficult, so this experiment was conducted in a driving simulator. Giving subjects complete control over both the glance interval and the time between glances complicates analysis, because the tradeoff of these two characteristics is unknown. There were inadequate resources to conduct a tradeoff study within the context of this project.

Therefore, to avoid a complicating tradeoff, subjects pressed a button in order to view the road (for 0.5 seconds), a procedure that has been used before (Tsimhoni and Green, 1999). At all other times, the road scene was a uniform gray field roughly matching the luminance of the un-occluded screen. The percentage of time the road scene was visible is an effective indicator of visual demand.

At 50% demand, a reasonable level for these experiments, there was about 1 button press per second, a stark contrast to the 1 per 60 seconds for response time. Furthermore, although visual demand can be estimated by the number of button presses over a series of events, a more accurate estimate of demand can be obtained from the interval between key presses (the interarrival time) as one would expect from queueing theory.

Thus, the approach in this project is to determine the relationship between visual demand and response, and then use the more numerous demand data to predict response time. Again, given the low number of test conditions that can be explored in a braking response time experiment, an unacceptably large number of experiments would be required to collect the data necessary to build a workload manager.

There is some risk in only using occlusion data to assess visual demand. Therefore, as a backup and to provide supporting evidence, subjective workload ratings were collected after each road segment. This was easy to do.

#### **2.1.4 What Are the Research Issues?**

Accordingly, 4 issues were examined in this experiment:

1. How does braking event response time vary as a function of road geometry and subject differences?
2. How does visual demand (measured using the visual occlusion method) vary as a function of road geometry, presence of a lead vehicle, subject differences, and how speed is controlled?
3. How does rated visual demand vary as a function of road geometry, subject differences, and how speed is controlled?
4. How closely does visual demand (measured by the visual occlusion method) relate to rated visual demand in terms of road geometry, subject differences, and how speed is controlled?

There was also interest in differences in driver performance between conditions, but that topic was secondary and was not examined in this report.





## 2.2 TEST PLAN

### 2.2.1 Overview

To determine the relationship between visual demand and brake response time, subjects drove a two-lane rural road in the UMTRI simulator, sometimes following a lead vehicle that braked. The road consisted of straight and curved sections with varying sight distances (due to fog), and therefore visual demand varied. Visual demand was measured using the visual occlusion method and by ratings.

### 2.2.2 Roads

Two simulated worlds of two-lane rural roads were used in this experiment: “square world” and “zig-zag world.” Square world (Figure 2.1) was a loop of four left curves connected by straight road sections used to familiarize subjects with simulator dynamics in a brief period of time, and hence, was used only in practice sessions. To simplify the driving task, no traffic or fog was present.

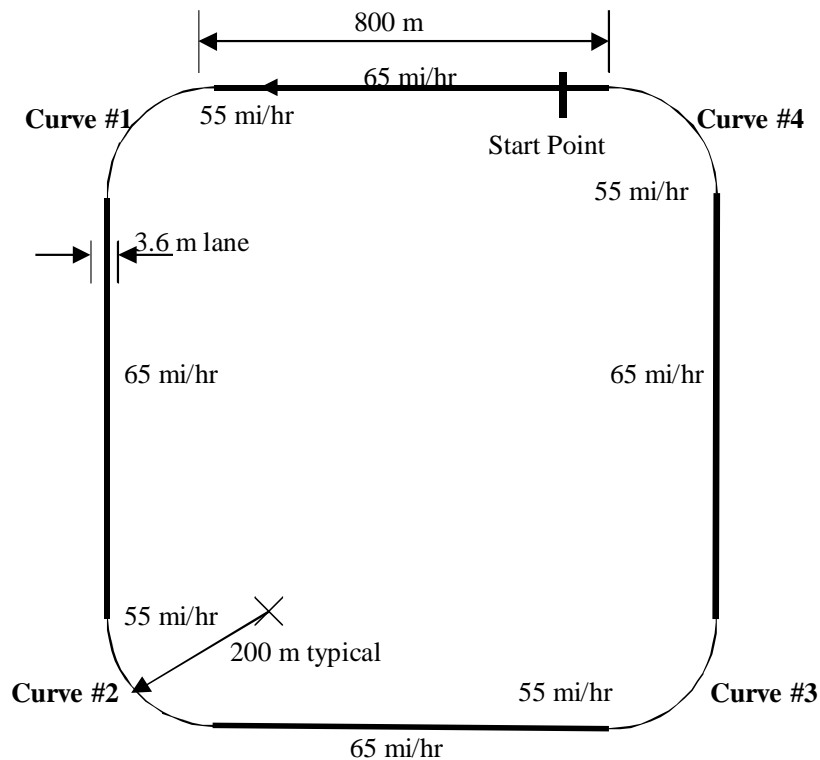


Figure 2.1. Practice Square World

The main test portions of this experiment were carried out in “zig-zag world” (Figure 2.2). The test world was designed to allow for several visual demand levels (straight plus two curve radii, three sight distances limited by fog and, in some cases, traffic) and for the sequence of those levels to be unpredictable / difficult to memorize. Furthermore, each of the major variations of interest (curve radius, fog sight distance)

was experienced at least twice per drive, allowing for some replication of test conditions within runs. To maximize test time, the time spent loading worlds and saving data had to be minimized, so the same basic world was used for all test runs. The complete rationale for the design of the roads appears in Appendix A. Session time limits did not allow for a factorial exploration of all combinations of curvature, sight distance, and traffic.

Sight distance was manipulated by varying the density of the intervening fog using the standard setfog command in the DriveSafety software. The transmissivity (1-opaqueness) of the road scene declined exponentially with distance, dropping to almost zero at the set distance. Beyond the set distance, no objects were visible, that is, the scene was opaque. This decline is believed to reasonably mimic the atmospheric effects of fog. Implementation details differ between versions 1.6.x and 1.9 of the software. Some details of the 1.6.x version (used for this study) are not available because the source code for the routines called by the DriveSafety software is not available.

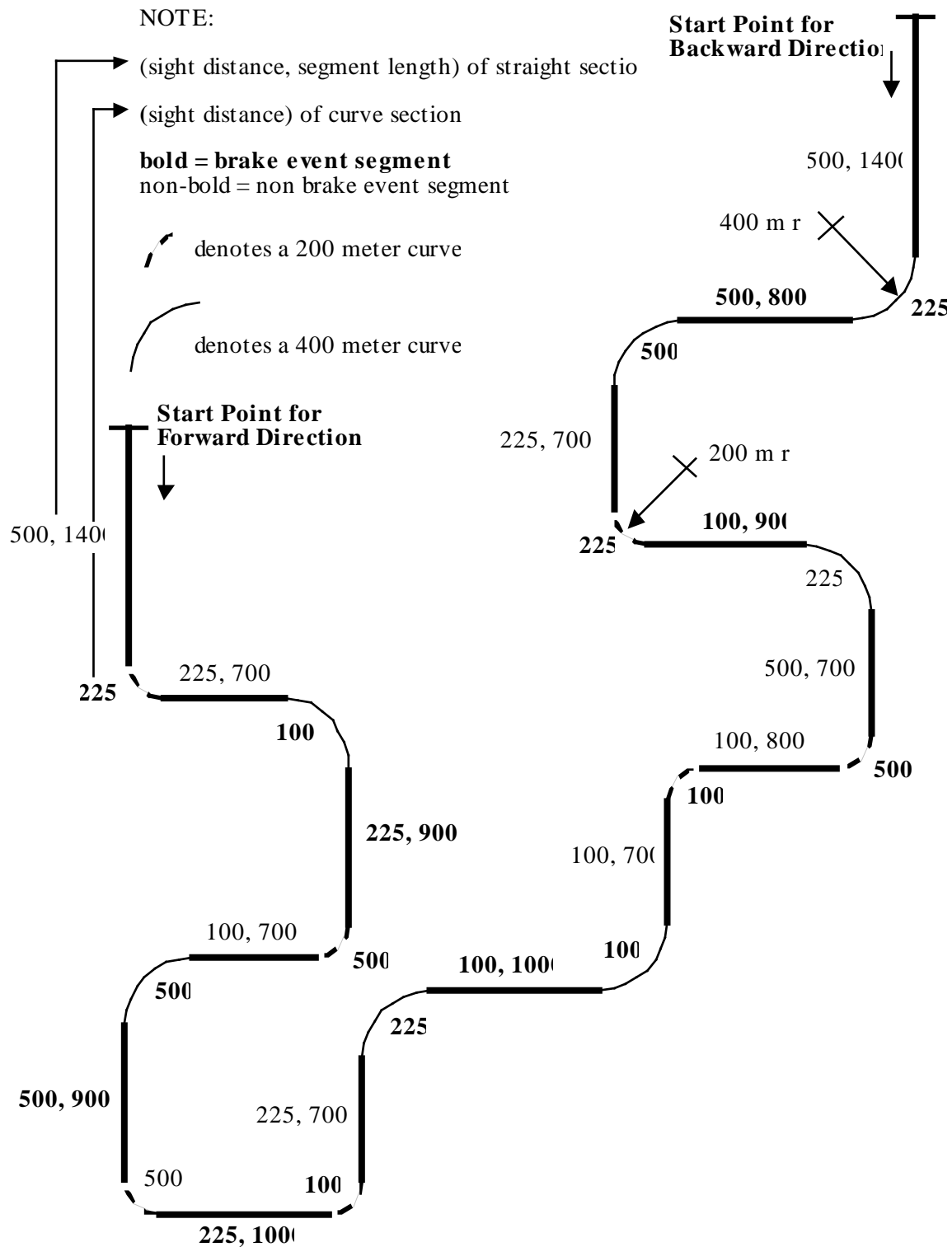


Figure 2.2. Curve Radii and Section Lengths for Zig-Zag (Test) World

Observations in prior research indicated that driving performance declined in occlusion conditions, but that finding had been not examined to the detail desired. Therefore,

conditions were included in this experiment in which subjects drove the same road occluded and un-occluded. Furthermore, since subjects often compensate for increased workload by slowing down (to reduce workload), it was important to have uncontaminated conditions where speed is cruise controlled (and not able to be reduced by the subject).

Just as with road geometry variations, the two-hour maximum session duration (and 19 minutes required for each drive of the “zig-zag world”) limited the combinations of other major factors of interest (lead vehicle, occlusion, speed control) that could be explored. (See Table 2.2.) The un-occluded cruise control pair (B & F in Table 2.2) were not examined as performance in those conditions (namely lateral control) should be very similar to the subject-controlled speed conditions. Forcing the speed (cruise) suggests lateral variance would increase slightly. However, reducing the number of tasks (accelerator use not required when using the cruise control) should decrease workload.

Table 2.2. Test Condition Combinations (Selected Conditions in Bold)

	Not occluded (w/o fog)		Occluded (w/ fog)	
	Subject-controlled	Cruise	Subject-controlled	Cruise
No lead vehicle	<b>A. “free” drive</b>  (only need short drive)	B. baseline cruise (only need short drive)	<b>C. baseline demand of road “contaminated” unsteady speed (ratings collected)</b>	<b>D. “pure” measure of the demand of the road (ratings collected)</b>
Lead vehicle	<b>E. baseline RT (RT collected)</b>	F. RT to lead with cruise  (not needed, similar to 5, maybe more stable)	<b>G. demand with lead vehicle “contaminated” by subject speed</b>	H. “pure” demand with lead vehicle

Further, cell H, the “pure” demand option (response time to lead vehicle braking with occlusion while under cruise control), was not examined because there was thought to be little difference between the cruise and subject-controlled speed conditions. The difference between cells C & D could be used to examine this hypothesis. Also, the software to control speed for cell H, in particular after a braking event, might have been a development effort that would have challenged the project schedule.

### **2.2.3 Test Activities and Their Sequence**

Table 2.3 shows the sequence of activities in this experiment, which was partially counterbalanced (for activities 5–7 only where it was thought to be crucial), with the easier conditions occurring first. The extensive practice provided was thought to be sufficient to stabilize driving performance. The alternative, counterbalancing all of the conditions, might have overwhelmed subjects if some of the more difficult combinations occurred earlier in the experiment. (Note: The ordering of activities 5-7 by subject is shown in Appendix B.) To minimize effects due to the order in which road features were encountered, half of the subjects drove the world from each of the two potential start points.

Table 2.3. Sequence of Activities (Note: The bold letter in the activity column refers to the prior table.)

Activity	Block type - world	Occlude Vision	Speed control	Lead car	Purpose	Time (min)
1. Intro & consent form	-	-	-	-	Obtain description of subject & permission	12
2. Practice drive	Practice square, 1 loop	No	Subject	No	Learn how to drive simulator	7
3. Baseline drive - just drive ( <b>A</b> )	Test - zig-zag, second half	No	Subject	No	Obtain baseline data on how people drive when they control their speed	9
4. Occlusion practice ( <b>B</b> )	Practice -square, 1 loop	Yes	Subject	No	Learn to use the occlusion method	7
5. Demand of road when cruise control is used ( <b>D</b> )	Test - zig-zag	Yes	Cruise	No	Determine demand when cruise control is used	19
6. Baseline RT ( <b>E</b> )	Test - zig-zag	No	Subject	Yes	Obtain "uncontaminated" RT data	19
7. Demand of road when subj. controls speed ( <b>C</b> )	Test - zig-zag	Yes	Subject	No	Determine demand when subject controls the speed	19
8. Demand of road + lead vehicle ( <b>G</b> )	Test - zig-zag	Yes	Subject	Yes	Total demand	19
9. Final comments	-	-	-	-	Obtain explanations for responses	5
<b>Total</b>						<b>116</b>

The behavior of the lead vehicle followed a script that had been used in other experiments within this project. Braking events were to occur approximately once per minute when the time headway was 1.8 s, with the lead vehicle braking at .2 g for 4-5 s (specified later), causing the lead vehicle's brake lights to illuminate and the lead vehicle to pitch forward slightly. The subject was unable to lag the lead vehicle by more the 1.8 s, pass the vehicle, or go through it. To make braking events somewhat unexpected, braking events only occurred on straight sections.

After completing each curve or straight section for all sections, subjects rated the workload of driving that section using a 1 to 10 rating scale (Table 2.4). To avoid overloading subjects, ratings were only taken for the two conditions (activities 5 and 7 in Test Plan) in which occlusion was present, a lead vehicle was not, and the subjects' velocity was either self- or cruise-controlled. Before beginning the runs in which ratings were collected, each subject was required to read all 10 of the possible options and rate one of the curves they had just experienced in an initial test run. The rating scale was discussed at length before the next run was presented. Instruction continued until subjects fully understood the rating scale. The subjects were instructed to look at the ratings listed on a card only if necessary (located slightly down and to the right of straight ahead) to choose a risk rating. When subjects looked, glances were brief, and hence, the added load of the rating task was minimal.

Table 2.4. Subjective Risk Ratings

Risk Rating	As Risky As:
10	Driving with my eyes closed. A crash is bound to occur every time I do this.
9	Passing a school bus that has its red lights flashing and the stop arm in full view
8	Driving just under the legal alcohol limit with observed weaving in the lane
7	
6	Driving 20 miles an hour faster than traffic on an expressway
5	
4	Driving 10 miles an hour faster than traffic on an expressway
3	
2	Driving on an average road under average conditions
1	Driving on an easy road with no traffic, pedestrians, or animals while perfectly alert

As subjects drove, run time, subject velocity, lane position, lane number, steering wheel value, accelerator position, brake position, subject heading, subject lateral position and distance traveled, headway time and distance (if applicable), time to collision (TTC), and lead vehicle velocity (if applicable) were collected at 20 Hz, as well as the current state of occlusion pertaining to each button press. In addition, (1) the road scene ahead, (2) the road scene behind, (3) the driver's face, and (4) the speedometer/tachometer cluster were recorded by a VCR as a quad-split image.

To un-occlude the screen, subjects pressed a finger switch (attached to their finger via a Velcro ring) against the steering wheel. Subjects were told that when the button was pressed, the screen would become visible for 0.5 seconds and then turn gray again. Subjects were told "As much as you need to, you can press the button in order to see



the screen. Please do not simply hold the button down unless feel you must in order to drive effectively. Just act and drive as you would normally through fog.”

## 2.2.4 Driving Simulator

Each of the three experiments took place in the third generation UMTRI Driving Simulator ([www.umich.edu/~driving/simulator.html](http://www.umich.edu/~driving/simulator.html)). The simulator consisted of a full size cab, computers, video projectors, cameras, audio equipment, and other items (Figure 2.3). The simulator has a forward field of view of 120 degrees (3 channels) and a rear field of view of 40 degrees (1 channel). The forward screen was approximately 16-17 feet (4.9-5.2 m) from the driver's eyes, close to the 20-foot (6 m) distance often approximating optical infinity in accommodation studies. To reduce the likelihood of motion sickness, only the center front and rear channels were used.



Figure 2.3. Simulator Screen, Cab, and Control Room

The vehicle mockup consisted of the A-to-B pillar section of a 1985 Chrysler Laser with a custom-made hood and back end. Mounted in the mockup was a torque motor connected to the steering wheel (to provide steering feedback), an LCD projector under the hood (to show the speedometer/tachometer cluster), a touch screen monitor in the center console (for in-vehicle tasks), a 10-speaker sound system (for auditory warnings), a sub-bass sound system (to provide vertical vibration), and a 5-speaker surround system (to provide simulated background road noise). The 10-speaker sound system was from a 2002 Nissan Altima and was installed in the A-pillars and lower door panel, and behind each of the two front seats. The stock amplifier (from the 2002 Nissan Altima) drove the speakers. The main simulator hardware and software was a DriveSafety Vection simulator running version 1.6.1 of the software. The display cards, GeForce3's, did not support anti-aliasing.

The simulator was controlled from a “room” on the driver’s side of the vehicle and behind it. The room contained a large table with multiple quad-split video monitors to show the output of every camera and computer, a keyboard and LCD for the driving simulator computers, and a second keyboard and LCD to control the instrument panel and touch screen software. Also in the control room was a 19-inch rack containing all of the audio and video equipment (audio mixers, video patch panel and switchers, distribution amplifiers, VCR, quad splitter, etc.) and two separate racks for the instrument panel and touch screen computers, the simulator host computers, and the four simulator image generators. The instrument panel and center console computers ran under the Mac OS. The user interface to the simulator ran under Windows and the simulators ran under Linux.

Additional information on the simulator (e.g. a plan view of the facility with dimensions and the manufacturer and model numbers of key components) appears in Appendix C.

### **2.2.5 Test Participants**

A total of 16 licensed drivers, eight ages 35-55 and eight ages 65-75, served as subjects. Within each age group there were an equal number of men and women. Most of the subjects were recruited from a list of people who had previously participated in driver interface studies. None of the subjects had previously participated in occlusion studies.

Most subjects listed their primary vehicle as a mid-sized car, while two listed a mini-van or SUV. The mean average mileage driven by the subjects was approximately 11,250 miles, with a range of 2,000 to 25,000 miles per year. Three subjects had special driver’s licenses: a cycle, chauffeur, and commercial drivers license (CDL).

In this experiment, 12 subjects wore glasses while driving, one subject wore contacts, and three did not require any vision correction. The mean far acuity was 20/24, with a range of 20/17 to 20/30. The mean near acuity was 20/30, with a range of 20/17 to 20/50 (the maximum allowed).

As a group, participants were not aggressive drivers. When asked where they would drive on a 3-lane highway (3=left, 2=middle, or 1=right lane), the mean was 1.9. Six of the 16 participants claimed having an accident within the last 5 years, but none of the subjects had more than one accident during that time period. Five subjects reported a moving violation within the last year (3 subjects with 1 violation, 1 with 2 violations, and 1 with 3).



## 2.3 RESULTS

### 2.3.1 Visual Occlusion/Visual Demand Analysis

How does visual demand (measured using the visual occlusion method) vary as a function of road geometry, subject differences and how speed is controlled?

#### 2.3.1.1 *How Was Visual Demand Computed?*

Visual demand was defined as the percentage of time the screen was un-occluded (i.e., the road scene was visible) for a segment of a set distance. For this analysis, a distance of 20 meters was chosen as the segment length to provide one data point per second; that is, second-by-second analysis. (Note: Subjects drove at approximately 45 miles per hour, which is about 66 feet per second or 22 meters per second.)

There are at least three methods to calculate visual demand: simulator sampling state, interkeypress interval, and keypress counting method. In the simulator sampling state method, each time the simulator samples the driving performance variables (speed, lateral position, steering wheel angle, etc.), it also records if the road scene was occluded or un-occluded in one field of the sample record. Computation of demand began by setting a distance counter to 0. The counter was incremented one record at a time (one line at a time) until the distance traveled was equal to or greater than 20 meters. Within that set of lines, the percentage flagged as un-occluded determined demand for that segment.

For subsequent segments, the distance counter was set back to 0 and the process continued in 20-meter increments until the subject reached the end of the section, either the beginning of a curve (the point of curvature, PC) or the end of a curve (the point of tangency, PT). If the section did not end exactly at the end of a 20-meter segment, the remaining segment (<20 m) was viewed as insignificant and discarded.

For the interkeypress interval (arrival method), visual demand is proportional to the inverse of the time between keypresses. Because keypresses are often recorded with millisecond accuracy, this method has the promise of high accuracy. However, how to analyze keypress pairs that span segment boundaries, a nontrivial computational problem, has yet to be decided.

The simplest method to compute demand is to count the number of keypresses within a fixed time interval. The demand is equal to the number of keypresses in an interval times the viewing duration (usually 0.5 s), divided by the sampling interval. So, if the duration is 1 s, there can be none, one, or two keypresses in that time period, resulting in demand values of 0, 50, or 100 %. This method leads to estimates that are crude.

For this report, the simulator sampling method was used to compute visual demand. The sampling frequency of 20 Hz was a compromise of providing desired accuracy but avoiding data management problems. For other channels, such as steering wheel

position and throttle position, most of the signal is at a maximum of 5 Hz so, according to the Nyquist folding principle, sampling at above 10 Hz was not needed. Sampling could have been as high as 60 Hz, which would have improved the accuracy of the visual demand estimates but tripled the amount of data saved. For this initial examination of demand on this simulator, 20 Hz was chosen as a compromise, leading to demand estimates to the nearest 5% for each second. Because of time constraints, each subject drove each road only once (versus 6 times in Tsimhoni and Green, 1999). However, each subject drove all curvature-sight distance combinations twice and demand could be averaged over successive segments, leading to improvements in accuracy. Had there been more repetitions of roads, fewer variables could have been explored.

### 2.3.1.2 What Were Typical Visual Demand Curves?

Before describing the results with regard to the specific experimental data, it is useful to provide a more general impression of the data. Figure 2.4 shows visual demand results for a representative subject (Subject 9, 68-year-old male) for each of his three runs involving occlusion: (1) subject-controlled speed, (2) cruise-controlled speed, and (3) subject-controlled speed with a lead vehicle. As a reminder, all runs occurred in the “zig-zag world.” For the subject-controlled condition, the subject controlled his/her velocity and there was no lead vehicle or fog present (cell C of Table 3). For cruise controlled, the test conditions were the same except that the speed driven was externally controlled and fixed (cell D of Table 3). The “subject controlled with a lead vehicle” condition corresponds to cell G of Table 3. Fog was present for all three conditions.

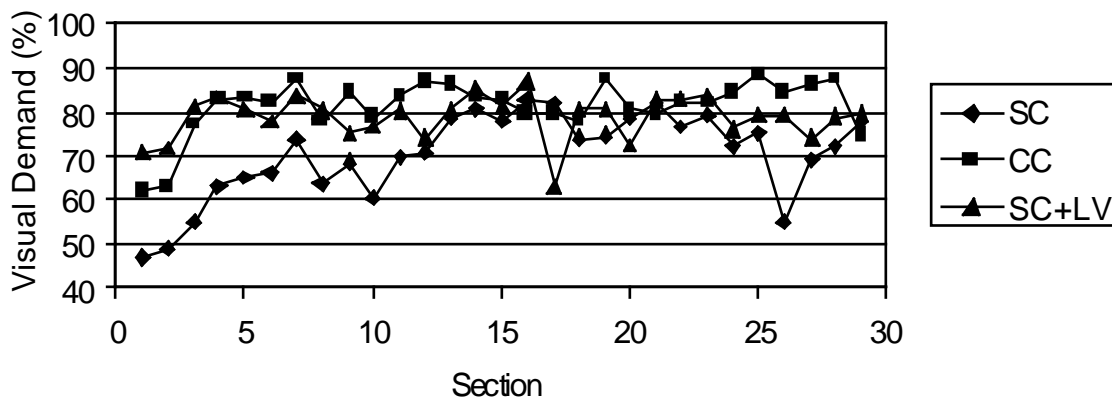


Figure 2.4. Visual Demand Observations for Representative Subject

SC=subject-controlled speed, CC=cruise-controlled speed, SC+LV=subject-controlled speed with lead vehicle

As can be seen in Figure 2.4, the three trials show a similar pattern of visual demand: an initial period of increasing demand, then a more stable level of demand for the rest of the experiment. The hills and valleys of demand correspond to differences in road geometry (sight distance, curvature) as described later. The initial increase may

represent some adjustment of the subjects' behavior in this experiment (the first segment was a long straight section of low demand). The occurrence of this increase is particularly surprising given subjects had completed a practice occlusion block on the square world before the test block. It may be that the practice condition was too easy with no fog present, and time was required to adjust to fog. However, that does not explain why there were initial ramp-ups in demand in the subsequent subject-controlled and subject-controlled, with-lead-vehicle runs that occurred after an additional 19 and 38 minutes of driving.

Using the data from this subject as a guide for future studies, the authors recommend discarding the data for the first 2,500 feet if that distance includes a mixture of low and high demand situations. If high demand is not present, then at least the first high demand segment should be discarded. Furthermore, there may be value in more carefully reviewing the data from all subjects to assure they all have adequate time to adapt to the occlusion conditions.

As shown here, the largest difference between sections was about 20%, but most differences were about 5%. Keep in mind, though, that this is the data only for 1 subject, and that each segment represented the means of several data points.

As an example, Figure 2.5 shows the visual demand profile for a representative subject (Subject 5, 35-year-old female) entering a 400-meter radius right hand curve. In a manner consistent with Tsimhoni and Green (1999), the visual demand increases sharply as the subject reaches the point of curvature (approximately 150 m before the curve), reaches a peak near the beginning of the curve, declines to a more moderate level, and then returns to a lower level near the curve exit. Again, there is considerable variability in the curve because of the small number of data points in the estimate and the fact that estimates for a single run were rounded to the nearest 5%.

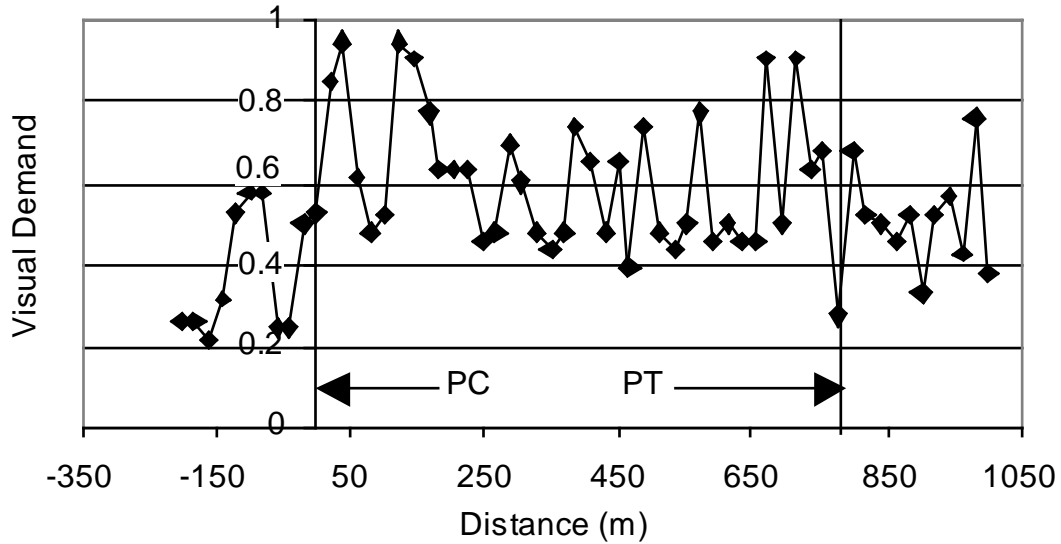


Figure 2.5. Visual Demand Profile for a Sample Subject (400 m Right Curve)

Note: PC = Point of Curvature, where the curve begins  
 PT = Point of Tangency, where the curve ends

### 2.3.2 ANOVA of Visual Demand

The analysis was based on the mean demands from three runs/subject (subject controlled, cruise controlled, cruise controlled with lead vehicle) \* 16 subjects \* 29 segments = 1392 data points. Demand values ranged from 16.2 to 94.3 with a mean of 61.6 and a standard deviation of 17.7. Figure 2.6 shows the distribution of demand values.

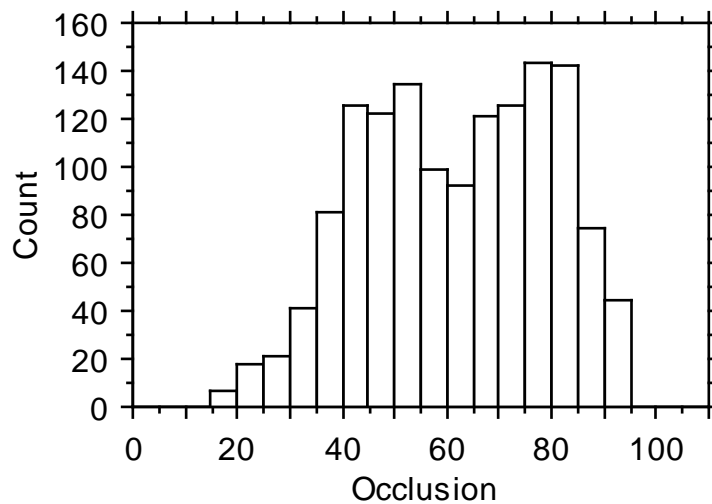


Figure 2.6. Distribution of Visual Demand Values

To provide a sense of the relative impact of all of the experimental factors as guide further analysis, a series of 1-way ANOVAs was carried out (Table 2.5). The outcome of this analysis was used to guide the other ANOVAs computed as other dependent variables had common independent variables.

For simplicity, all values were treated as nominal. In order of importance, the factors that had an effect on the demand values were subject, road geometry, and others in that order.

Table 2.5. Summary of Initial ANOVAs of Visual Demand

Factor	# Levels	P	Largest Delta	Means
Section of Road	29	<.0001	16.8	51.6 – 68.4
Radius & Direction (confounded with fog)	5	<.0001	7.5	200L=64.0,200R=66.7, 400L=63.3,400R=63.4, S=59.2
Inverse Radius	3	<.0001	5.9	Straight (0.0) = 59.2, .003 (1/400) = 63.3, .005 (1/400) = 65.2
Straight Section Length (confounded with fog), straight sections only	5	.02	7.6	700=60.5, 800=59.8, 900=59.4, 1000=60.7, 1400=53.1
For or Log (sight distance)	3	<.0001	6.2	2.0 (100) = 65.3, 2.35 (225)=60.9, 2.70 (500) = 59.1
Subject	16	<.0001	52.8	36.3 – 89.1
Sex	2	.02	2.3	Female=62.8, male=60.5
Age	2	<.0001	7.7	Middle=57.8, older=65.5
Cruise & Lead Vehicle	3	.0001	4.9	Subject-controlled=59.3, cruise controlled =61.4, subject controlled + lead = 64.2 Control effect = 2.1 Lead vehicle=2.8
Braking Trials (for subject controlled + lead vehicle only)	2	.09	2.4	No brake=62.7, brake=65.1
Block (confounded)	3	.0007	4.0	1=60.3, 2=60.5, 3=64.2

To examine the interactions that might be significant, an ANOVA was computed with Inverse curve radius, Log (sight distance), Age, Sex, Subject nested with Age and Sex, and Speed Control-Lead Vehicle (three levels: subject controlled, cruise controlled, subject controlled with lead vehicle) as the independent variables. For simplicity, interactions involving all pairs of factors were included in the model except subject. Age, Sex, and Speed Control-Lead Vehicle were all discrete variables. All others were continuous. In that ANOVA, all of the main effects were highly statistically significant as were the Age \* Sex, Age \* Speed Control-Lead Vehicle and the Sex \* Speed Control-



Lead Vehicle interactions (all  $p < .0001$ ). Also significant was the Age \* Inverse Radius combination ( $p = .03$ ). The ANOVA table appears in Appendix D.

Each of these factors were examined, usually in combination with others, to provide a greater understanding of the data. Figure 2.7 shows the mean occlusion ratings for all 16 subjects. The figure clearly indicates an interaction between age and sex, though the pattern is the opposite of what is typical, with demand being lowest for middle-aged women and greatest for older women. There was no age effect on mean occlusion for male subjects.

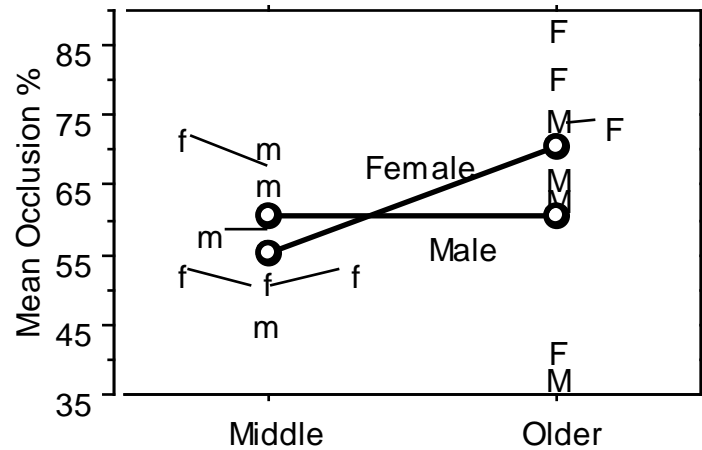


Figure 2.7. Age and Sex vs. Visual Demand

f,F = female subjects; m,M = male subjects

Figure 2.8 shows the relationship between demand and curve direction/radius. Notice that demand decreases as curvature decreases, and that in three of the four cases, the demand for left curves was slightly less than right curves, though the difference was small. It is uncertain why. In subsequent analyses, differences between left and right curves were ignored.

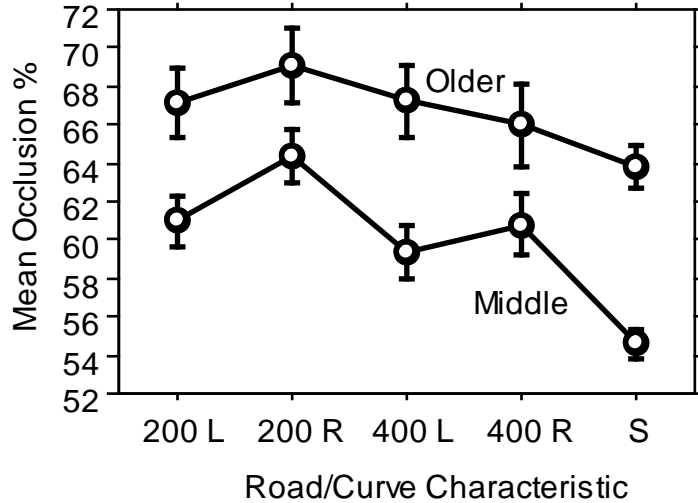


Figure 2.8. Road/Curve Characteristics vs. Visual Demand

L = Left; R = Right; S = Straight; 200, 400 = radii (m)

Figure 2.9 shows the relationship between the log of sight distance and inverse curve radius. Demand increases as a function of both. However, the two effects are not completely additive; that is, there is a suggestion of an interaction (though it was not statistically significant), with curvature having less of an impact for short sight distances (100, 225 feet). Apparently for shorter sight distances, curvature is relatively less important because sight distance is limited by fog.

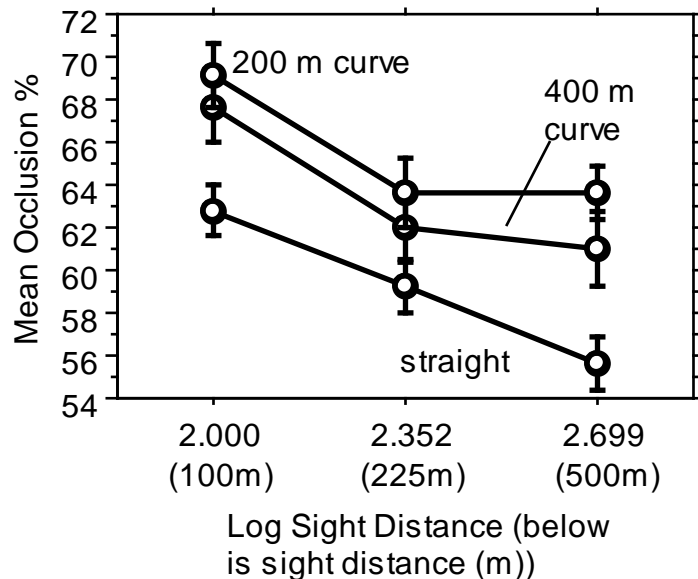


Figure 2.9. Log (Sight Distance) & Inverse Curve Radius vs. Visual Demand

For straight section length, the means suggest an odd pattern for long sight distances, with the demand for 1000 feet and 1400 feet being different from the other distances.

However, as shown in Figure 2.10, not all sight distance \* fog combinations were expressed during the experiment, so looking at the mean demand average across fog levels can be misleading.

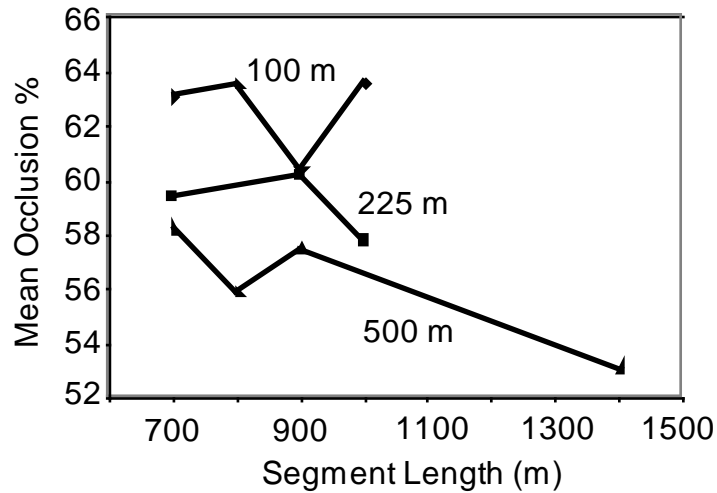


Figure 2.10. Sight Distance & Segment Length vs. Visual Demand

As shown in Figure 2.11, the demand when driving using cruise control was consistently greater than when the subject controlled speed even though the subject had more to do. It may be that because the subjects were often driving in fog, they were not able to reduce their speed, which elevated demand. Also, note that for all trials, providing a lead vehicle (when the subject controlled the speed) added to workload by about the same amount as providing the cruise control, and this increment occurred consistently for all sight distances.

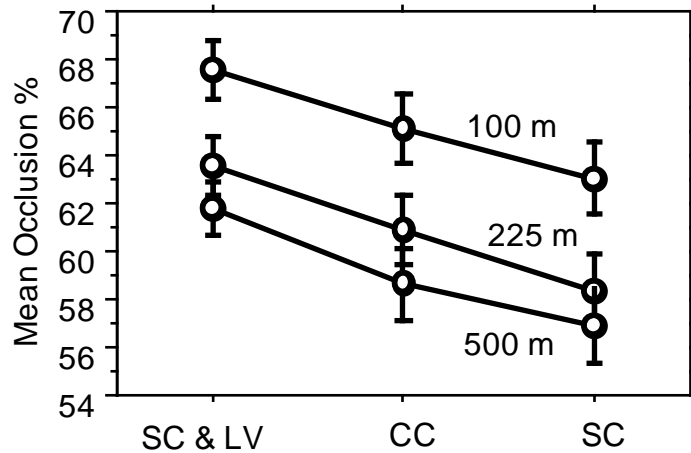


Figure 2.11. Control Type & Sight Distance vs. Visual Demand

SC=subject-controlled speed, CC=cruise-controlled speed, SC+LV=subject-controlled speed with lead vehicle

Figure 2.12 shows the effect of the presence of a braking event on visual demand. For this figure analysis, only trials where a lead vehicle was present were used, whether a braking event occurred or not. No occlusion data was included if a lead vehicle was not present. It is uncertain why the effect was slightly less for the 225 m sight distance condition.

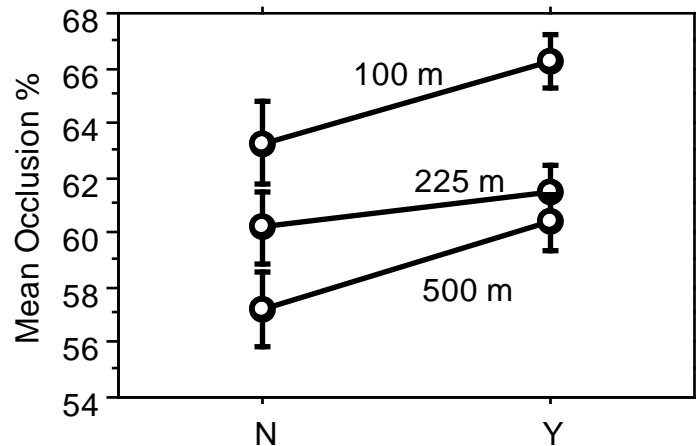


Figure 2.12. Presence of a Braking Event & Sight Distance vs. Visual Demand

Given these results and previous research (e.g., Hulse, et al., 1998), it made sense to include log (sight distance), inverse curve radius, subject age, subject sex, cruise control on/off, and lead vehicle present in the model. The lead-vehicle braking factor was not included in the model. In a real world situation, if a lead vehicle was braking, the driver should not be performing an in-vehicle task anyway. Block was not included because it was a confounding factor and would not be present in a real system.

In that model, the r-squared was fairly low (.152), in part because the fit was to data from individual trials, not means for conditions across subjects. The best-fit equation was:

$$\begin{aligned}
 \text{Demand (0 to 1)} = & 73.65 - 9.42 (\log (\text{sight distance})) \\
 & + 1325.90 (1/\text{curve radius}) \\
 & + 15.35 (\text{Age code, } 0=\text{middle, } 1=\text{old}), \\
 & + 5.40 (\text{Sex code, } 0=\text{female, } 1=\text{male}) \\
 & - 15.23 * \text{Age code} * \text{Sex code} \\
 & + 3.83 (\text{Lead Vehicle code, } 0=\text{no lead, } 1=\text{lead vehicle}).
 \end{aligned}$$

The effect of the cruise control did not enter the model. Forcing that term into the model led to the following equation that increases the r-squared value to only .154.

$$\begin{aligned}
 \text{Demand (0 to 1)} = & 72.59 - 9.42 (\log (\text{sight distance})) \\
 & + 1325.90 (1/\text{radius}) \\
 & + 15.35 (\text{Age Code}) \\
 & + 5.40 (\text{Sex Code}) \\
 & - 15.23 (\text{Age code}) * (\text{Sex Code})
 \end{aligned}$$

- + 4.90 Lead Vehicle Code
- + 2.13 Cruise Code (1=cruise control)

### 2.3.3 Subjective Ratings of Visual Demand

How does rated visual demand vary as a function road geometry, subject differences, and how speed is controlled?

Because of time constraints, each of the 29 road segments was rated once by each of the 16 subjects for the two runs when no lead vehicle was present, one subject controlled and one cruise controlled, for a total of 928 ratings. There was no missing data. Those ratings were examined using ANOVA with main effects of Age (middle and older), Sex (male, female), Speed Control (subject, cruise), Sight Distance due to fog (100, 225, or 500 m), Block (1 or 2), and Road Segment Type/Curve-Direction-Radius. The segment type variable had five levels (left curve-200 m, left curve-500 m, right curve-200 m, right curve-500 m, straight). For simplicity, only interactions including two factors were included in the model except for subject effects, where, for simplicity, interactions were not examined. Sight Distance and Block were treated as continuous variables. All others were nominal.

All of the main effects were highly statistically significant ( $p < .0001$ ) except for Block and Speed Control. Of the interactions, only the Age \* Sex and Block \* Speed control were highly significant ( $p < .0001$ ), though Sex \* Curve-Direction-Radius was also significant ( $p = .02$ ). The ANOVA table appears in Appendix D.

As shown in Figure 2.13, older subjects had higher ratings than younger subjects (visual demand was greater). Inter-subject deviation from the mean rating value for the younger male subjects was much larger than seen with the younger females. All younger female subjects produced mean rating values that were closely located to the mean rating value. The same large deviation seen with the younger male subjects exists for both the older male and female subject groups.

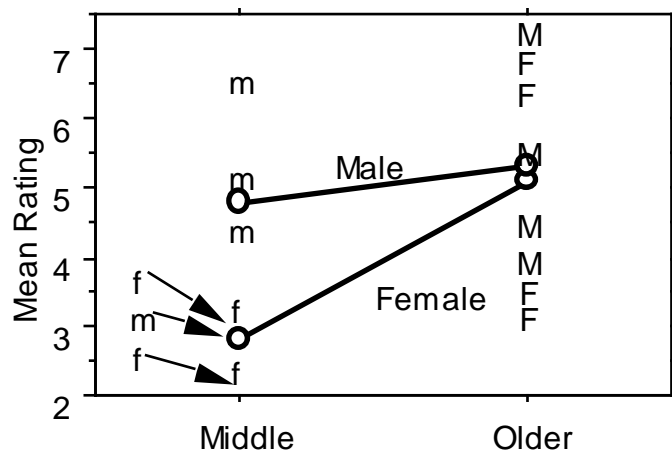


Figure 2.13. Age/Sex vs. Mean Rating

In terms of experimental factors, subjects rated the cruise-controlled condition (4.4) as being slightly less demanding than the subject-controlled condition (4.6), which makes sense since in the cruise-controlled condition there was less for subjects to control. As shown in Figure 2.14, there was a statistically significant interaction between speed control and block number, with the demand being lower when the cruise-controlled condition occurred first.

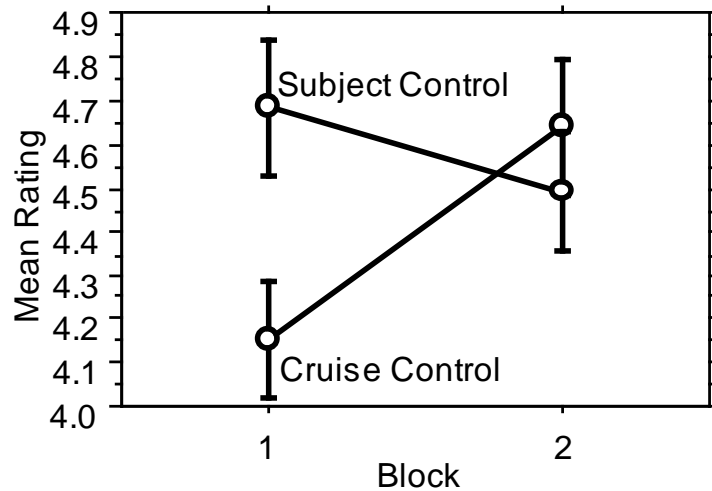


Figure 2.14. Block Effect on Mean Rating

Given there is less to do when driving with cruise control than when under driver control, the lower rating for the cruise-controlled condition in block 1 makes sense. However, there are no explanations for the reversed relationship seen for block 2, other than some effect associated with familiarity with the route or task.

Figure 2.15 shows both the overall effects of curvature and the effects of fog (sight distance), clearly indicating the lack of an interaction. The inverse relationship between the mean rating values and sight distance can also be seen in the highest mean ratings with the 100 m distance for all characteristic types of road section. Similarly, the 500 m sight distance resulted in the lowest mean rating value for all road section characteristics.

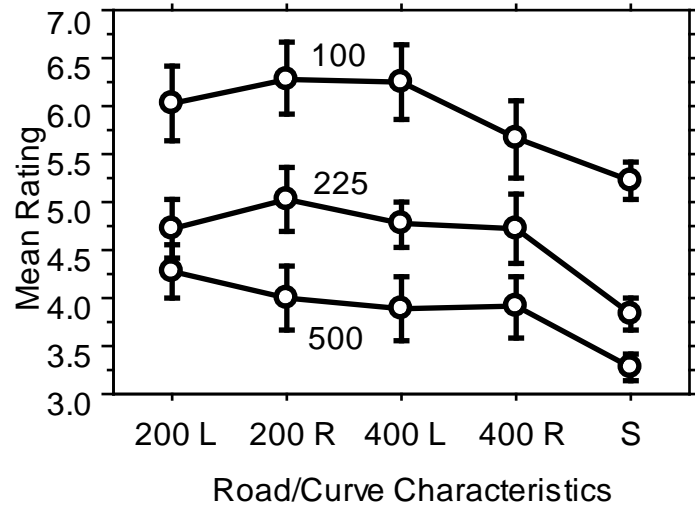


Figure 2.15, Ratings as a Function of Road Section Type and Fog Sight Distance

L = Left; R = Right; S = Straight; 200, 400 = radii (m)

It was postulated from previous research (Tsimhoni and Green, 1999) that ratings of demand should be proportional to inverse curve radius and also proportional to the log of sight distance (Hulse, et al., 1989). As shown in Figure 2.16, the demand from sight distance and curvature are additive (there is no interaction) and the decrease was almost linear for log sight distance. However, the actual rating was slightly greater than would be predicted by a strictly log model. (The mean ratings were 5.6, 4.3, and 3.7 for 100, 225, and 500 m respectively.) This could represent a floor effect in the use of ratings.

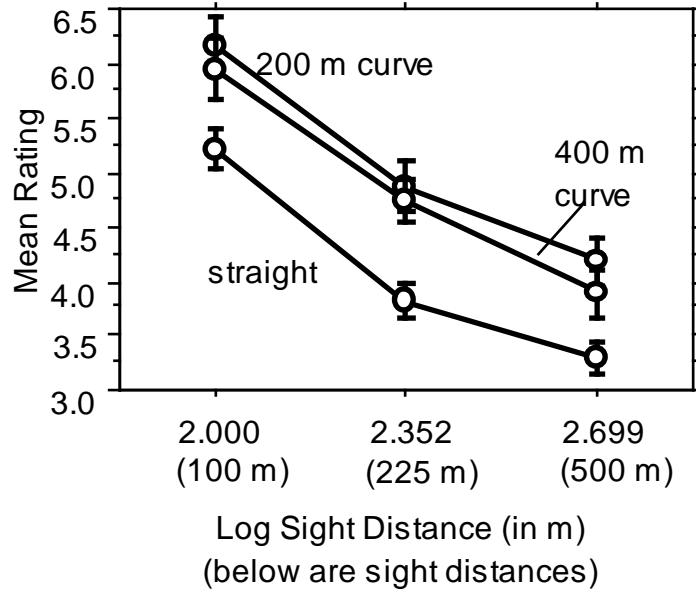


Figure 2.16. Relationship between Ratings of Demand, Log Sight Distance, and Radius of Curvature

The effect of inverse curve radius is shown in Figure 2.17. Notice that the  $1/r$  relationship holds, but that the relationship departs from linearity. This may be because the straight sections were presented many more times than the other two radius conditions, so they became easier to drive as subjects experienced them more.

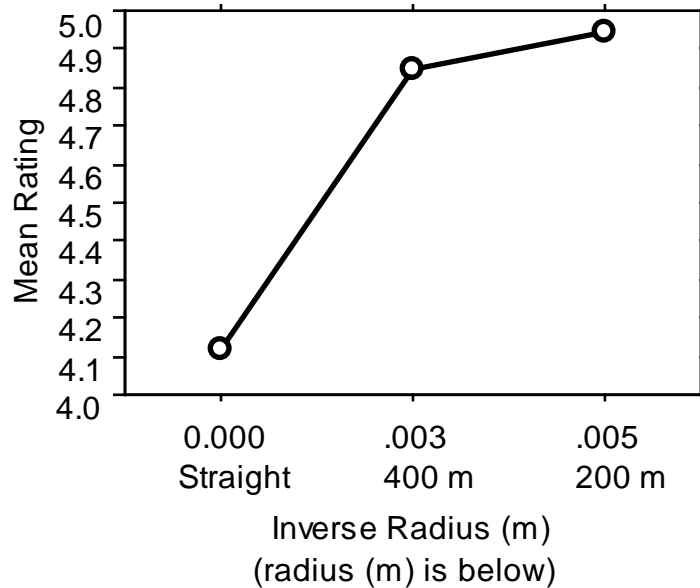


Figure 2.17. Relationship between Curve Radius and Ratings of Demand



After this initial analysis was completed, a second model was created to consider the effects of road segment length for straight sections (700, 800, 900, 1000, 1400 m) in lieu of a post hoc test, where section length was treated as a continuous factor. (See Appendix D for the ANOVA table.) The effect of section length was not significant ( $p=.75$ ), as shown in Figure 2.18. Furthermore, there seemed to be no explainable pattern to the results. Section length did not interact with any of the other factors examined.

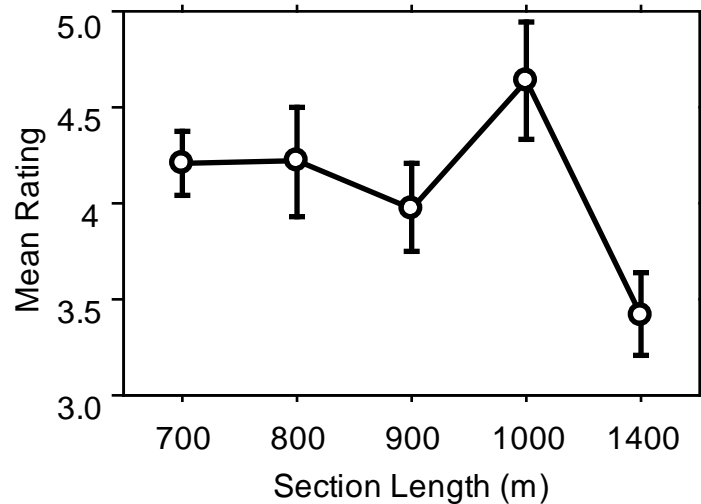


Figure 2.18. Effect of Section Length on Ratings of Demand

As shown in Figure 2.19, unbalanced sampling of different section length-sight distance combinations resulted in the apparent differences due to section length.

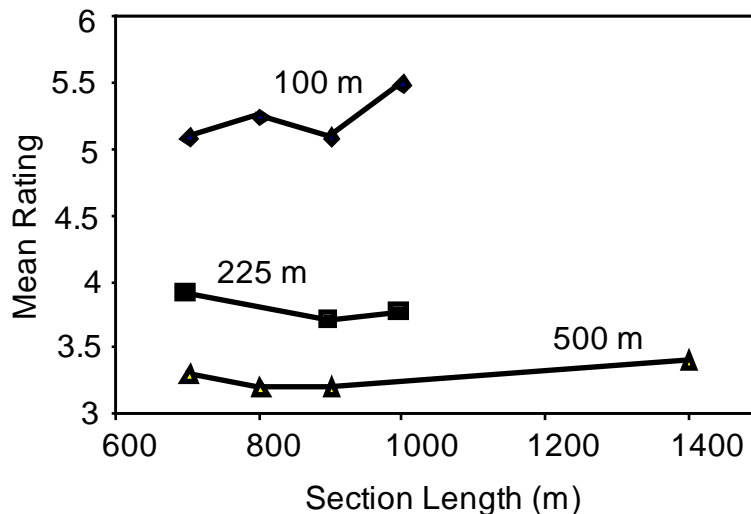


Figure 2.19. Segment Length & Sight Distance vs. Mean Rating

In a stepwise regression analysis of the data, the following equation resulted:

$$\begin{aligned}
\text{Rating} &= 9.078 \\
&+ 204.002 * \text{Inverse Radius (m)} \\
&- 2.820 * \text{Log (Sight Distance (m))} \\
&+ 2.293 * \text{Age Code (0=middle, 1=old)} \\
&+ 1.987 * \text{Sex Code (0=female, 1=male)} \\
&- 1.724 * \text{Age*Sex Code}
\end{aligned}$$

For that model, the r-squared value is .361.

### 2.3.4 Response Times to Lead Vehicle Braking

How does braking event response time vary as a function of road geometry and subject differences?

Figure 2.20 illustrates the average response to a braking event for a representative subject. Before the initiation of the braking event at three seconds, the subject is holding the accelerator in a fixed position, a common occurrence directly before a braking event for most of the braking trials. After the initiation of the braking event, there is a delay before the subject recognizes the braking event and responds. In most cases, the subject quickly lifts their foot, decreasing the throttle value to a minimal or zero value. After braking, the lead vehicle again accelerates, leading to the subject again pressing the accelerator pedal to follow the lead vehicle.

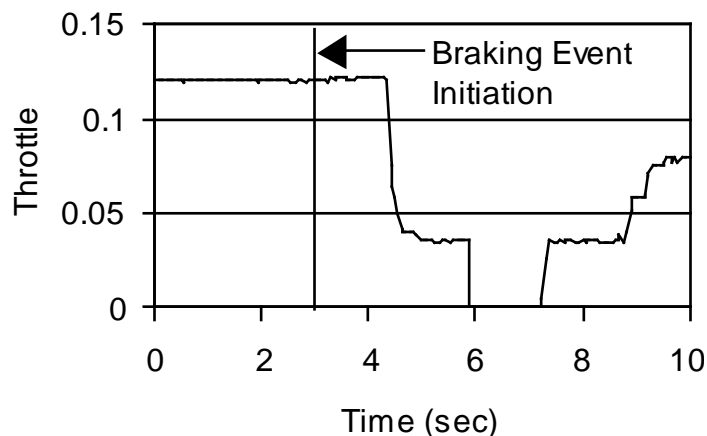


Figure 2.20. Acceleration Behavior for a Typical Braking Event

Response time measurement began when the lead vehicle's tail lights illuminated and it simultaneously began to decelerate. Response time measurement ended when the subject lifted their foot off of the throttle (accelerator lift off time). Situations where the throttle was released for other reasons (coasting) were rare.

The throttle signal had a range of 0.0 (not depressed) to 1.0 (fully depressed), and as with all other vehicle performance channels, was sampled at 20 Hz. Inspection of the data from multiple subjects revealed that at points around which braking might have occurred, throttle position changes in excess of .01 between samples were invariably

associated with overt braking and not normal adjustments in speed; hence, any change of that magnitude when followed by additional decreases in throttle position was used to signal throttle release braking. It should be noted that for <2.3% of all potential braking events, there was no throttle change exceeding .01 for a 10-second response window. In subsequent analyses, these data were treated as missing responses. Any subsequent increase in the throttle position beyond 0.00 (as the subject returned to the suggested speed of 45 mi/hr) started the search for a new braking event.

Another alternative would have been to select when the brake was pressed (brake response time, when the brake value changed from 0 to not 0). Unfortunately, for 35% of the trials, subjects responded to the lead vehicle braking by removing their foot from the throttle but did not press the brake pedal, a situation that lead to excessive missing data.

In addition to ease of measurement, implications of the measures were also considered. Brake RT is more directly related to crash performance because it represents when the vehicle velocity changes substantially in response to driver input. However, there is some slowing when the throttle is released, and furthermore, because it is not “contaminated” by the variability of movement from the throttle to the brake, throttle RT could be more highly correlated with factors influencing driver response than brake RT. Overall the differences in correlations between these two measures and other measures of performance should be slight.

### 2.3.5 Mean Response Time Profiles

To provide a sense of the response time data, mean throttle values for a representative subject for an entire run (trial block) appear in Figure 2.21. There was a fair amount of variability between individual sections (due to fog, etc.) and there was about a 10% increase in response time across all trials.

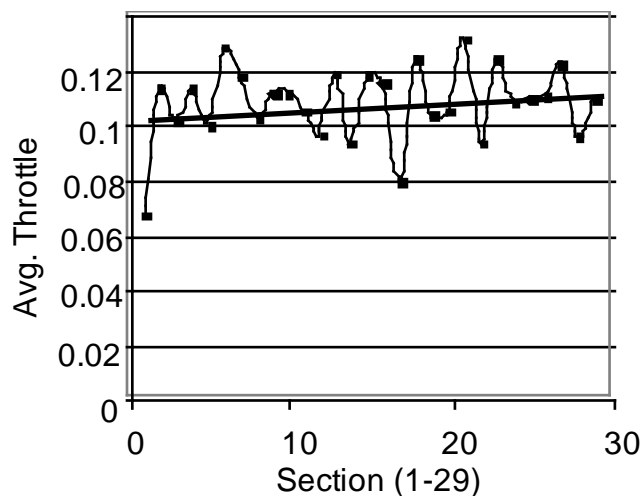


Figure 2.21. Average Accelerator Response Time Over Entire RT Test Run (Activity 6)

### 2.3.5.1 ANOVA of Throttle Lift Off Response Time

Only values of response time calculated from accelerator lift off were examined. There were a total of 576 potential responses (16 subjects \* 18 response/subject/condition \* 2 conditions (fog with occlusion, no fog with no occlusion)), for which 13 were missing because subjects did not respond or had already released their foot from the accelerator at braking event initiation. Of those missing responses, five were from middle-aged subjects and eight from older subjects. The largest number of missed responses per subject was five (out of 36) for an older subject. That subject did not have the longest mean response time.

The factors in the ANOVA of throttle lift off response time were: (1) Sight Condition (no fog, 500 m, 225 m, 100m), (2) Curve/Direction/Radius (left 200 m, left 400 m, right 200 m, right 400 m, straight), (3) Age (middle, old), Sex (female, male), Subject nested within Age and Sex, and all first order interactions except those with Subjects. Only Subject was a random effect. The length of straight sections was addressed separately. Also, Block effects were not examined as order and condition type (no fog-no occlusion, fog-occlusion) were confounded.

In that analysis, only Sight Condition (basically fog) was highly significant ( $p < .0001$ ). Also significant were Sex ( $p = .009$ ), Subject ( $p = .002$ ), and Age \* Sex ( $p = .02$ ). The full ANOVA table is in Appendix D.

Distribution of response time values can be seen below in Figure 2.22.

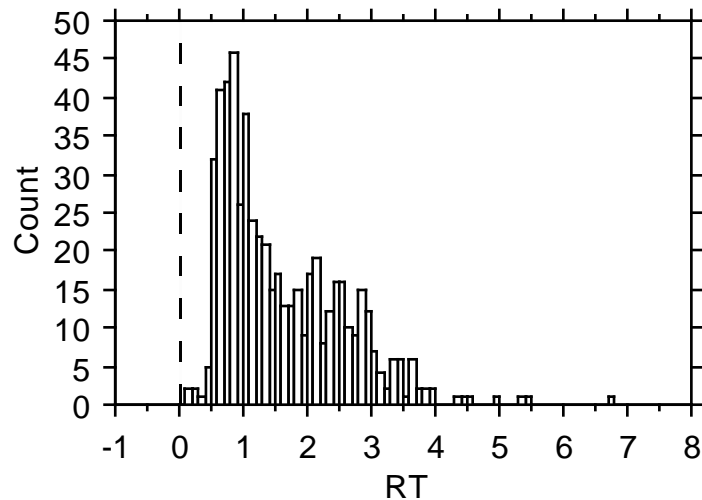


Figure 2.22. Distribution of RT Values

Figure 2.23 shows the subject differences. Consistent with typical findings, middle-aged men had the shortest response times and older men had the longest response times.

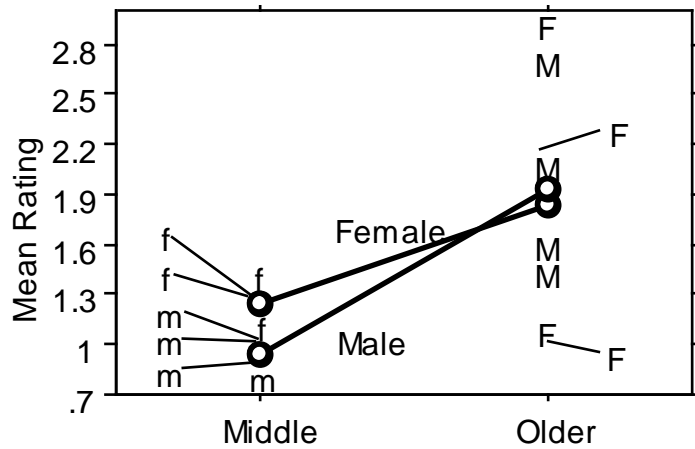


Figure 2.23. Response Times by Subject Age and Sex

Figure 2.24 shows the sight condition results. Notice that response times were clearly elevated for the 100 m sight distance (2.29 s) and that as sight distance increased, response time decreased, though the difference between 225 and 500 m was somewhat small (1.58 and 1.37 s respectively). Interestingly, the response time for the no occlusion-no fog condition was between those 2 values, at 1.41 s. Given it was easier (longer sight distance, no occlusion), the time should have been less. The lack of a difference may reflect statistical error in the measurements or confounding of factors.

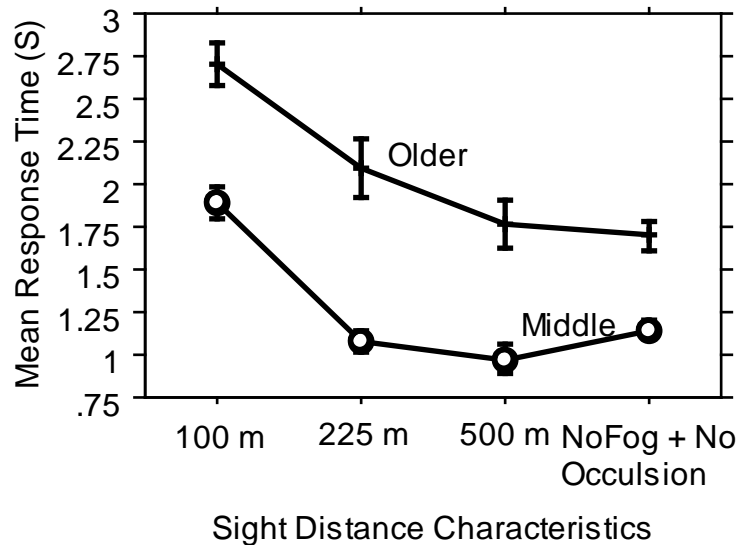


Figure 2.24. Effect of Sight Condition on Response Time

It was thought that when visual demand increased (as when curve radius decreased), that response time would increase. As shown in Figure 2.25, demand due to curvature had no effect on response time, nor did curve direction when grouping the subjects by age.

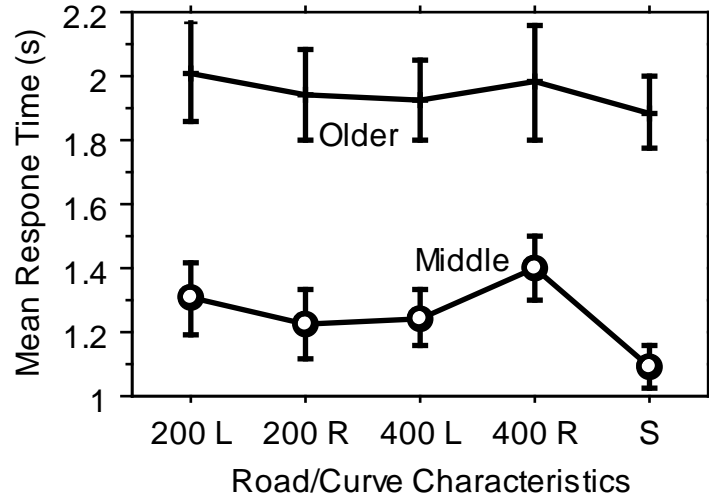


Figure 2.25. Response Time as a Function of Curve Direction and Radius

When splitting the data by sight distance, demand due to curvature also had no effect on response time, as seen in Figure 2.26 below. Curve direction also did not produce any effect on response time.

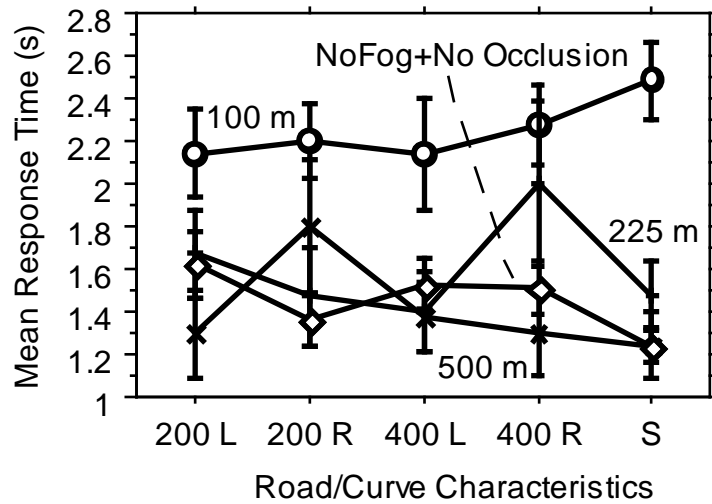


Figure 2.26. Response Time as a Function of Road/Curve Characteristics and Sight Distance

Expected results of the effect of fog on response time were found as response time was always lower when there was no fog present in the subjects' view. Figure 2.27 shows that as for all tested curve radii as well as curve directions, the presence of fog led to an increase in response time.

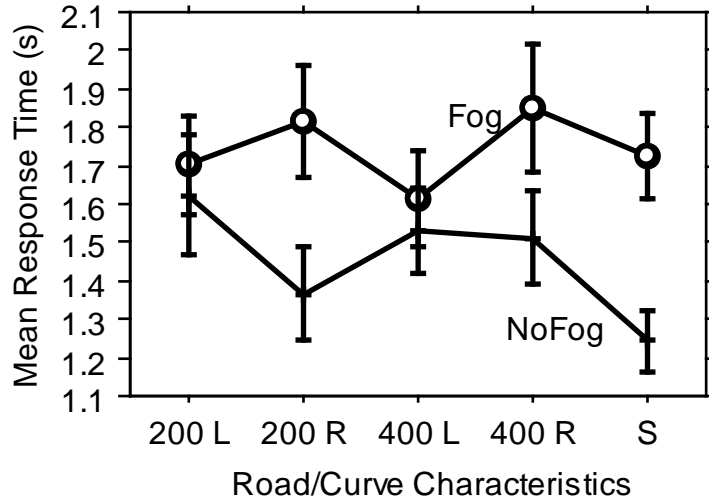


Figure 2.27. Effect of Fog on Response Time Split by Road/Curve Characteristics

As with the previous dependent measures, the effect of straight section length on response time was examined. As shown in Figure 2.28, section length had no effect. Section length effect on response time was not intended to be analyzed when this experiment was designed, hence the number of actual data points for Figure 2.27 are limited. While no major conclusions could be drawn from this figure, the effect of section length on mean response time seems to be relatively small.

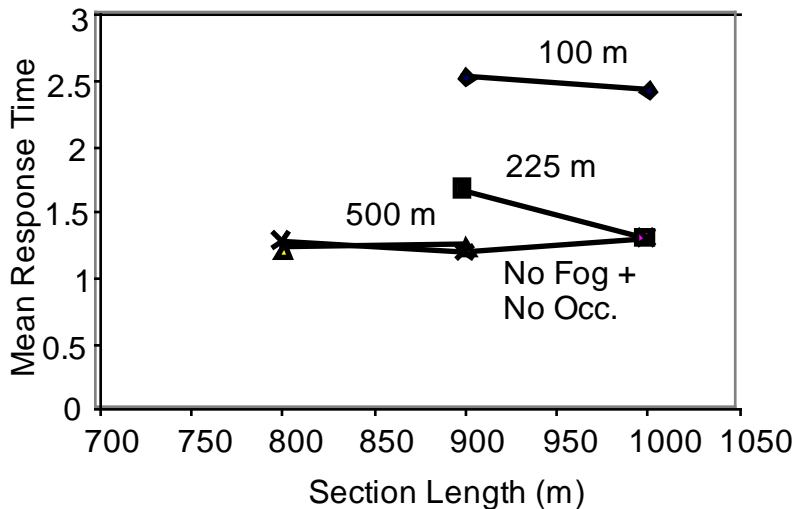


Figure 2.28. Response Time as a Function of Straight Section Length

### 2.3.5.2 Prediction of Brake Response Time and Visual Demand

A goal of this experiment was to examine whether brake response time could be predicted from other measurements because so few response times can be collected in a typical experimental session. In order to examine if this prediction was possible, a

correlation table was created between the independent and dependent measures throughout the experiment. Table 2.6 shows the correlation values between the primary measures of interest pooled across subjects. Inverse curve radius and log (sight distance) were used because the research of Hulse had shown they were better predictors than curve radius and sight distances, findings that were verified for this data. Given that there were 3 curve radii (none, 200 m, 400 m) and 3 sight distances (100, 225, 500 m), 9 data points were used in the correlation analysis. Bolded values shown were significantly correlated ( $p < .05$ ). Most interesting is the absence of a statistically significant correlation with inverse radius with any of the dependent measures. (The correlation with visual demand was almost significant ( $p = .0501$ .) However, all of the dependent measures were highly correlated with each other.

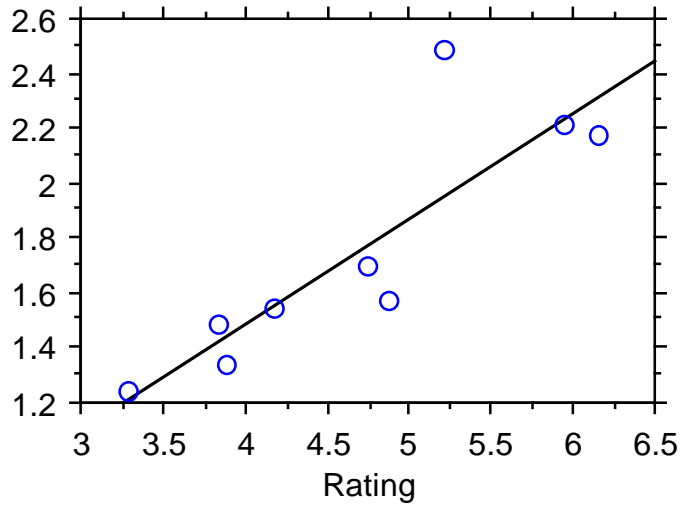
Table 2.6. Correlation of Independent and Dependent Measures

	1/Radius	Log (Sight Distance)	Brake RT	Occlusion	Rating
1/Radius	1				
Log (Sight Distance)	1.50E-15	1			
Brake RT	0.027	<b>-0.913</b>	1		
Occlusion	0.664	<b>-0.684</b>	0.703	1	
Rating	0.424	<b>-0.881</b>	<b>0.862</b>	<b>0.928</b>	1

Note: Statistically significant differences ( $p < .05$ ) are shown in bold.

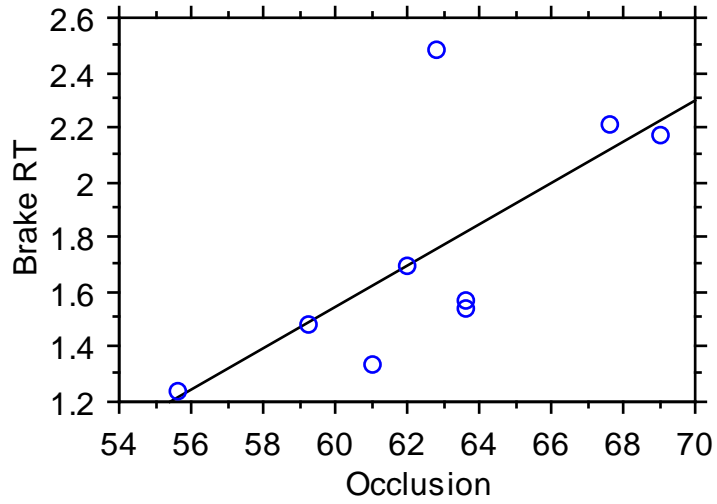
Figures 2.29, 2.30, and 2.31 show the relationships among the dependent measures of interest (visual demand as measured by the percentage of time the forward scene was visible, the brake response time (in s), and the rating of visual demand on a 1 to 10 scale). Notice that for the relationships with brake RT, there is one rating data point and one occlusion data point that seem to depart from the correlation. This departure is due to the unique interaction that occurs at straight sections with the 100 m sight distance characteristic. The three data points located on the upper right side of both Figures 2.29 and 2.30 are representative of the 100 m sight distance characteristic at the 200 m curve radii, 400 m curve radii, and straight sections, but the outlier from the correlation line is the point for straight sections. As subjects experienced the 100 m sight distance for all three radii sections, they adapted their ratings and occlusions to be higher in curved sections as compared to straight sections. Therefore, the straight section data point will be shifted more left on both figures. At the same time though, as less attention is being paid (i.e. lower occlusion values) to the world, response time increases, leading to the longest response time values for any data point in either figure.





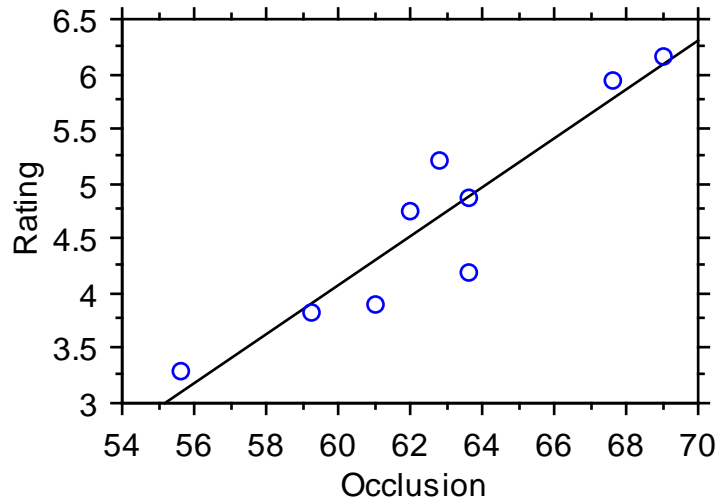
Brake RT =  $-.051 + .384 * \text{Rating}$ ;  $R^2 = .743$

Figure 2.29. Relationship between Ratings of Demand and Brake Response Time



Brake RT =  $-2.964 + .075 * \text{Occlusion}$ ;  $R^2 = .494$

Figure 2.30. Relationship between Visual Demand and Brake Response Time



$$\text{Rating} = -9.282 + .223 * \text{Occlusion}; R^2 = .862$$

Figure 2.31. Relationship between Visual Demand Measured Using Occlusion and Ratings of Demand

Stepwise regression modeling was used to predict the dependent measures, the most important of which was brake response time. Two sets of equations were developed to suit the various ways in which the findings could be applied. In the first approach (Table 2.7, equations 1-3), it was assumed that the workload manager would have data from the navigation system and other sensors on curve radius and sight distance. In addition, it was assumed that some limited information was available concerning the driver, in particular their age category and sex. A total of 36 data points were used in the analysis (age (2) \* sex (2) \* sight distance (3) \* curve radius (3)). As was shown in earlier ANOVAs, age and sex have significant effects on brake response time and visual demand.

Table 2.7. Regression Equations Coefficients

#	R2	Dependent Measure	Intercept	1/Radius (m)	Log (sight distance (m))	Age Code	Sex Code	Age Code * Sex Code
1	.87	Response Time (s)	4.58	0	-1.33	0.58	-0.28	0.60
2	.93	Visual Demand (%)	74.99	1248.93	-9.20	14.71	5.47	-15.39
3	.84	Rating	8.65	174.10	-2.54	2.06	1.87	-1.38
4	.87	Response Time (s)	4.83	0	-1.31			
5	.91	Visual Demand (%)	81.34	+1249.00	-9.20			
6	.96	Rating	10.89	191.47	-2.84			

Age code (0=middle, 1=old)  
Sex code (0=female, 1=male)

All of the predictions make sense, with all dependent measures decreasing as radius is increasing, as well as decreasing with greater sight distance (hence negative log values) and increasing with age. Sex and Age \* Sex values vary to fit the particular experimental data.

The resulting predictions of brake response time were quite good, with the three independent variable model ( $4.58 - 1.33 \text{ Log}(\text{Sight Distance}) + 0.58 \text{ Age Code} - 0.28 \text{ Sex Code} + 0.60 \text{ Age Code} * \text{Sex Code}$ ) accounting for 87% of the variance. Notice that inverse curve radius did not enter into the model. Forcing  $1/r$  into the equation ( $RT = 4.82 - 1.31 (\text{Log}(\text{Sight Distance (m)})) + 5.40(1/r (m))$ ) increased  $r^2$  by .001, a small amount. For visual demand, the 4-factor model accounted for 93% of the variance, and for ratings of demand, a 4-factor model accounted for 84% of the variance. These  $r$ -squared values are all quite high.

If the Age and Sex data are not included, then equations 4, 5, and 6 result. The  $r$ -squared values remain high because the data set consisted of only nine points (3 curve radii \* 3 sight distances). In both cases, the  $r$ -squared values would be much lower if the raw data or subject means for various conditions were used. For those interested in computing other regression models using other combinations of independent measures, the 27 data point means are in Appendix E.

## 2.4 CONCLUSIONS

In the experiment, 16 subjects (8 middle-aged, 8 older) drove 2-lane rural roads in a driving simulator, sometimes following a lead vehicle that braked for which response time was measured. The road, consisting of straight and curved sections (of varying radii), was at times obscured by varying levels of fog. The visual demand of the driving task for each road segment was measured using the visual occlusion method and by ratings.

The overall goal of this experiment described in this report was to relate response time to a lead vehicle braking to the visual demand of the driving situation under which that data was collected. More specifically, four questions were addressed, each of which is covered in separate sections that follow.

### 2.4.1. How does braking event response time vary as a function of road geometry and subject differences?

Response time to a braking event was longer when the stimulus occurred on a curve as opposed to a straight section when sight distance was unlimited (meaning there was no fog). Average response times were 1.51 s on curves and 1.24 s on straight sections. When sight distance was limited (averaged over all tested distances), the difference between curved and straight sections was less than 0.05 s (1.76 s for curved; 1.73 s for straight). Curve radius had very little effect on response time to a lead vehicle braking with the mean response times for the 200 m and 400 m curve both being 1.63 s.

As expected, the direction of the curvature did not affect response time to a braking event, with the difference in response time between the left and the right curves being 0.02 s (1.62 s for left; 1.64 s for right).

Response time to a lead vehicle braking was inversely proportional to sight distance and was reasonably well correlated with the log of sight distance. Response time at a limited sight distance of 100 m was found to be approximately 2.29 s with 225 m and 500 m sight distances, resulting in response times of 1.58 and 1.37 s, respectively.

As expected, older subjects had longer response times to braking events than younger subjects, regardless of sex. When sight distance was not limited, older subjects' response time was 0.55 s longer than that of the middle-aged subjects (1.70 s to 1.55 s), but when sight distance was limited by varying levels of fog, the difference increased to 0.88 s (2.19 s to 1.31 s). Older men and women had very similar response times (difference  $\leq 0.02$ ) when sight distance was not limited, but a difference of 0.31 s when fog was present (1.71 s to 1.69 s and 2.34 s to 2.03 s, males over females respectively). Middle-aged males had a lower response time than the middle-aged females in both situations, with no limited sight distance (1.04 s to 1.26 s) and limited sight distance (1.17 s to 1.44 s).

Based on these analyses, the best prediction of response time is:

$$\text{Response time (s)} = 4.58 - 1.33 \log(\text{sight distance (m)}) \\ + .58 * \text{Age Code} - 0.28 \text{ Sex Code} + .60 * \text{Age Code} * \text{Sex Code}$$

where the Age Code is 0 for middle aged subjects and 1 for older subjects, and the Sex Code is 0 for women and 1 for men. Notice that curvature was not part of the model.

#### **2.4.2. How does visual demand (measured using the visual occlusion method) vary as a function of road geometry, presence of a lead vehicle, subject differences, and how speed is controlled?**

Visual demand, as measured using the visual occlusion method, was roughly proportional to inverse curve radius as indicated by the literature; that is, it was more demanding to drive tighter curves. The demand on straight sections (infinite curvature) was approximately 59%. The demands for 200 m and 400 m were found to have demand levels of 65% and 63%, respectively.

There was also a noticeable difference in the visual demand as a function of the direction of curvature. When experiencing a left curve, the average visual demand was 64%, but the demand increased 1% for right curves.

As expected, visual demand increased as the sight distance decreased. When the sight distance was 100 m, the visual demand was approximately 65%. However, demand increased for the 225 m and 500 m distances at 61% and 59%, respectively. The rate of change of this relationship at the 500 m sight distance approaches zero, suggesting that 500 m is approximately equivalent to the absence of fog or unlimited sight distance. Further tests with greater sight distances should be conducted to verify this conclusion.

Visual demand increased almost 3% when a lead vehicle was present, rising from 60% to 63%. This project did not separate the demand due to the mere presence of a vehicle from the demand associated with responding to a braking event.

Visual demand was higher when vehicle velocity was cruise controlled than when subject controlled, which was an unexpected finding. It was hypothesized that when subjects were in charge of their velocity, as well as occlusion and steering, the level of visual demand would be higher than with cruise control. Subject-controlled velocity lead to a visual demand level of 59%, but cruise-controlled velocity produced a visual demand of 61%.

Measured visual demand depended on the age and sex of the driver to a significant degree. For women, the visual demand increased substantially with age (55% for middle aged women, 70% for older women). For the men, the age difference was .1%, with both values between 60 and 61%. Thus, there was a substantial age by sex interaction. The size of these differences was generally larger than some of the effect differences, suggesting that a workload manager may need to be tailored to particular age-sex groups.

Based on these analyses, the best prediction of visual demand is:

$$\text{Visual demand (\%)} = 74.99 + 1248.93*(1/\text{Radius(m)}) - 9.20*\text{Log}(\text{Sight distance(m)}) \\ +14.71*\text{Age Code} +5.47 \text{ Sex Code} -15.39*\text{Age Code}*\text{Sex Code}.$$

#### **2.4.3. How does rated visual demand vary as a function of road geometry, subject differences, and how speed is controlled?**

Visual demand, as measured in ratings, increased as the radius of curvature decreased, again appearing to be related to inverse curve radius. For straight sections (infinite radius of curvature), the mean rating was 4.1, but it increased to 4.9 for 400 m curves and 5.0 for 200 m curves. As a reminder, the rating “4” was presented as “driving 10 miles an hour faster than traffic on an expressway,” while a rating of “6” was “driving 20 miles an hour faster than traffic on an expressway”.

There was also a noticeable difference in the visual demand as a function of the direction of curvature. For both left and right curves, the mean visual demand rating was approximately 4.9. Straight sections had a rating of only 4.1.

Visual demand as assessed by subjective ratings decreased as the sight distance increased. Ratings were 5.6 for 100 m, 4.3 for 225 m, and 3.68 for 500 m.

Age and sex had an interesting effect on visual demand as determined by subjective ratings. For the middle-aged subjects, men had higher subjective ratings than the women: 4.8 to 2.8. The increase of 2.0 points is quite surprising. As expected, the mean ratings for the older subjects were higher than that of the middle-aged subjects. Interestingly, the older male and female subjects had similar mean ratings (5.3 and 5.1, respectively).

Ratings for cruise-controlled velocity were lower than that of subject-controlled velocity, as expected. Having velocity under cruise control produced an average rating of 4.4 with subject control equaling 4.6, a 4 % increase.

Based on these analyses, the best prediction of subjective ratings is:

$$\text{Rating (1 to 10)} = 8.65 + 174.10*(1/\text{Radius(m)}) -2.54*\text{Log}(\text{Sight distance(m)}) \\ +2.06*\text{Age Code} +1.87*\text{Sex Code} -1.38*\text{Age Code}*\text{Sex Code}.$$

#### **2.4.4. How closely does visual demand (measured by the visual occlusion method) relate to rated visual demand in terms of road geometry, subject differences, and how speed is controlled?**

Overall, the correlation of the two means (average across subjects) was 0.928, quite high. More specifically, the percentage of visual demand increasing from 400 m to 200 m radius of curvature for the rating system closely resembles the relationship seen

in the visual occlusion method: an increase of 2.0% for the ratings versus 2.9% for the visual occlusion method. When examining the difference in terms of direction of curvature, the ratings increased by 1.2% for right curves over left curves. The visual occlusion method indicated a 1.4% increase for right over left curves. Differences in the effect of sight distance were noted between the two methods. The visual occlusion method had a 6.6% decrease from 100 m to 225 m sight distances and a 3.0% decrease from 225 m to 500 m, while the decreases for the subjective ratings were much greater at 22.8% and 14.8%, respectively. The age/sex interaction for both methods did not produce similar results, except for the average upward trend when looking from middle-aged to older subjects. Results pertaining to means of control were opposite across the two visual demand methods. Use of cruise control led to a greater visual demand than when the subject controlled speed, as assessed by the visual occlusion method, but the opposite held true for the subjective ratings.

#### **2.4.5 Closing Thoughts**

The overall goal of establishing a quantitative relationship between response time to a lead vehicle braking and visual demand measured using the visual occlusion method was achieved. Visual demand was well correlated with sight distance and response time, but surprising, curve radius was not (as was expected from the literature).

Nonetheless, the use of visual occlusion as a predictor for brake response time deserves further investigation for other factors that affect driving demand (such as traffic) as it continues to be a more efficient experimental method than collecting brake response time directly.

## 2.5 REFERENCES

- Alliance of Automobile Manufacturers (2002 April 15). *Statement of Principles, Criteria and Verification Procedures on Driver Interactions with Advanced In-Vehicle Information and Communication Systems*, Washington, D.C.: Alliance of Automobile Manufacturers.
- Brookhuis, K.A. and de Waard, D. (2001). Assessment of Drivers' Workload: Performance and Subjective and Physiological Indices, (chapter 2.5, 321-333), in Hancock, P.A. and Desmond, P.A. *Stress, Workload, and Fatigue*, Mahwah, NJ: Lawrence Erlbaum Associates.
- Eby, D.W. & Kostyniuk, L.P. (2003). Crashes and Driver Distraction: An Assessment of Databases, Crash Scenarios, and Distracted-Driving Scenarios. Cambridge, MA: The Volpe National Transportation Systems Center.
- Gawron, V. (2000). *Human Performance Measures Handbook*. Mahwah, N.J.: Erlbaum, Lawrence, Associates.
- Green, P. (2000). *Crashes Induced by Driver Information Systems and What Can Be Done to Reduce Them* (SAE paper 2000-01-C008), *Convergence 2000 Conference Proceedings*, (SAE publication P-360), Warrendale, PA: Society of Automotive Engineers, 26-36.
- Green, P., Cullinane, B., Zylstra, B., and Smith, D.T. (2003). *Standard Deviation of Lane Position, Speed, and Other Driving Performance Measures: A Tabular Summary of the Literature*, (Technical report UMTRI-2003-42), Ann Arbor, MI: University of Michigan Transportation Research Institute.
- Green, P. and Shah, R. (2003), *Task Time and Glance Measures of the Use of Telematics: A Tabular Summary of the Literature* (Technical Report UMTRI 2003-33), Ann Arbor, MI: University of Michigan Transportation Research Institute.
- Hoedemaeker, M., de Ridder, S.N., and Janssen, W. H. (2002). *Review of European Human Factors Research on Adaptive Interface Technologies for Automobile* (Technical report TM - 02 - C031), Soesterberg, The Netherlands: TNO Human Factors Institute.
- Hulse, M.C., Dingus, T. A., Fisher, T., and Wierwille, W.W. (1989). The Influences of Roadway Parameters on Driver Perception of Attentional Demand, *Advances in Industrial Ergonomics and Safety I*, 451-456.
- Kantowitz, B.H. and Simsek, O. (2001). Secondary-Task Measures of Driver Workload (chapter 2.10, 395-408) in Hancock, P.A. and Desmond, P.A. *Stress, Workload, and Fatigue*, Mahwah, NJ: Lawrence Erlbaum Associates.



- Kiefer, R., LeBlanc, D., Palmer, M., Salinger, J., Deering, R., and Shulman, M. (1999). *Development and Validation of Functional Definitions and Evaluation Procedures for Collision Warning/Avoidance System*, National Highway Traffic Safety Administration Technical Report, Contract No: DTNH22-95-H-07301, Washington, D.C., DOT HS 808 964.
- Michon, J. (1993). *Generic Intelligent Driver Support*. London, U.K.: Taylor and Francis.
- Remboski, D., Gardner, J., Wheatley, D., Hurwitz, J., MacTavish, T., and Gardner, R. (2000). *Driver Performance Improvement through the Driver Advocate: A Research Initiative toward Automotive Safety* (SAE-01-C075). (SAE publication P-350), 509-518. Warrendale, PA: Society of Automotive Engineers.
- Senders, J.W., Kristofferson, A.B., Levison, W.H., Dietrich, C.W., and Ward, J.L. (1966). An Investigation of Automobile Driver Information Processing (BBN Technical Report 1335), Cambridge, MA: Bolt Beranek and Newman.
- Senders, J.W., Kristofferson, A.B., Levison, W.H., Dietrich, C.W. and Ward, J.L. (1967a). An Investigation of Automobile Driver Information Processing (BBN Technical Report 1482), Cambridge, MA: Bolt Beranek and Newman.
- Senders, J.W., Kristofferson, A.B., Levison, W.H., Dietrich, C.W., and Ward, J.L. (1967b). The Attentional Demand of Automobile Driving, Highway Research Record #195, 15-33.
- Senders, J.W. and Ward, J.L. (1968). Additional Studies of Driver Information Processing (BBN Technical Report 1738), Cambridge, MA: Bolt Beranek and Newman.
- Sivak, M. (1996). The information that drivers use: Is it indeed 90 percent visual? *Perception*, 25, 1081-1089.
- Society of Automotive Engineers (2002). *Calculation of the Time to complete In-Vehicle Navigation and Route Guidance Tasks* (SAE Recommended Practice J2365), Warrendale, PA: Society of Automotive Engineers.
- Society of Automotive Engineers (2003a). *Navigation and Route Guidance Function Accessibility while Driving* (SAE Recommended Practice J2364), Warrendale, PA: Society of Automotive Engineers.
- Society of Automotive Engineers (2003b). *Rationale to J2364: Navigation and Route Guidance Function Accessibility while Driving* (SAE Information Report J2678), Warrendale, PA: Society of Automotive Engineers.

- Stutts, J.C., Reinfurt, D.W., Staplin, L., and Rodgman, E.A. (2001). *The Role of Driver Distraction in Traffic Crashes* (Technical Report). Washington, D.C.: AAA Foundation for Traffic Safety.
- Tijerina, L, Angell, L., Austria, A., Tan, A., and Kochhar, D. (2003). *Driver Workload Metrics Literature Review* (technical report), Washington, D.C. U.S. Department of Transportation.
- Tsimhoni, O. and Green, P. (1999). Visual Demand of Driving Curves Determined by Visual Occlusion. Paper presented at the Vision in Vehicles 8 Conference, Boston, MA.
- Van der Horst, R. (2001). Occlusion as a Measure for Visual Load, an Overview of Occlusion Research at TNO Human Factors, paper presented at the workshop: Exploring the Occlusion Technique: Progress in Recent Research and Applications, <http://www.umich.edu/~driving/occlusionworkshop2001/>.
- Wang, J-S., Knipling, R.R., and Goodman, M.J. (1996). The Role of Driver Inattention in Crashes; New Statistics from the 1995 Crashworthiness Data System. *40<sup>th</sup> Annual Proceedings of the Association for the Advancement of Automotive Medicine*, 377-392.
- Wooldridge, M., Bauer, K., Green, P., and Fitzpatrick, K. (2000). Comparison of Workload Values Obtained from Test Track, Simulator, and On-Road Experiments. Paper presented at the Transportation Research Board Annual Meeting, Washington, D.C.



## 2.6 APPENDIX A – RATIONALE FOR CURVE-SIGHT DISTANCE COMBINATIONS

### Experiment Design

Table 2.8 shows the curve radius – direction combinations explored for the road driven in the “forward” direction. Curves on which braking events occur are shown in bold, with only two curves having no events in order to make event occurrence less predictable. This design allows the effect of visual demand (curvature) on braking response time (RT) to be explored efficiently.

Table 2.8. Curve Radius – Direction Combinations Explored  
(Curves with braking events in bold)

	200 m curve	400 m curve	Total
Left	<b>100,</b> <b>225,</b> <b>500, 500</b>	<b>100</b> <b>225, 225</b> <b>500</b>	7 curves
Right	<b>100,</b> <b>225,</b> <b>500</b>	<b>100,</b> <b>225,</b> <b>500</b>	7 curves
Total	7 curves	7 curves	

Table 2.9 shows the sight distances (due to fog) used for various straight section lengths. Examination of the interaction of curvature and sight distance was beyond the scope of this experiment. Notice that braking events only occurred on longer straight sections. At the beginning of each straight section, subjects did not know its length, so having braking events on only long straights was not a confounding factor. All braking events during straight sections occurred at the middle of the section length.

Table 2.9. Straight Section Length – Sight Distance Combinations Explored  
(Cell entry is the number of sections, braking events are in bold)

Sight Distance (m)	Section Length			
	(no lead vehicle braking)		(lead vehicle braking)	
	700	800	900	1000
100	2	1	<b>1</b>	<b>1</b>
225	3		<b>1</b>	<b>1</b>
500	1		<b>1</b>	<b>1</b>

There were 3 sight distance limits examined in this experiment. The longest distance, 500 m, represents the longest distance for which some fog was present but which may not affect visual demand (Hulse, Dingus, Fisher, Wierwille, 1989). The shortest distance is based on the shortest stopping distance required for a vehicle when the deceleration value is at its maximum. For 45 mi/hr, 1% of the drivers would achieve 0.21 g (and 99% would be lower) (Kiefer, LeBlanc, Palmer, Salinger, Deering, and Shulman, 1999).

leading to a stopping distance of 100 m. Since the relationship between visual demand and sight distance is logarithmic, 225 m is a reasonable middle value.

For curves with braking events, the events occurred either approximately 90 m from the beginning or end of the curve. Braking event occurrence was balanced across curve direction and radius.

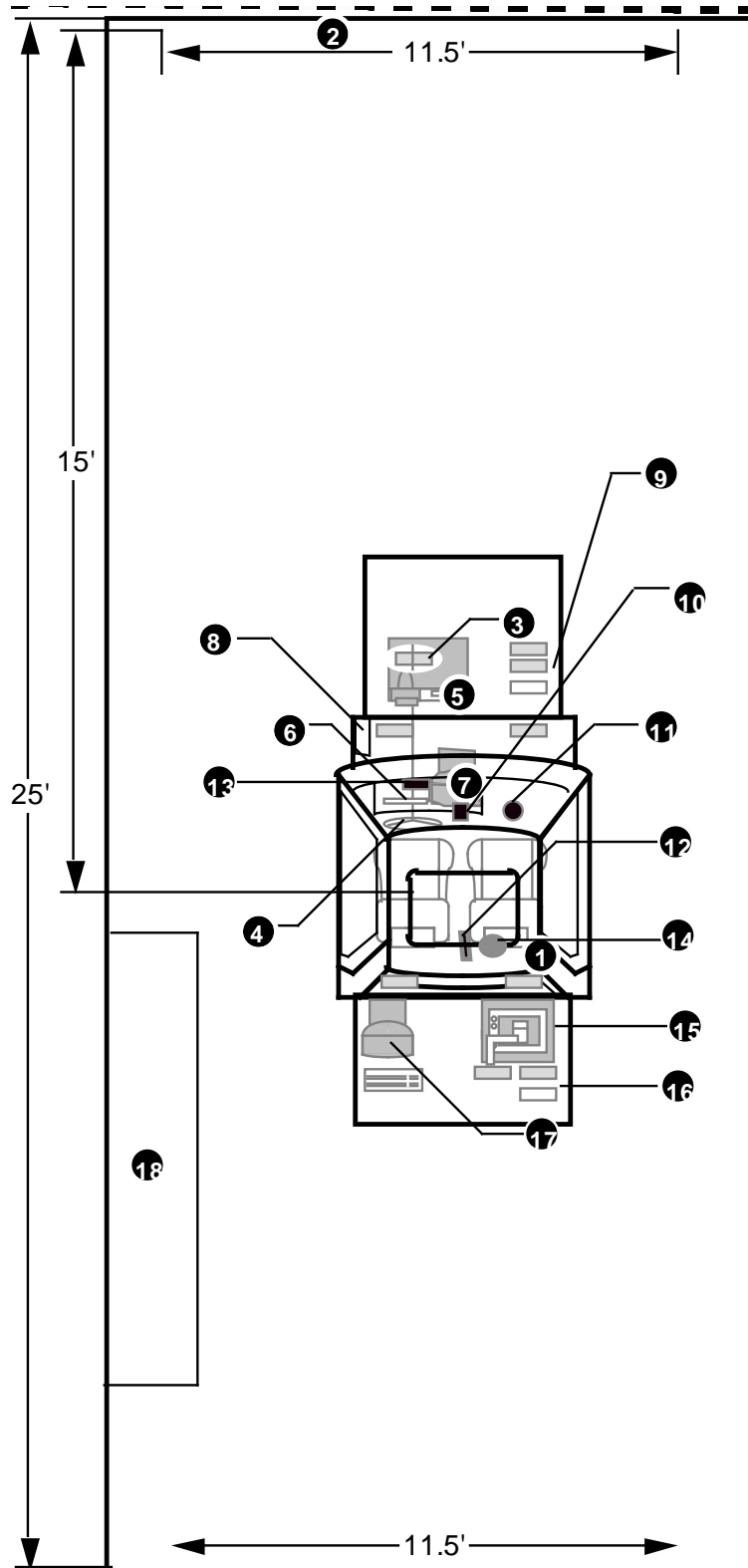
## 2.7 APPENDIX B – ACTIVITY SEQUENCE RANDOMIZATION

Table 2.10. Order Sequence for Activities 5-7

Subject #	Order		
	1 <sup>st</sup> (Activity #)	2 <sup>nd</sup> (Activity #)	3 <sup>rd</sup> (Activity #)
1	Subject Controlled (7)	Response Time (6)	Cruise Controlled (5)
2	Subject Controlled (7)	Response Time (6)	Cruise Controlled (5)
3	Cruise Controlled (5)	Response Time (6)	Subject Controlled (7)
4	Cruise Controlled (5)	Response Time (6)	Subject Controlled (7)
5	Subject Controlled (7)	Response Time (6)	Cruise Controlled (5)
6	Subject Controlled (7)	Response Time (6)	Cruise Controlled (5)
7	Cruise Controlled (5)	Response Time (6)	Subject Controlled (7)
8	Cruise Controlled (5)	Response Time (6)	Subject Controlled (7)
9	Subject Controlled (7)	Response Time (6)	Cruise Controlled (5)
10	Subject Controlled (7)	Response Time (6)	Cruise Controlled (5)
11	Cruise Controlled (5)	Response Time (6)	Subject Controlled (7)
12	Cruise Controlled (5)	Response Time (6)	Subject Controlled (7)
13	Subject Controlled (7)	Response Time (6)	Cruise Controlled (5)
14	Subject Controlled (7)	Response Time (6)	Cruise Controlled (5)
15	Cruise Controlled (5)	Response Time (6)	Subject Controlled (7)
16	Cruise Controlled (5)	Response Time (6)	Subject Controlled (7)



## 2.7 APPENDIX C – SIMULATOR INFORMATION



- 1 1985 Chrysler Laser mockup with simulated hood
- 2 White Projection Wall for front projection screen
- 3 Tourque Motor - SE 808, Model #56728
- 4 3-spoke steering wheel
- 5 Sharp color LCD projection system (model XG-E850U)
- 6 4"X13" plexiglas screen
- 7 ELO Touch Systems Intellitouch monitor (model E284A-1345)
- 8 Bass Shaker - Autotek Street Machine, #sX 275 - 50 Watts
- 9 2-10 Amp , 13.8 VDC Radio Shack Power Supply (1-Shaker Amp, 1-Control Loader/Torque Motor) & 1 Back UPS Pro 1400
- 10 Face Cam - EIA B/W CCD Camera, Model# - KPC - 5400
- 11 Shoulder Cam - KT&C CCD Camera - EX Vision
- 12 Secondary Task Cam - KT&C DSP Color, H1 - res EX Vision
- 13 Foot Cam - Panasonic CCU - WV - BP550
- 14 Dome Light - Incandescent
- 15 Monsoon Sound System for Simulator noise - #E203436
- 16 2-10 Amp , 13.8 VDC Radio Shack Power Supply (1-Audio Power Supply, 1 for Dome, PRNDL, E stop, Seat motor ) & 1 Back UPS Pro 1400
- 17 Secondary Task Computer - Power Mac 9500/G3 upgrade/ 350 Hz
- 18 Simulator Control Room - See Appendix XX



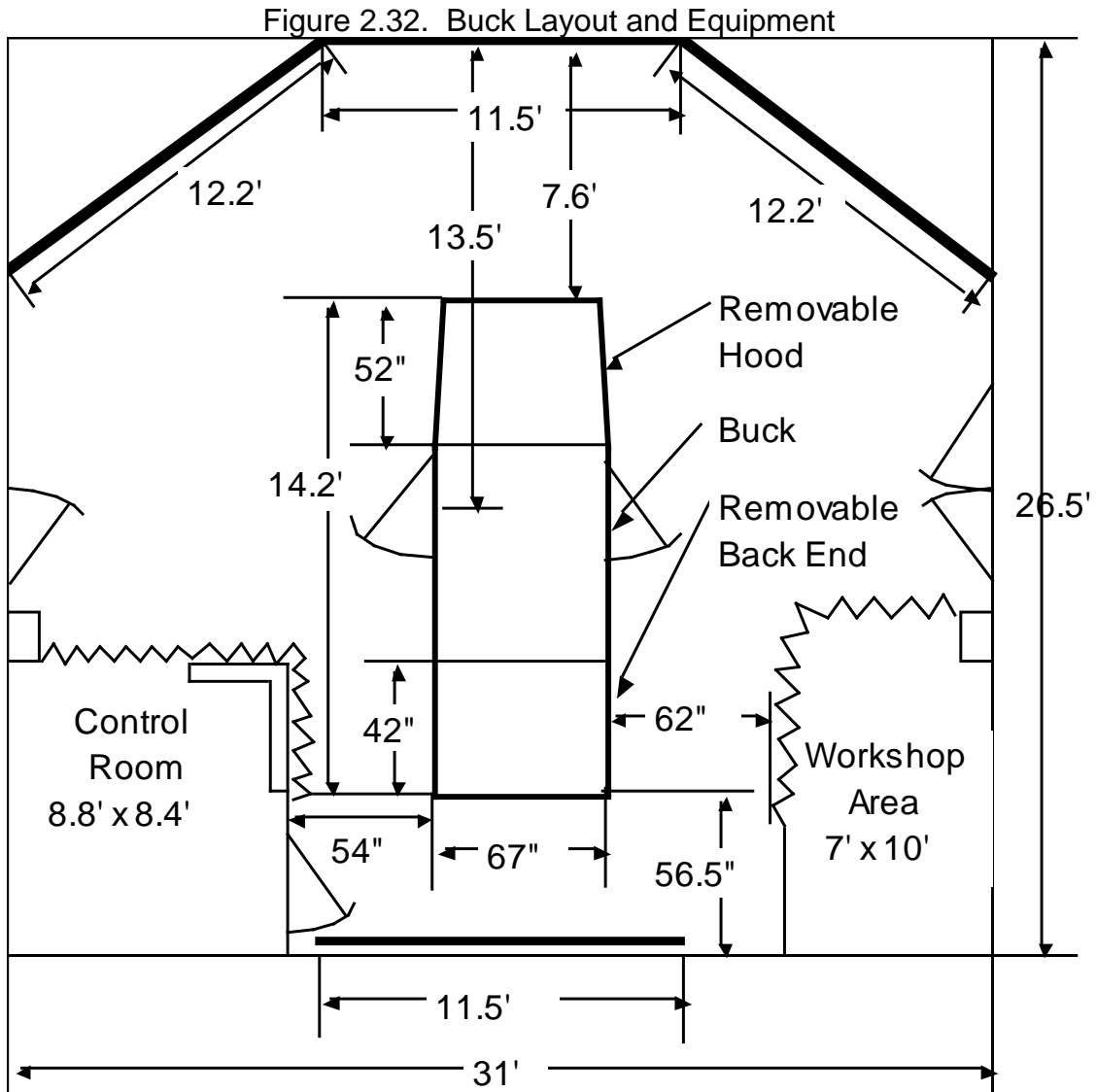


Figure 2.33. Overall Simulator Room Layout

## 2.7 APPENDIX D – ADDITIONAL ANOVA ANALYSIS

Table 2.11. Visual Demand ANOVA (from Occlusion Data)

<b>Source</b>	<b>DF</b>	<b>SS</b>	<b>F Ratio</b>	<b>P</b>
Inverse radius	1	10222.660	53.0389	<.0001
Log (sight distance)	1	9826.758	50.9848	<.0001
Sex	1	13399.579	69.5219	<.0001
Age	1	54380.932	282.1480	<.0001
SpeedControl-LV	2	5592.707	14.5085	<.0001
Subject[Sex,Age]	4	99747.039	129.3810	<.0001
Inverse radius*Sex	1	0.330	0.0017	0.9670
Inverse radius*Age	1	940.855	4.8815	0.0273
Inverse radius*SpeedControl-LV	2	574.597	1.4906	0.2256
Inverse radius*log (sight distance)	1	141.414	0.7337	0.3918
Log (sight distance)*Sex	1	0.095	0.0005	0.9823
Log (sight distance)*Age	1	488.841	2.5363	0.1115
Log (sight distance)*SpeedControl-LV	2	33.128	0.0859	0.9177
Sex*Age	1	4334.549	22.4892	<.0001
Sex* SpeedControl-LV	2	3632.451	9.4232	<.0001
Age* SpeedControl-LV	2	283.846	0.7363	0.4790
Error	1367	263474.26		

Table 2.12. Ratings of Demand ANOVA

Source	DF	Sum of Squares	F Ratio	P
CurveDirexRadius	4	168.30201	16.3709	<.0001
Log Sight Distance	1	407.60224	158.5913	<.0001
Sex	1	232.87833	90.6091	<.0001
Age	1	463.39719	180.3002	<.0001
Block	1	1.32993	0.5175	0.4721
SpeedControl	1	7.71722	3.0026	0.0835
Subject[Sex,Age]	4	525.26724	51.0932	<.0001
CurveDirexRadius*Sex	4	30.40392	2.9574	0.0192
CurveDirexRadius*Age	4	2.97708	0.2896	0.8848
CurveDirexRadius*Block	4	7.07207	0.6879	0.6004
CurveDirexRadius* SpeedControl	4	2.59042	0.2520	0.9085
CurveDirexRadius*Log Sight Distance	4	6.79052	0.6605	0.6196
Log Sight Distance*Sex	1	0.76867	0.2991	0.5846
Log Sight Distance*Age	1	5.05806	1.9680	0.1610
Log Sight Distance*Block	1	0.20376	0.0793	0.7783
Log Sight Distance* SpeedControl	1	0.48391	0.1883	0.6645
Sex*Age	1	42.87156	16.6806	<.0001
Sex*Block	1	0.72845	0.2834	0.5946
Sex* SpeedControl	1	3.37931	1.3148	0.2518
Age*Block	1	3.37931	1.3148	0.2518
Age* SpeedControl	1	9.12069	3.5487	0.0599
Block* SpeedControl	1	172.24914	67.0193	<.0001
Error	884	2272.0064		

Table 2.13. Response Time ANOVA

Source	DF	SS	F Ratio	P
Sight Condition	3	44.697125	22.9427	<.0001
CurveDirexRadius	4	1.394686	0.5369	0.7087
Sex	1	4.428647	6.8196	0.0093
Age	1	2.019417	3.1097	0.0784
Subject[Sex,Age]	4	11.068152	4.2609	0.0021
Sight Distance*Sex	3	0.674149	0.3460	0.7920
Sight Distance*Age	3	4.437385	2.2777	0.0787
Sight Distance *CurveDirexRadius	12	12.453102	1.5980	0.0882
CurveDirexRadius*Sex	4	1.083963	0.4173	0.7962
CurveDirexRadius*Age	4	1.014777	0.3907	0.8154
Sex*Age	1	3.717758	5.7249	0.0171
Error	522	338.98750		

## 2.8 APPENDIX E - ADDITIONAL INFORMATION ABOUT REGRESSION

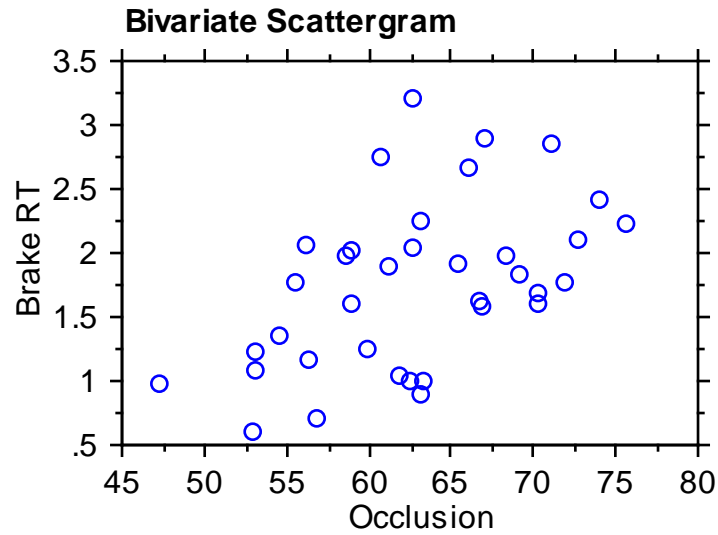


Figure 2.34. Visual Demand (%) versus Brake Response Time (s)

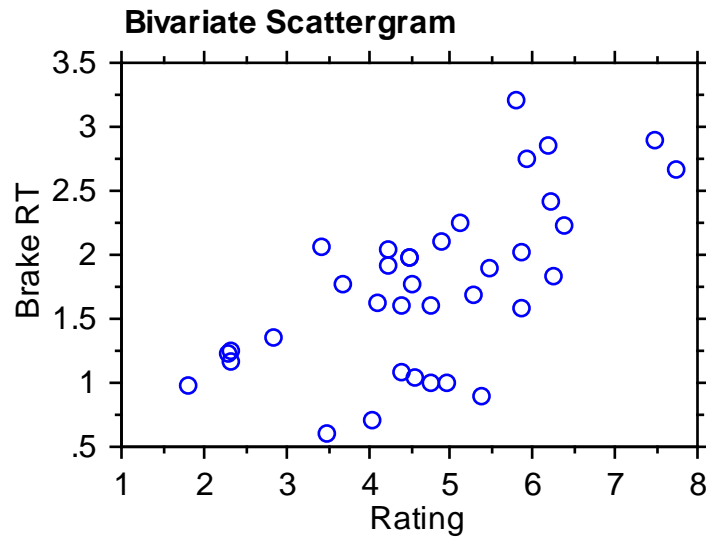


Figure 2.35. Ratings of Demand versus Brake Response Time (s)

Table 2.13. Means Used for Regression Analysis

Age	Sex	Sight Distance	Radius	Brake RT	Occlusion	Rating
middle	female	100	200	1.921	65.426	4.250
middle	female	100	400	2.043	62.602	4.250
middle	female	225	200	1.250	59.975	2.333
middle	female	225	400	1.356	54.506	2.833
middle	female	500	200	1.169	56.282	2.333
middle	female	500	400	1.081	53.023	4.406
middle	female	100	straight	2.069	56.185	3.425
middle	female	225	straight	1.238	53.154	2.300
middle	female	500	straight	0.969	47.252	1.825
middle	male	100	200	1.825	69.218	6.250
middle	male	100	400	1.588	66.868	5.875
middle	male	225	200	0.906	63.073	5.375
middle	male	225	400	1.006	62.440	4.958
middle	male	500	200	0.994	63.234	4.750
middle	male	500	400	1.044	61.802	4.562
middle	male	100	straight	1.894	61.254	5.475
middle	male	225	straight	0.713	56.770	4.050
middle	male	500	straight	0.594	52.987	3.500
old	female	100	200	2.231	75.593	6.375
old	female	100	400	2.407	74.063	6.219
old	female	225	200	2.094	72.628	4.875
old	female	225	400	1.694	70.236	5.292
old	female	500	200	1.775	71.860	4.542
old	female	500	400	1.600	70.277	4.406
old	female	100	straight	2.863	71.111	6.175
old	female	225	straight	1.988	68.366	4.500
old	female	500	straight	1.631	66.669	4.125
old	male	100	200	2.675	66.046	7.750
old	male	100	400	2.893	67.080	7.469
old	male	225	200	2.031	58.889	5.875
old	male	225	400	2.744	60.662	5.917
old	male	500	200	2.244	63.222	5.125
old	male	500	400	1.613	58.912	4.750
old	male	100	straight	3.207	62.613	5.812
old	male	225	straight	1.981	58.680	4.500
old	male	500	straight	1.763	55.469	3.700