Intersection Stopping Behavior as Influenced by Driver State: Implications for Intersection Decision Support Systems

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Abstract

It is estimated that as many as 2.7 million crashes occur each year at intersections or are intersection related; resulting in over 8500 fatalities each year. These statistics have prompted government and corporate sponsored research into collision countermeasure systems that can enhance safety at intersections. Researchers are investigating technologies to provide an infrastructure-based or infrastructure-cooperative Intersection Decision Support (IDS) systems. Such systems would use pre-specified algorithms to identify drivers that have a high likelihood of violating the traffic signal and thus increase the risk of a collision. The system would subsequently warn the violating driver to stop though an in-vehicle or infrastructure-mounted interface. An IDS algorithm must be designed to provide adequate time for the driver to perceive, react, and stop the vehicle, while simultaneously avoiding a high false alarm rate.

Prior to developing these algorithms, scientists must understand how drivers respond to traffic signals. Little research has focused on the influence of driver state on red-light running behavior or methods for distinguishing red light violators from non-violators. The objective of the present study was to define trends associated with intersection crossings under different driver states and to explore the point detection method of predicting red light running upstream of the intersection. This was accomplished through a test-track mixed-factor experiment with 28 participants. Each participant experienced a baseline (complete a full stop at the red light), distracted (misses signal phase change due to inattention), and willful (driver knowingly makes a late crossing in an attempt to 'beat the light') driver state conditions. To provide the opportunity for red-light running behavior from participants, the amber change interval began at five different distances from the intersection. These distances were located near and within the dilemma zone, a region in which drivers have a difficult time deciding whether to go or to stop. Data collected from in-vehicle sensors was statistically analyzed to determine significant effects between driver states, and to investigate point detection algorithms.

Dedication

This work is dedicated to my father Richard Doerzaph, whose life was needless stolen from us when a commercial truck struck his vehicle. To all those working to enhance the safety of our transportation system, you are not just saving people, your saving brothers, sisters, mothers, and fathers.

Death is not a period, but a comma in the story of life.
They are not dead who live in lives they leave behind,
In those whom they have blessed, they live a life again,
And shall live throughout the years.

Richard Doerzaph

Born: March 23, 1948
Died: March 17, 2002

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"To Infinity and Beyond"

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A.0 Review of Literature

J.1 BACKGROUND

Intersections, defined as locations where vehicles are required to cross paths to proceed along their intended route, are prime areas for the occurrence of vehicle crashes. Of the 6.3 million police reported crashes in 1998, 2.7 million (43 percent) occurred at intersections or were intersection related (NHTSA, 1999). Of these crashes, 8,595 were fatal (23.2 percent of all fatal crashes). In 1999 about 25 percent of all highway fatalities occurred at high-speed intersections (encompassing speed limits at or above 35mph) (Bonneson, 2001).

In 2001, the most recent crash database available, there were nearly 218,000 crashes as a result of red light violations (ITE, 2003). These produced 181,000 injuries, 880 fatalities, and over 14 billion dollars in estimated economic losses. There is also indication that the prevalence of red-light-running is on the rise along with aggressive driving behaviors such as tailgating, speeding, and failure to yield (ITE, 2003).

Driver error is frequently regarded as the primary casual factor for red light running – through either intentional or unintentional disregard of the traffic control device (TCD). Forty percent of red-light violators claimed that they did not see the TCD and another 12 percent apparently mistook the signal claiming they had a green indication (ITE, 2003). Other drivers “push the limits” of the TCD by attempting to “beat” the amber indication. Although these drivers do not typically intend to run the red light, they did intend to cross late in the cycle knowing that there was a potential that they would violate the signal (ITE, 2003). Finally, in some cases, the design of the infrastructure, including roadway geometry, TCD configurations, and phase timing can unfairly predispose drivers to commit a violation.

Extensive intersection research and development to enhance safety at intersections has been completed over the last few decades. Several devised methods demonstrate a reduction in intersection conflicts. A few of these methods have seen wide-scale implementation, although intersection crashes still continue to represent a substantial portion of the overall crash picture.

Red light photo enforcement, although effective (Insurance Institute for Highway Safety, 2001), has been a source of controversy since its introduction. Ongoing debate is occurring at local and federal levels regarding red light photo enforcement and its implications to society and human rights. Thus, many regions have opted not to use red light photo enforcement even though the systems have shown significant reduction in intersection collisions (as much as 32%) at the installation site as well as across the cities that employ them (Insurance Institute for Highway Safety, 2001)..

Green-extension systems operate by delaying phase changes until approaching traffic is either close to the intersection such that the decision to go is clear, or far enough from the intersection such that the decision to stop is clear. This decreases the chance that an approaching driver may be caught in a region were it is difficult to decide whether to stop or go, known as the dilemma zone. When a standard intersection would switch phase, the green-extension system begins monitoring approaching traffic instead. The system waits until the dilemma zone is clear and then switches to the amber phase. However, the system will time-out and change phase regardless of vehicle position, reducing its safety advantage. In addition, this system is not capable of distinguishing high risk approaches (e.g. a distracted driver) nor does it offer any stimulus beyond the traffic signal to capture the distracted driver's attention.

Active advanced warning signs have also been implemented in many high-speed signalized intersections. These signs are typically variations of passive-signal-ahead signs that include a set of lights that flash when a signal is nearing a phase change. However, before and after studies of active advanced warning signs have not shown a reduction in intersection conflicts and in some instances encouraged higher traffic speeds (Pant, Xie, & Huang, 1996).

Of course, the standard method to prevent intersection conflicts is the application of an amber change interval. This interval consists of a steady amber signal which warns of an imminent change in the right-of-way. The amber interval is often followed by an all-red phase during which traffic approaching the intersection is required to stop and conflicting traffic is delayed from entering the intersection (Retting, Chapline, & Williams, 2002). It may seem that proper signal phase timing, particularly during the amber change interval, could eliminate the intersection crash problem; however, no universal practice for setting phase timing exits. This has lead to discrepancies in the time allowed to cross similar intersections.

Research has shown a reduction in the number of intersection conflicts when signals are re-timed to conform to the Institute of Transportation Engineers recommended amber change and red clearance intervals (Retting et al., 2002). However, even properly timed signals do not decrease the crash risk for distracted drivers or reduce the motivation for willful drivers. Thus, changes in phase timing, by themselves, do not address some of the main causes for intersection conflicts (Hendricks, Fell, & Freedman, 1999) .

Intersection decision support (IDS) systems are the topic of several research efforts, as they afford means for mitigating intersection collisions. An IDS system either provides additional information to a driver as they approach an intersection, or modifies the behavior of the traffic control device (TCD) to accommodate the violator. Information provided to the driver, either through an infrastructure-based or an in-vehicle system, may act as a warning to mitigate a collision. A countermeasure is deployed, when a violation is likely to occur, in an attempt to inform drivers that action may be necessary to avoid a collision. Alternatively, the TCD can modify the standard controller program to accommodate the violation (e.g. by extending the red clearance interval) with the goal of enhancing safety. For example, if a vehicle is determined to have a high probability of violating the signal, the amber change interval can be lengthened, or the signal can go to an all-red phase. Either of these methods would stop other vehicles from entering the intersection.

Three types of IDS systems are currently under simultaneous development (Ferlis, 2001). First, the infrastructure-only systems use roadside sensors, processors and warning devices for mitigation. Second, vehicle-only systems use information gained by vehicle-mounted sensor and data logging equipment to predict and warn the driver of impending intersection collisions. The third system integrates the previous two into a cooperative IDS system. In this design the vehicle may communicate information such as position, velocity and brake engagement while the intersection sends back the location of other vehicles and phase and timing of the traffic signal. The cooperative system could decide which vehicle(s) to warn using a combination of roadside and in-vehicle interfaces. The research described in this report has been scoped such that infrastructure-only and cooperative systems are the main focus. However, results from this research may have utility for vehicle-only systems as well.

A functional IDS system must have the ability to distinguish between the behavior of a driver adhering to traffic laws (plans to stop) and one who may violate them (does not plan to stop). For infrastructure systems, this determination must be made using devices mounted on or near the roadway (e.g., radar and loop detectors) without direct knowledge of the driver's actions. The objective of this research is to determine the maximum distance at which violators can be distinguished from non-violators using variables that can be measured by infrastructure mounted and in-vehicle equipment.

The remainder of the literature review section is a collection of information that is necessary for the design of this study. Each subsection is devoted to infrastructure or driver related factors that contribute to intersection crash risk. The Methods section will then use the literature review as justification for the factors and variables used in the experimental design.

J.2 AFFECT OF DRIVER CHARACTERISTICS ON INTERSECTION CRASH RISK

J.2.1 Age

Driver age has shown mixed results across studies trying to determine driver's performance at intersections. Overall research suggests that intersection crash risk is high for both younger and older drivers when compared to middle age drivers (Chovan, Tijerina, Pierowicz, & Hendricks, 1994; Tijerina, Chovan, Pierowicz, & Hendricks, 1994; Wang & Knipling, 1994). The increased risk for younger drivers may be due to an increased probability for younger drivers attempting a crossing (Sivak, Soler, & Trankle, 1989). For older drivers the increased risk may be a result of a higher probability of violating a TCD when they are required to yield to opposing traffic (Garber & Srinivasan, 1991; Wang & Knipling, 1994).

Factors such as inexperience for younger drivers, or insufficient compensation for degradation in psychomotor functions for older drivers, could be possible explanations for the increased intersection crash rates of these age groups. Inexperienced drivers are not as diligent at predicting future traffic and TCD patterns and often focus their attention on less critical information. On the other hand, the considerable decline within older age groups in some sensory capabilities (e.g., reduced visual capabilities) and an associated increase in time necessary to process sensory inputs and perform accordingly have been established in the past (Preusser, Williams, Ferguson, Ulmer, & Weinstein, 1998). Factors common in driving tasks (specifically at intersections), such as visual clutter and the requirement for divided attention, may exacerbate these experience and sensory limitations for younger and older drivers respectively.

Some driver capabilities, however, appear to remain unchanged in older drivers. Studies using simple evasive braking tasks, outside of intersection environments, determined that perception-reaction time did not vary between younger (20-40 years) and older (70+ years) drivers (Green, 2000; Lerner, 1993). These results indicate that drivers should be physically capable of reacting to an intersection TCD within relatively the same time regardless of age. Thus, the differences in crash rates between age groups noted earlier are presumably due to problems in either the perception of the TCD, or the decision process in which the driver determines the appropriate action.

J.2.2 Gender

Research completed in the area of gender as it relates to intersection collision risk has shown mixed results. Wang & Knipling (1994) demonstrated that straight-crossing-path collision *rates* (per 100 million vehicle miles traveled) are higher for females than males, but *likelihoods* (involvements per 1000 registered drivers) are higher for males than for females. At signalized intersections for drivers 24 years old and younger, involvement rate is only slightly higher for males than for females. However, for drivers 25 years and older, involvement rates for females are higher than for males. The likelihood rates are higher for males than for females for all age groups. However, an epidemiological study indicates gender is not generally indicative of the involvement in most intersection crashes (Tijerina et al., 1994).

Males are more likely to exhibit less cautious behaviors than females when crossing intersections (Sivak et al., 1989). Caird & Hancock (1994) investigated driver perceptions of opposing vehicle arrival times at intersections and the effect on the timing of their own left-turn task. Men were generally more accurate in their estimations, and women tended to underestimate arrival time more often than men. The authors hypothesize that these results reflect the fact that men are more likely to turn into gaps between vehicles and to proceed through amber lights. Studies by Hankey and colleagues, based on driving simulator data, found that male drivers reacted in an appropriate manner (i.e., did not over-steer) to an unexpected intersection incursion more often than female drivers (one third vs. one fifth of the respective male and female samples reacted appropriately) (Hankey, 1996; Hankey, McGehee, Dingus, Mazzae, & Garrott, 1996). However, these researchers reported no significant difference in initial reaction time behavior due to gender.

J.2.3 Driver Awareness and Judgment

Driver behavioral state is a known risk factor in intersection related collisions. An investigation of 723 crashes showed that 99 percent of the time driver behavior error contributed to, or caused the collision (Hendricks et al., 1999). A commonly reported error in these crashes was driver inattention. Activities that led to inattention included focusing on internal thought processes (20%), looking for street address (10%), hanging up cell phone (10%), and talking with a passenger (10%). These drivers might benefit from an IDS system that could successfully draw their attention to the presence of an intersection and the status of the signal.

Causal factors that imply a deliberate disobedience of the traffic signal have also been defined (Pierowicz, Jocoy, Lloyd, Bittner, & Pirson, 2000). The decision to run or attempt to beat a traffic signal is partially due to a belief that a collision can be avoided. Presumably, the probability of an intentional attempt for a late crossing could be lessened by an IDS system if an indication of the likelihood of a resulting upcoming crash was provided.

Driver-related factors are linked to as much as 93 percent of all crashes, with decision errors accounting for the largest percentage (47 percent) of these factors (Alicandri, 2001). Decision errors are made primarily with respect to maneuvers, for example, overestimation of the time remaining for an amber change interval. In a study of driver error at intersections, it was found that 3.3% of all drivers entering the intersection made some sort of driver error (Wierwille et al., 2001; Wierwille, Kieliszewski, Hanowski, Keisler, & Olsen, 2000). The probability of proceeding on red (running the red light) was 41 out of 10,000 vehicles for left turns, right turns, and going forward combined. Most of these red light running errors occurred during left turns (31 out of 10,000), followed by going forward (8 out of 10,000) and right turns (2 out of 10,000).

An intersection conflict is essentially a failure of the traffic control system. Failure of the system is usually the result of a disconnect between the infrastructure, vehicle, and driver. To better understand how the three components interact, it is appropriate to examine the intersection approach.

J.3 ANATOMY OF THE INTERSECTION APPROACH

J.3.1 The Dilemma and Option Zones

At high speed intersections there exists a region near the stopbar at which a driver will not only have insufficient time to stop, but will be unable to cross through the intersection legally if they decide to go (Huang, 1993). This region is called the dilemma zone. As its name implies, drivers who are in this region during the onset of the amber phase will have a difficult time deciding whether to go, or to stop. This occurs because the driver may "not be able to stop in advance of the stop line at an acceptable deceleration rate or be able to clear the intersection during the yellow interval" (Huang, 1993).

A schematic representation of a dilemma zone is depicted in Figure 1. X_s is the minimum distance from the stop line that would ensure the driver sufficient time to recognize the amber signal, decide on the appropriate action, execute that action, and stop the vehicle. Although a vehicle could theoretically be stopped at distances less than X_s, it would require a driver to brake at a rate that is outside their comfort zone. Similarly X_c is the maximum distance from the stopbar at which the vehicle can pass through the intersection prior to the red phase irregardless of acceleration. The dilemma zone occurs when X_c is smaller than X_s (ITE, 1991). The dilemma zone is particularly dangerous because a decision to stop increases the risk of a rear end collision, and the decision to go increases the risk of a adjacent vehicle collision (Huang, 1993).

On the other hand, if X_c is larger than X_s, the dilemma zone is replaced by an option zone. When drivers are inside the option zone they may either make a decision to stop or to go and do so without violating the signal (ITE, 1991). Traffic engineers attempt to avoid large option zones as they create an increased probably for rear-end collisions. This occurs when a lead vehicle decides to stop, while the following vehicle decides to go. The third possibility occurs when X_c equals X_s in which case neither the option or dilemma zone exist. Variability in driver's allowable rate of acceleration and reaction times prohibit the realization of this situation for large groups of drivers.

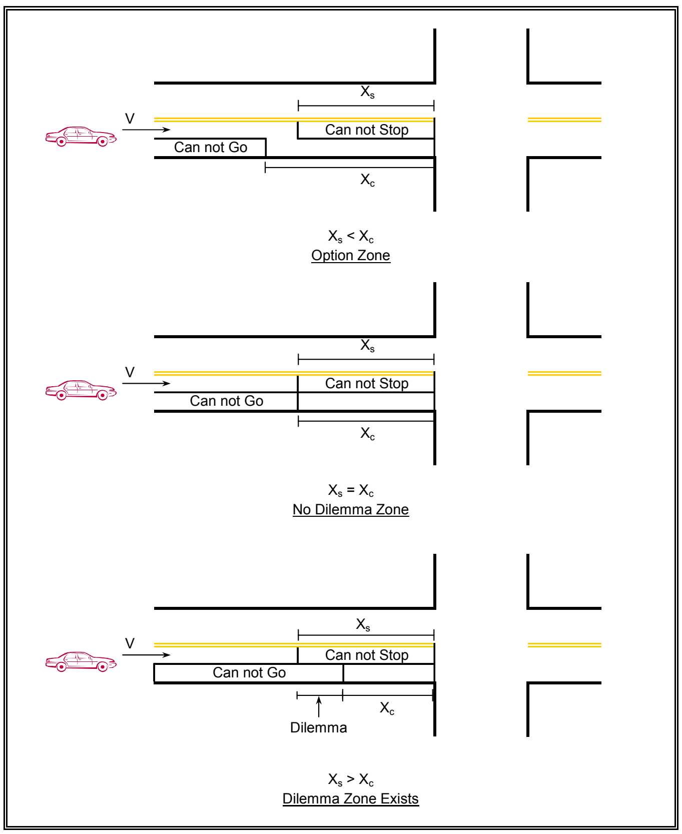

Figure 1: Illustration of the dilemma and option zones

Combining equations of motion from dynamics with intersection specific characteristics, the length of the dilemma/option zones can be quantitatively estimated (Huang, 1993; ITE, 1991). The W+L term in equation 2 is frequently ignored for situations in which drivers need only enter the intersection prior to red presentation rather than cross through the intersection.

$$X_s = Vt_{prt} + \frac{V^2}{2d} \qquad \text{(Equation 1)}$$

$$X_c = Vt_{prt} + 0.5(16 - 0.213V)(t - t_{prt})^2 + V(t - t_{prt}) - (W + L) \qquad \text{(Equation 2)}$$

Where:

t_{prt} = perception-reaction time
t = amber interval
W = intersection width
L = vehicle length
V = vehicular speed

Based on the equations 1 and 2, Huang (1993) provides the following generalizations:

1. For a given length of the amber interval, vehicle speed is directly proportional to the length of the dilemma zone.
2. For a given speed and amber interval, deceleration rate is inversely proportional to the size of the dilemma zone.
3. For a given vehicle speed the dilemma zone is inversely proportional to the length of the amber change interval.

In theory, a sufficiently long amber phase could completely abolish the dilemma zone; however, factors not considered in the mathematics undermine the effectiveness of this solution. For instance, Gipps (1981) concluded that long amber intervals may cause some drivers to "take advantage of the long amber by treating it as part of the green".

Other researchers have defined the dilemma zone empirically rather than analytically (ITE, 1991). The dilemma zone is thus redefined as the region of intersection approach between where most drivers will stop at the amber and where most will go. In general, the term "most" is defined as the 90th percentile. Dilemma zones have been recorded using this approach and are summarized as a function of speed (Table 1). However, this generalized data does not consider all the intersection characteristics that have an effect on the size of the dilemma zone. For instance, Equations 1 and 2 consider factors such as the width of the intersection, the length of the amber interval, and the length of the vehicle.

Table 1: Empirical Dilemma Zone

Approach Speed		**Distance from intersection for probabilities of stopping**			
		Feet		**Meters**	
Mph	***Kph***	***90%***	***10%***	***90%***	***10%***
35	56	254	102	77	31
40	64	284	122	87	37
45	72	327	152	100	46
50	80	353	172	108	52
55	88	386	234	118	71

J.3.2 Signal Phase Timing

The amber interval has been previously analyzed with respect to its influence on the dilemma zone and considering driver's behavioral response (i.e. treating the amber as part of the green). The Manual on Uniform Traffic Control Devices (MUTCD) provides a guideline for amber change intervals of approximately three to six seconds (ATSSA/ITE/AASHTO, 2001). According to the Transportation and Traffic Engineering Handbook an amber interval of three to five seconds is sufficient for most high speed intersections. The Institute of Transportation Engineers proposes an equation for determining the length of the amber interval as well as the all-red clearance interval (ITE, 1985).

$$Y = \frac{t + V}{2a + 2Gg} \qquad \text{(Equation 3)}$$

$$R = \frac{W + L}{V} \qquad \text{(Equation 4)}$$

Where:

Y = Length of amber light
R = Length of red light
t = Driver perception reaction time
a = Deceleration rate, recommended as 10 $^{ft}/_{sec2}$
G = Acceleration due to gravity, 32 $^{ft}/_{sec2}$
g = Grade of approach, in percent divided by 100
W = Width of intersection
L = Length of vehicle, recommended as 20 ft
V = Vehicular speed

The Manual of Traffic Signal Design (MTSD) uses a similar combination of equations to develop their recommended amber and clearance intervals (Table 2). The clearance interval is defined as the amber plus all-red clearance (Kell & Fullerton, 1991).

Table 2: MTSD Recommended Change Intervals

Approach Speed (mph)	Amber Interval (sec)	Total Clearance interval (sec) for crossing roadway widths (ft)				
		30	50	70	90	110
20	3.0	4.2	4.9	5.5	6.2	6.9
40	3.9	4.8	5.1	5.5	5.8	6.1
45	4.5	5.1	5.4	5.7	3.0	6.3
50	4.7	5.3	5.6	5.9	6.2	6.4
55	5.0	5.7	5.9	6.2	6.4	6.7

J.3.3 The Human Component

As a vehicle approaches a red-light intersection, the driver must complete a series of actions to appropriately stop the vehicle. These actions include detecting the stimulus, recognizing it, deciding on an action, and initiating and completing that action (Fambro, Koppa, Picha, & Fitzpatrick, 1998). However, it is difficult to directly measure detection, recognition, and decision stages. Rather, most researchers looking at stopping behavior rely on more functional surrogate measures. These measures encompass a breakdown of driver actions measured through reaction times (RTs). Across the literature there are several schemes for dividing up the reaction components, often with different names for the same component (Green, 2000; Hankey, 1996; Lerner, 1993; Sohn & Stepleman, 1998). For the sake of clarity, the stopping variables presented in the literature are renamed using the naming convention provided below. Many of the variables overlap such that portions of the measurement are redundant. The relationship between variables is best depicted in the temporal domain (Figure 2). RT variables can also be described in the spatial domain (Figure 3).

- **TAR** = Time to accelerator release: time from initial stimulus appearance to beginning of accelerator release.
- **TS** = Time to steering: Time from initial stimulus appearance to initiation of steering input.
- **TSS** = Time to severe steering: Time from initial stimulus appearance and initiation of a severe steering input. While no set definition is available, lateral acceleration values over 0.2g caused by steering can be considered moderate.
- **TB** = Time to brake
- **TFB** = Time to full brake: time from the stimulus until the brake pedal was fully depressed
- **TSAB** = Transition time from accelerator to brake: time from the beginning of accelerator release to the point where the foot was positioned over the brake
- **TSAFB** = Transition time from accelerator to full brake: time from the beginning of accelerator release until the foot fully depresses the brake
- **TSBFB** = Transition time from brake to full brake: time from initiation of braking to full braking
- **TIDA** = Time to initial driver action: time between stimulus and first subject action performed
- **TGDA =** Time from glance to driver action: time between the drivers first glance at the stimulus and the first action performed.
- **TFS** = Time to full stop: Time to come to a full stop measured from initial stimulus appearance

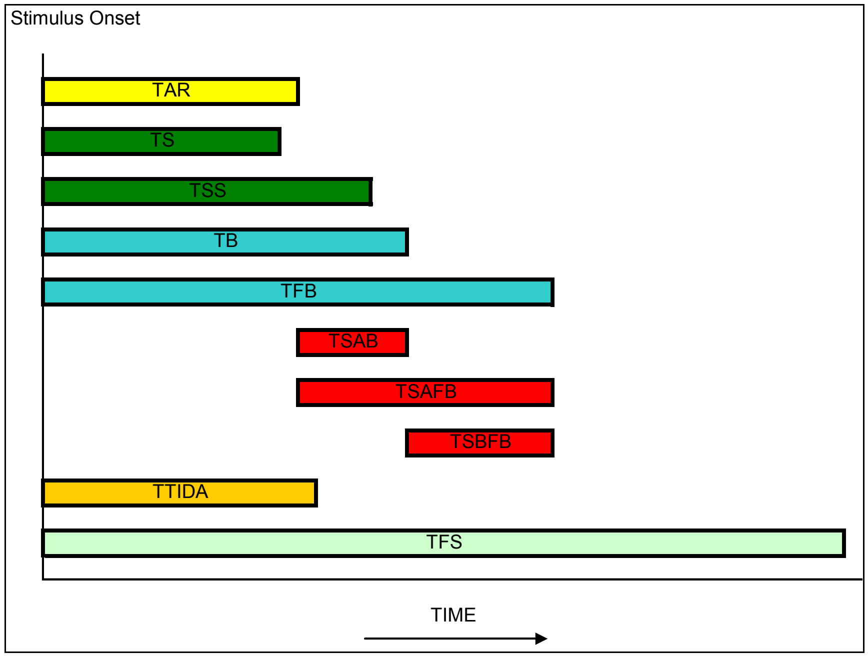

Figure 2: Temporal representation of RT variables

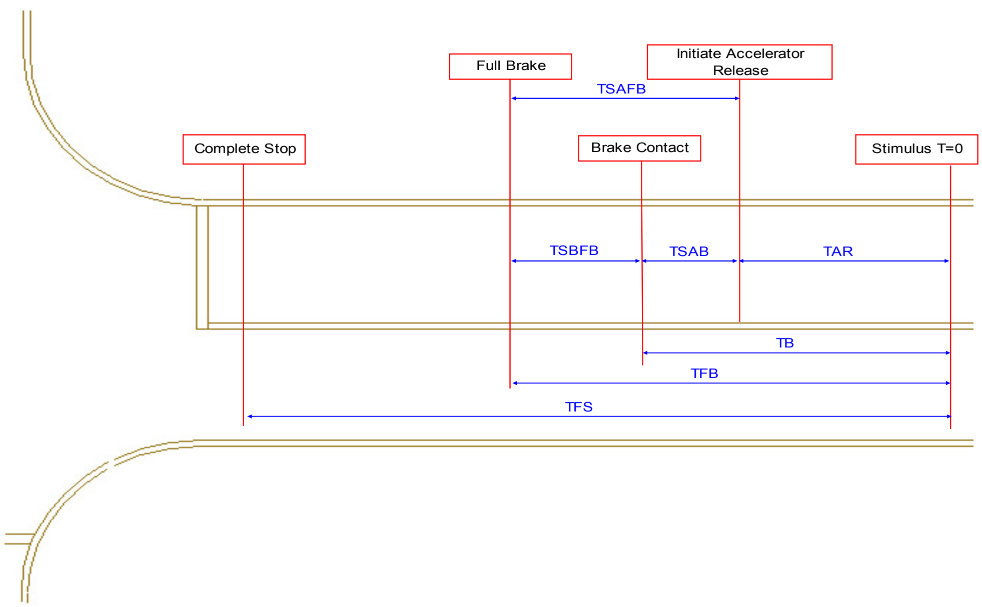

Figure 3: Spatial representation of RT variables

Time-to-intersection (TTI) can also be used as a surrogate measure of driver behavior in intersection crossings. This measure is similar to the frequently applied time-to-collision (TTC) variable; which defines the time that will elapse prior to a collision assuming no change in velocity. Similarly, TTI defines the time that will elapse prior to vehicle entrance into the intersection (measured from the stop line) if no changes in velocity occur (Hankey, 1996). Indeed, for the scenario under consideration, the vehicle would optimally stop prior to entering the intersection rather than just before the crash. Once the vehicle enters the intersection, there is the increased potential for a secondary collision. Unfortunately, few studies have measured TTI rather than TTC.

General models for driver behavior at signalized intersections are also available in the literature. For example, (Tijerina et al., 1994) summarize the decisions made by the ideal driver when approaching a signalized intersection:

1. Detect the presence of an intersection and decelerate accordingly
2. Detect and properly process the signal status
3. If the light changes from green to amber, determine if it is safe to proceed through the intersection
4. Anticipate sudden deceleration of vehicle(s) that are being followed
5. Detect the presence of cross traffic and determine whether collisions are likely, based upon distance, velocity, and direction
6. Recognize and avoid visual obstacles

If a driver fails to complete one the first three decisions, or makes an error, the probability of violating the TCD increases. For example, if a driver fails to perceive an upcoming intersection or properly estimate the signal duration or status, they are likely to “run the red”. Indeed, the intention of the present study is to elicit errors in each of the first three steps by modifying the driver’s state of mind. For instance, a distracted driver may not detect the intersection, and a hurried (or otherwise motivated) driver may over estimate the amber change interval.

J.3.4 Differentiating Violators from non-Violators

Little research has been completed with regard to the upstream prediction of a violator. Although camera-based red light enforcement systems delineate the violator, they are largely a reactive system. The determination is not made until after, or shortly before, the violation begins. Effective IDS systems must identify a violator sufficiently upstream such that the presented countermeasure allows the driver adequate distance to perceive, react, and stop the vehicle prior to crossing the stopbar.

In Huang’s (1993) dissertation, a computer-based intersection simulation program was developed and evaluated against actual traffic. The graph displayed below (Figure 4) depicts the range vs. rate distribution for vehicles approaching three intersections and suggests a method to differentiate violators from compliant drivers. Note the top three plots (each for a different set of conditions) represent drivers who traveled through the intersection during the amber change interval. On the other hand, the corresponding lower three plots represent those drivers who opted to stop at the intersection during the amber change interval. These two groups of plots become intermixed with increasing distance from the intersection. However, as the intersection is approached they diverge into two distinguishable groupings. It is thus suggested that violator and non-violator clusters can be separated using range and rate information. Range and rate are readily measured by infrastructure mounted equipment and may be a viable method for violator identification.

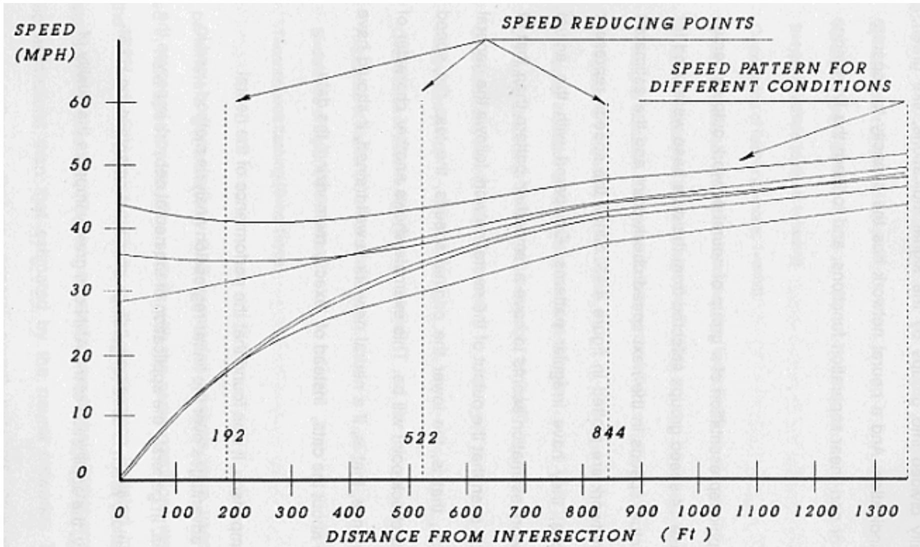

Figure 4: Range vs Rate for vehicles approaching intersection *(adapted from Huang, 1993).*

In the context of IDS, the point of divergence is of particular interest. The critical point, as it will now be referred to, represents the physical location at which a potential violator can be identified and warned. The IDS system may then provide that warning such that a driver who is in a position to violate the signal may alter their behavior to safely avoid a conflict.

There are essentially two methods for developing warning algorithms. Point detection samples vehicle information and discrete intervals, while continuous detection monitors vehicle information throughout the intersection approach. A point detection system would be able to use relatively simple and inexpensive in-pavement loop detectors for sensing vehicle position and speed. Continuous detection requires expensive and typically complicated sensing technology such as radar, lidar, and machine vision. For this reason there has been a significant interest in point detection among IDS designers. Although results of this analysis are applicable to all types of warning algorithms, point detection will be the focus.

J.3.5 Aggressive Driving and Red Light Violations

It is known that aggressive driving increases the likelihood for a driver to violate a TCD (ITE, 2003). The term, "aggressive" driving is somewhat ambiguous across the literature making a consistent definition difficult to identify. Dula and Geller (2002) instead propose three definitions of dangerous driving: 1) Intentional acts of bodily and/or psychological aggression toward other drivers, passengers, and/or pedestrians (acts may be physical, gestural, and/or verbal in nature); 2) Negative emotions felt while driving (including frustration, anger, and range, but which might also include sadness, frustration, dejection, jealously, etc); and 3) Risk-taking behaviors (dangerous behaviors performed without intent to arm self or others). Research has shown that drivers who exhibit these traits are more likely to be involved in a traffic conflict. Questionnaires that quantify these parameters have been shown to correlate well with adverse driving measures such as accidents and convictions (Dula & Ballard, 2003; Matthews, 1998, 2002; Matthews, Desmond, Joyner, Carcary, & Gilliland, 1996). However, it does not appear these questionnaires have been applied to the intersection scenario. In particular it seems that drivers with higher risk-taking personality will be more likely to make a late crossing and thus have an increased potential for violation.

J.4 RESEARCH QUESTIONS

The review of the literature suggests that, while substantial research has been performed to understand the causes for the intersection crash problem, more work is needed to develop methods to distinguish between violators and non-violators of an intersection TCD. In particular, there appears to be little or no research on methods for predicting an intersection violation significantly upstream of the TCD to allow for the deployment of countermeasures that prevent the violation. In addition, little appears to be known about how an unaware violator's actions are different from those of an aware violator. It was the purpose of this research to address the three following questions.

RQ 1: How does driver state affect intersection performance?

Driver state is expected to alter the way in which drivers approach intersections. In some behavior states drivers may react later, or perhaps brake harder. This question looks at what influences driver state has on stopping performance measures.

RQ 2: Where should the critical point of divergence be located?

Of vital concern to designers of IDS systems is discriminating violators from compliant drivers. This research question addressed when violators can be distinguished using single point detection information that is measurable from infrastructure mounted equipment.

RQ 3: Can potential violators be predicted using the questioner-based measures of aggressiveness

The Dula Dangerous Driving Index and the Driver Stress Inventory have been shown to predict drivers that tend to drive in a risky or dangerous manner. This question determined if drivers who score high on the index are more likely to violate the TCD.

With these considerations, a research experiment was conducted to assess driver approach profiles, taking into account whether the driver was in a simulated "distracted" condition, motivated to willfully violate, or in a baseline driving condition. Details on the methods used to conduct this experiment and the results obtained are presented in the following sections.

B.0 Methods

J.1 General Approach

The research questions posted in the previous section were studied with an on-road, mixed subject full-factorial design testing drivers from high risk age groups that approached a signalized intersection under various driver states. The experimental design manipulated driver state throughout a series of intersection stops. Furthermore, red-light violations were elicited by trapping drivers in the dilemma zone where incorrect decisions were likely. Performance measures such as reaction time and range-rate provided the data needed to answer each research question.

J.2 Experimental Design

J.2.1 Experimental Design Matrix

A 2 (Gender) x 2 (Age) x 3 (Driver State) x 5 (Phase Change Distance) complete factorial design was used to address the research questions. The independent variables and participants were organized as shown in the matrix below (Table 3). Driver state and Time-To-Intersection–red-phase (TTIrp) represent the within subject factors while age group and gender represented the between subject factors for this mixed design.

Table 3: Experimental Design Matrix.

		Age Group	
Diver State	**TTIrp**	**18-25**	**55+**
Baseline	1	S_{1-14}	S_{15-28}
	2	S_{1-14}	S_{15-28}
	3	S_{1-14}	S_{15-28}
	4	S_{1-14}	S_{15-28}
	5	S_{1-14}	S_{15-28}
Distracted	1	S_{1-14}	S_{15-28}
	2	S_{1-14}	S_{15-28}
	3	S_{1-14}	S_{15-28}
	4	S_{1-14}	S_{15-28}
	5	S_{1-14}	S_{15-28}
Willful	1	S_{1-14}	S_{15-28}
	2	S_{1-14}	S_{15-28}
	3	S_{1-14}	S_{15-28}
	4	S_{1-14}	S_{15-28}
	5	S_{1-14}	S_{15-28}

J.2.2 Independent Variables

J.2.2.1 Age group (between)

Two age groups were used to represent the driving population. The drivers were classified as Younger (18-25) and Older (55+). These groups of drivers were selected because they exhibit the highest risk for intersection collisions. Participants under 18 were eliminated from the study due to insurance, liability, and consent issues.

J.2.2.2 Gender (between)

Although there is little evidence for a gender effect in stopping behavior, there have been some mixed results in past studies. Thus, for this research gender was evenly distributed across each condition.

J.2.2.3 TTIrp – Time-to-intersection for red phase (within)

As discussed previously, TTI defines the predicted time interval in which a vehicle will cross the stopbar assuming no change in velocity. The TTIrp represents a TTI at which the amber change interval is replaced with a red. For a given speed, this variable is analogous to vehicle distance from the intersection when the red light is first presented. The red, rather than amber, phase is used as a reference point in calculating TTIrp so that the measure is not dependent on the duration of the amber change interval. This allows direct comparison between trials in which the amber change interval is altered. For this experiment TTIrp had five levels distributed through the intersection approach and concentrated around dilemma/option zone region.

The intersection at VTTI was designed to meet the geometric and timing standards set by ASHTO and ITE recommendations. The result is an intersection without a dilemma zone and a negligible option zone (2.3ft) at a distance of 183 feet (Equations 1 and 2). Thus, for this intersection it is relatively simple for an aware and law abiding driver to decide whether it is appropriate to go or stop; regardless of when the signal changes phase. However, for a willful or distracted driver the distance at which the signal changes affect ability to make a correct decision in a timely fashion. For the distracted driver the difficulty stems from a large dilemma zone created by an increase of the reaction time components from Equations 1 and 2. If the driver is inside this dilemma zone when the signal changes, it is difficult to discern whether it is more appropriate to stop or go. The willful driver may also find it more difficult to decide on the appropriate action because they are trying to use the entire amber phase; requiring accurate timing judgments. These judgments are particularly important when the signal will switch to a red phase when the "go" vehicle is close to the stopbar.

To determine TTIrp that would elicit the desired behavior, merging of available data was necessary. A normal distribution was fit to the empirical data presented by ITE (Table 1) using the 10 and 90 percentile values as initial boundaries (i.e. percentage of drivers stop at a specified distance). Pilot testing demonstrated that simply selecting the ITE distribution resulted in distances that were too conservative. At the furthest TTIrp it was too apparent that a stop was necessary under all conditions. This was not a surprise given that the ITE values are a conservative generalization that is dependent on factors such as intersection design and the locality of measured installations. To better configure the TTIrp values for the Smartroad intersection, the distributions were adjusted.

These adjustments were judiciously made based on pilot data, kinematics analysis, and information from the Collision Avoidance Metrics Partnership (CAMP). CAMP developed useful metrics for forward collision avoidance systems (Kiefer, 1999), which were combined with kinematic equations to roughly define intersection approach behavior at larger TTIrp values and interpolated to fit the ITE curves at shorter TTIrp values. Additional details of the methods used to obtain the final TTIrp values are omitted because they are based primarily on engineering judgment. The goal for this process was to generate a TTIrp distribution that would place drivers from a region in which most would decide to go (10^{th} percentile) to a region where most drivers would decide to stop (90^{th} percentile) (Table 4). A second set of pilot participants were used to verify the appropriateness of the new TTIrp settings. Results demonstrated that the stop decisions were better approximated by the new distribution than the original ITE distribution.

Table 4: TTIrp Values - negative values indicate that the light will change to red after crossing the stopbar. The resultant phase change distance is also provided.

Index	TTIrp (seconds)	Intersection Distance @35mph (ft)	Expected stopping drivers
1	-1.62	100	10%
2	-1.09	127	30%
3	-0.51	157	50%
4	0.04	185	70%
5	0.87	228	90%

J.2.2.4 Driver State (within)

To simulate a variety of driver states, participant behavior was modified through the experimental design. The driver states were designed to represent normal drivers (Baseline) and drivers with a high violation propensity (Willful and Distracted). The three levels of driver state are briefly described below with further detailed discussions in the experimental procedure section.

- *Baseline*: The baseline state represented an aware and undistracted driver's response to the traffic control device. Most drivers in this state react appropriately, either stopping the vehicle prior to entering the intersection, or safely passing through the intersection during the amber change interval. Intersection violations are rare within this group of drivers when the intersection timing is set appropriately.

- *Distracted*: The distracted driver is one which either does not notice the green to amber phase change or over-estimates the amber phase duration. Reliably distracting drivers is a difficult task to control. For instance, if an in-vehicle task is used for distraction, a temporary glance away from the roadway is required. This glance time is the duration during which the participant is distracted. However, some people may be willing to use long glances, while others will only use very short glances. It is also extremely difficult to synchronize the participants glance with the actions of the TCD such that the phase change occurs during the distraction and at the desired location. Thus, to maintain control of the extent and timing of distraction it was decided to use a simulation method. To simulate distraction during a phase change, the amber interval was shortened. The subtracted amber presentation time is equivalent to the time during which a distracted driver would not perceive/recognize the signal. For instance, at 35mph the amber change interval should be 3.6sec (Equation 3). To simulate a 1.6 second distraction, the amber change interval was shortened to two seconds. The end effect simulated a driver who is unaware of the signal at the beginning of the phase change and subsequently shifts their attention to the TCD part way through the amber light.

The extent to which participants are distracted was held constant across all distracted trials. The objective of the simulated distraction is to approximate the actual time in which a driver may not be attending to the traffic signal or the extent to which the TCD is misjudged. Research in the area of distraction is usually derived from eye glance reduction because internal (mental) distraction is difficult to measure. Thus, the time in which a driver is not looking toward the front of the vehicle is frequently used to quantify distraction. During a comprehensive naturalistic study researchers used eye-glance reduction to determine distraction for many tasks (Hanowski, Olson, A., & Dingus, 2001). Mean distraction time ranged from 0.5 seconds (looking out left side) to 7.5 seconds (reading a paper). The mean distraction across all of the tasks is 1.45s. The current study is attempting to simulate a long, but realistic distraction; thus, a 1.6 second distraction was used. After the study, participants were asked if there was anything unusual about the TCD. Of the 28 participants, approximately half noticed that the amber light had shortened. However, most thought it had only occurred once, whereas it had really occurred in five of the 15 experimental trials that included a phase change during the intersection approach.

- *Willful*: This state represents the driver who purposefully attempts to "beat the light." This driving group tends to have a high motivation for crossing through the intersection and believes the risk associated with a late crossing is acceptable. This behavior was coerced by adjusting the driver's perceived cost-benefit ratio regarding intersection crossing. This portion of the study was perceived as a series of decision-making trials, where drivers are rewarded and penalized monetarily based on the "success" of their intersection crossing behavior.

  During a pilot study, several different attempts were made to influence participants to make willful crossings. They were told to try to imagine they were in a big hurry and that they might have a tendency to try to make later intersection crossings. Drivers were provided with verbal praise when successful attempts were made. However, results showed that drivers quickly became complacent and did not exhibit high-motivation crossings after a few runs. Thus, a monetary incentive system was enacted in which drivers were paid for successful intersection crossings. A storage bin in the center consul became a bank in which the experimenter physically deposited bonus cash after each run. Thus the incentive visibility was high and gave participants the necessary motivation.

Thus, willful behavior was coerced by providing drivers with a $5 bonus for every successful intersection crossing. A successful crossing occurred if any part of the vehicle crossed the stopbar prior to the red phase. However, to be realistic there must also be penalty for violations. Without a penalty drivers did not have a motivation to stop and could simply run though the red signal. This penalty was set at a lower rate such that driver's behavior would be skewed towards beating the light. The penalty was therefore set at $2 per violation. For drivers that opted to stop on the amber phase, or go on a green phase, no bonus or penalty was applied.

At the start of the willful block drivers received a $10 bonus in addition to the standard $10per hour rate. The intention of this bonus was to provide an extra cushion for participants to lose money and to induce an attitude that they could gamble with the "extra cash." The received bonuses ranged from $5 to $25 with most participants receiving $15.

J.2.3 Controlled Variables

J.2.3.1 Speed (within)

The data resulting from this study are intended for use on roadways across the United States. As such it was appropriate to select a common speed limit found on thoroughfares having intersections. To scope the project, only one speed was used, although future research will expand to include other speeds. A 35mph speed was selected because it is a common limit for high speed intersections and provides the safest speed during this first set of trials. Intersections having lower speed limits tend to result in less severe accidents and are not likely candidates for an IDS system.

J.2.4 Presentation Order

The experiment was divided into two separate blocks. These two blocks were necessary since information provided to the participant during the willful condition could effect their behavior in the other states. The following tables (Table 5 and Table 6) display the 21 treatment conditions that each participant encountered. Note, that for each state in the first block there were five TTIrp values and two "green" treatments. When the TTIrp was green, the participant was not presented with a changing signal as they approached the intersection; rather the participant drove through a green indication (the signal did change a few seconds after crossing was viewable in the rear view mirror). The green phases were placed into the design to enhance realism and to reduce the driver's anticipation of a signal status change. Within each block, participants received a balanced Latin Square presentation order of the conditions (Table 7 and Table 8) to reduce any bias in the results due to practice effects of the study.

Table 5: Block 1 - Treatment Conditions

Diver State	TTIrp	Treatment Condition
Baseline	1	A_1
	2	A_2
	3	A_3
	4	A_4
	5	A_5
	Green	A_6
	Green	A_7
Distracted	1	A_8
	2	A_9
	3	A_{10}
	4	A_{11}
	5	A_{12}
	Green	A_{13}
	Green	A_{14}

Table 6: Block 2 - Treatment Conditions

Willful	1	A_{15}
	2	A_{16}
	3	A_{17}
	4	A_{18}
	5	A_{19}
	Green	A_{20}
	Green	A_{21}

Table 7: Block 1 – Presentation order

Presentation Order	Subject													
	S_1	S_2	S_3	S_4	S_5	S_6	S_7	S_8	S_9	S_{10}	S_{11}	S_{12}	S_{13}	S_{14}
1	A_1	A_2	A_3	A_4	A_5	A_6	A_7	A_8	A_9	A_{10}	A_{11}	A_{12}	A_{13}	A_{14}
2	A_2	A_3	A_4	A_5	A_6	A_7	A_8	A_9	A_{10}	A_{11}	A_{12}	A_{13}	A_{14}	A_1
3	A_{14}	A_1	A_2	A_3	A_4	A_5	A_6	A_7	A_8	A_9	A_{10}	A_{11}	A_{12}	A_{13}
4	A_3	A_4	A_5	A_6	A_7	A_8	A_9	A_{10}	A_{11}	A_{12}	A_{13}	A_{14}	A_1	A_2
5	A_{13}	A_{14}	A_1	A_2	A_3	A_4	A_5	A_6	A_7	A_8	A_9	A_{10}	A_{11}	A_{12}
6	A_4	A_5	A_6	A_7	A_8	A_9	A_{10}	A_{11}	A_{12}	A_{13}	A_{14}	A_1	A_2	A_3
7	A_{12}	A_{13}	A_{14}	A_1	A_2	A_3	A_4	A_5	A_6	A_7	A_8	A_9	A_{10}	A_{11}
8	A_5	A_6	A_7	A_8	A_9	A_{10}	A_{11}	A_{12}	A_{13}	A_{14}	A_1	A_2	A_3	A_4
9	A_{11}	A_{12}	A_{13}	A_{14}	A_1	A_2	A_3	A_4	A_5	A_6	A_7	A_8	A_9	A_{10}
10	A_6	A_7	A_8	A_9	A_{10}	A_{11}	A_{12}	A_{13}	A_{14}	A_1	A_2	A_3	A_4	A_5
11	A_{10}	A_{11}	A_{12}	A_{13}	A_{14}	A_1	A_2	A_3	A_4	A_5	A_6	A_7	A_8	A_9
12	A_7	A_8	A_9	A_{10}	A_{11}	A_{12}	A_{13}	A_{14}	A_1	A_2	A_3	A_4	A_5	A_6
13	A_9	A_{10}	A_{11}	A_{12}	A_{13}	A_{14}	A_1	A_2	A_3	A_4	A_5	A_6	A_7	A_8
14	A_8	A_9	A_{10}	A_{11}	A_{12}	A_{13}	A_{14}	A_1	A_2	A_3	A_4	A_5	A_6	A_7

Table 8: Block 2 – Presentation order

Presentation Order	**Subject**													
	S_1	**S_2**	**S_3**	**S_4**	**S_5**	**S_6**	**S_7**	**S_8**	**S_9**	**S_{10}**	**S_{11}**	**S_{12}**	**S_{13}**	**S_{14}**
1	A_{15}	A_{16}	A_{17}	A_{18}	A_{19}	A_{20}	A_{21}	A_{19}	A_{20}	A_{21}	A_{15}	A_{16}	A_{17}	A_{18}
2	A_{16}	A_{17}	A_{18}	A_{19}	A_{20}	A_{21}	A_{15}	A_{18}	A_{19}	A_{20}	A_{21}	A_{15}	A_{16}	A_{17}
3	A_{21}	A_{15}	A_{16}	A_{17}	A_{18}	A_{19}	A_{20}	A_{20}	A_{21}	A_{15}	A_{16}	A_{17}	A_{18}	A_{19}
4	A_{17}	A_{18}	A_{19}	A_{20}	A_{21}	A_{15}	A_{16}	A_{17}	A_{18}	A_{19}	A_{20}	A_{21}	A_{15}	A_{16}
5	A_{20}	A_{21}	A_{15}	A_{16}	A_{17}	A_{18}	A_{19}	A_{21}	A_{15}	A_{16}	A_{17}	A_{18}	A_{19}	A_{20}
6	A_{18}	A_{19}	A_{20}	A_{21}	A_{15}	A_{16}	A_{17}	A_{16}	A_{17}	A_{18}	A_{19}	A_{20}	A_{21}	A_{15}
7	A_{19}	A_{20}	A_{21}	A_{15}	A_{16}	A_{17}	A_{18}	A_{15}	A_{16}	A_{17}	A_{18}	A_{19}	A_{20}	A_{21}

J.2.5 Dependent Variables

J.2.5.1 Range

Range is the distance from the intersection to the subject vehicle. As the vehicle passed over a reference point upstream of the intersection, it calibrated the range measurement. Continuous range measurement was then tracked and recorded by the vehicle's data acquisition system. Range measurement was calibrated during each intersection approach to minimize drift.

J.2.5.2 Range Rate

Range Rate is the instantaneous vehicle speed at a particular distance from the intersection. It was calculated by matching vehicular speed with the intersection range data. The result was a distance vs. speed profile for the approaching vehicle. This quantity was calculated and recorded by the in-vehicle data acquisition system.

J.2.5.3 Reaction time data

Reaction time was readily measured using in-vehicle sensors mounted to the pedals and aided by a corresponding video image of the feet. Many reaction time measures relating to stopping performance can be measured. Those of interest for this study included:

- **TAR** = Time to accelerator release: time from initial stimulus appearance to beginning of accelerator release. Operationally, the beginning of accelerator release was defined as the first decrease, after amber onset, in accelerator position of more than 2.5 percent in 0.1 sec
- **TB** = Time to brake: time from initial stimulus appearance to beginning of brake depression. Operationally, the beginning of brake depression was defined as the increase in brake position of more than 5 percent in 0.1 seconds that occurred after amber onset.

J.2.5.4 Braking intensity (inline acceleration)

Braking intensity is a measure of how hard a participant slows the vehicle. It was measured in terms of G-force (g) along the longitudinal axis by an accelerometer mounted in the vehicle.

J.2.5.5 Intersection violator

In general, a vehicle must have entered the intersection prior to the red phase or it is considered in violation of the TCD. Similarly, any driver in this study who crosses the stopbar while the red phase is presented is considered a violator. A second violation case occurs if a driver entered the intersection during an amber phase but failed to correctly clear the intersection. This occurred when a driver misjudged their ability to stop prior to the stop bar and instead stopped inside the intersection. An eight foot allowance was provided such that drivers could pass over the stopbar while stopping, without being tagged as a violator. Justification for this will be further discussed during the results section. All other drivers were considered non-violators.

J.2.5.6 Driving aggressivity rating

The Driver Stress Inventory (DSI) and Dula Dangerous Driving Index (DDDI) were calculated from a pre-experimental questionnaire given to participants (Appendix A and B). Both scales have been shown to predict an individual's willingness to operate a motor vehicle in a dangerous and aggressive manner (Dula & Ballard, 2003; Matthews et al., 1996). The DSI has been in development for over a decade and has been validated in numerous studies. It measures the participant on five factors related to driving. These include aggression ("I really dislike other drivers who cause me problems"), dislike of driving ("I feel tense or nervous when overtaking another vehicle"), hazard monitoring ("I make an effort to look for potential hazards when driving"), thrill seeking ("I get a real thrill out of driving fast"), and fatigue ("I become inattentive to road signs when I have to drive for several hours") (Matthews et al., 1996). Matthews (1996) characterized aggression items as relating to feelings of anger, impatience, hostility, and negative beliefs about other drivers. Dislike is associated with feelings of anxiety and tension and negative cognitive appraisals. Hazard monitoring is associated with safety-promoting behaviors and has shown high negative correlations with accident likelihoods. Thrill-seeking, as well as aggression, are related to dangerous behaviors, in particular high speed driving. In contrast to the DSI, the DDDI is a new scale that, to the author's knowledge, had only been validated using other questionnaires.

It is believed that the DDDI may include questions that are more directly related to risk-taking and may thus be a better predictor of violation propensity. The DDDI is divided into three subscales: Aggressive driving, negative emotional driving, and risky driving (Dula & Ballard, 2003). Dula and Ballard (2003) identify aggressive driving as behaviors intentionally meant to annoy, irritate, or punish other drivers. Negative emotional driving reflects irritability and anger, or the general tendency to become annoyed with other drivers. Lastly, risky driving represents the driver's willingness to engage in unsafe driving behaviors. The intention of these indices is to determine if a driver's allowable level of risk is related to their intersection crossing behavior.

J.3 PARTICIPANTS

Twenty-eight participants, equally split by gender and age group, volunteered for this research. Each participant was pre-screened during initial phone contact to verify possession of a valid United States driver's license, lack of medical conditions precluding them from the experiment, and appropriate age and gender demographics (Appendix C). On the day of experimentation participants filled out an informed consent (Appendix D) and a medical questionnaire (Appendix E) that incorporated an additional verification of their abilities to participate. A standard Snellen eye test was performed to ensure a corrected visual acuity of 20/40 or better (as required by Virginia law). Finally, a red/green color blindness test was also administered. All participants passed the health screening and vision tests.

VTTI maintains a database of previous participants organized by age and gender. From this list a group of participants was selected based on the criteria outlined above. Previous experimental experience was also considered during selection. Most participants had not previously participated in any studies at VTTI. Those who had been in studies previously were only allowed to participate if the previous study did not include any surprise events. Participants received compensation of $10/hr plus bonuses.

J.4 FACILITIES AND EQUIPMENT

J.4.1 The Smart Road

The test-track used during this research was the Virginia Department of Transportation Smart Road. The Smart Road is a unique, state-of-the-art, research facility used for the evaluation of Intelligent Transportation Systems (ITS) concepts, technologies, and products (Figure 5). It is currently a 2.2-mile two-lane roadway with a high-speed banked turnaround at one end and a medium speed flat turnaround on the opposing end. For the current research, only the section between the high-speed turnaround and marker 108 (where a third turnaround is located) was used. Thus most of the driving was near the intersection, which significantly decreased the overall time required for each participant. Access to the roadway is controlled by a dispatcher and electronic gateways making the test facility a safe location to conduct research. This allows scientists to complete experiments that would not be possible on the open roadway.

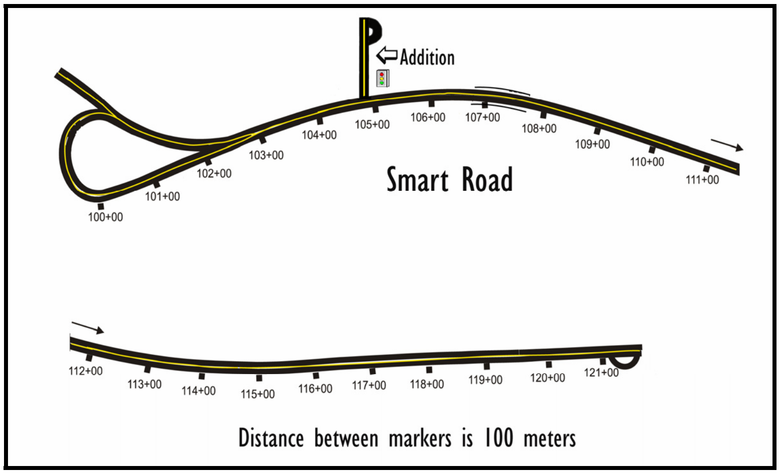

Figure 5: Plan View of Smart Road Test Track

A four-way signalized intersection was built on the Smart Road in the mid 2003 calendar year (Figure 6) It adds a four way signalized crossing with one high speed approach and a lower-speed approach with a turnaround. The intersection signal controller is a highly adaptable allowing the experimenter to customize signal behavior such as signal timing and phase.

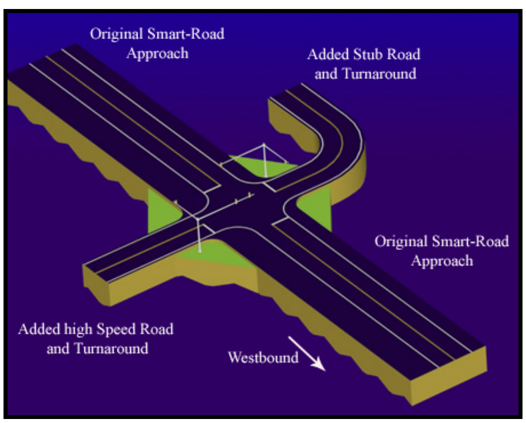

Figure 6: The Smart Road Intersection

Both North and Southbound intersection approaches were used for collecting stopping behavior data. On each approach a series of six photoelectric gates were located on the roadway. A gate was placed at the distance corresponding to each of the five TTIrp values with the sixth laser located on the final edge of the stopbar. As a vehicle passes through a gate, a signal is sent to the intersection controller providing the vehicle's precise location. When the gate corresponding to the current experimental conditions is crossed, the appropriately timed signal phase change is initiated by the controller.

The signal controller was designed and built in-house to allow for maximum flexibility (Figure 7). It was managed by a 233mhz PC104 computer using a RS232 communications bridge (Figure 8). The controller board is a dual purpose circuit board bridging communication between the PC104, signal heads, and photoelectric switches.

The controller uses a solid-state relay bank operating at 120v to switch the signal lights as requested by the PC104. In addition, it provides power to the lasers and monitors the transmitted interrupts which are addressed and passed to the PC104. The PC104 tracks vehicle location by monitoring the photo gate interrupts and executes phase changes using pre-programmed algorithms corresponding to each of the experimental trials.

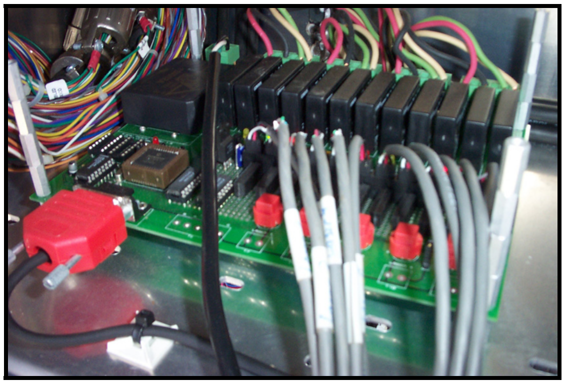

Figure 7: Intersection Controller

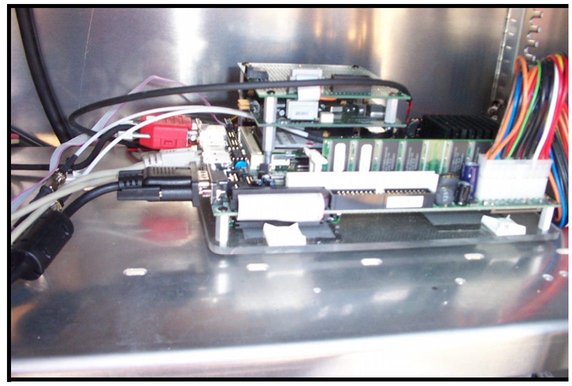

Figure 8: Intersection Computer

The intersection PC104 also communicated with the vehicle in two ways. First it received information regarding the next experimental trial. The PC104 used this information to determine which laser would trip the phase change, amber delay time (for the distracted case), amber phase length, and red phase length. Second it transmitted laser interrupts and signal status back to the vehicle. This information was then recorded by the vehicle's data acquisition system. The infrastructure/vehicle communication occurred via a prototype wireless Dedicated Short Range Communications (DSRC) link. DSRC is a wireless communication system currently being developed for future use in transportation. The prototype available at the time of the study operated at 8.2GHz using specialized set of omni-directional antennas mounted on the controller cabinet (Figure 9).

Figure 9: Intersection Cabinet with DSRC antennas

The final component of the infrastructure apparatus was a differential global positioning system (DGPS) and FM transmitter. DGPS uses a static base station GPS system that has an accurately defined location. The base-station GPS gathers and computes real time location and compares it with its actual location. The differential offset between the actual location and the real-time location is calculated and paired with a time stamp. This offset is then sent to the vehicle via an FM transmitter operating at 15 watts. The vehicle can then use this information to determine its position with a much higher degree of accuracy than would be possible without the differential correction.

J.4.2 Research Vehicle

VTTI has leased a 2002 Chevy Impala (Figure 10) for the intersection test bed.
The vehicle was delivered with safety equipment such as anti-lock brakes, dual front and side airbags, and traction control. For added safety an emergency passenger-side brake was also added such that the experimenter could take control of the vehicle if needed. The data acquisition system contained within the vehicle was custom built by VTTI.

Figure 10: GM Impala Experimental Vehicle

The data acquisition system was located inside the trunk and out of view of the participant (Figure 11). Hardware was contained in a custom mounting case designed to affix instrumentation in orientations necessary for accurate measurement and durability.

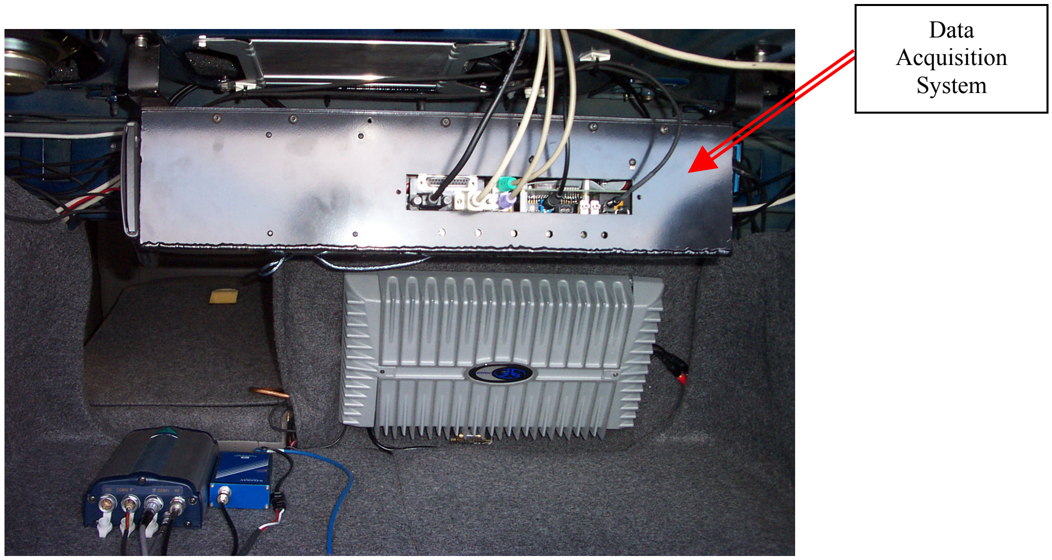

Figure 11: Vehicle Instrumentation

At the heart of the data acquisition system is a 200 MHz PC104 running Microsoft Windows 98® OS. Attached to the stack is a series of custom designed circuit boards that control the various functions of the acquisition device. This system included four video grabbers, two I/O, accelerometer/gyroscope and a power management board. The alighment and time stamping data retrieved from these boards is choreographed by X-Car; a customized VTTI proprietary software package.

The video grabbers converted an NTSC signal from the cameras into MPEG which is recorded to the hard drive in real time. Small cameras (1" square by ¼" deep, seeing through a 1/32" aperture) mounted inconspicuously within the vehicle collected the video data. For the current study four cameras were installed. A forward view provided a visual reference of the current vehicle location. A second camera focused on the driver's face such that eye glances are recorded. The third camera was located behind the passenger side A-pillar; collecting the driver's physical movements. Finally a fourth camera was mounted under the dash and focused on the pedal area for capturing foot movements. Due to the low-light conditions, this camera also used an infra-red light source. The four videos were multiplexed into a single image, digitized with a frame grabber, time stamped, and recorded to the hard drive at 30Hz.

The I/O boards acted as the bridge between onboard sensors and the data acquisition system. To get accurate reaction time data, pedal position for the brake, and accelerator, as well as steering position, were collected at 100Hz. This was accomplished by mounting string potentiometers to each device. The potentiometers feed an analogue signal into an analog-to-digital (D/A) board mounted under the dash which digitizes the information. Also feeding information to the D/A box was a Hall Effect sensor mounted on the drivers-side front wheel. The Hall Effect sensor used a magnetic pickup that counted pulses at 10 Hz from 32 magnets spaced 2.25" apart. The Hall Effect sensor is used to measure distance traveled. The digital information is then sent to the I/O board where it is recorded to the hard drive. The second I/O board interfaces with the experimenter and DSRC laptop (Figure 12).

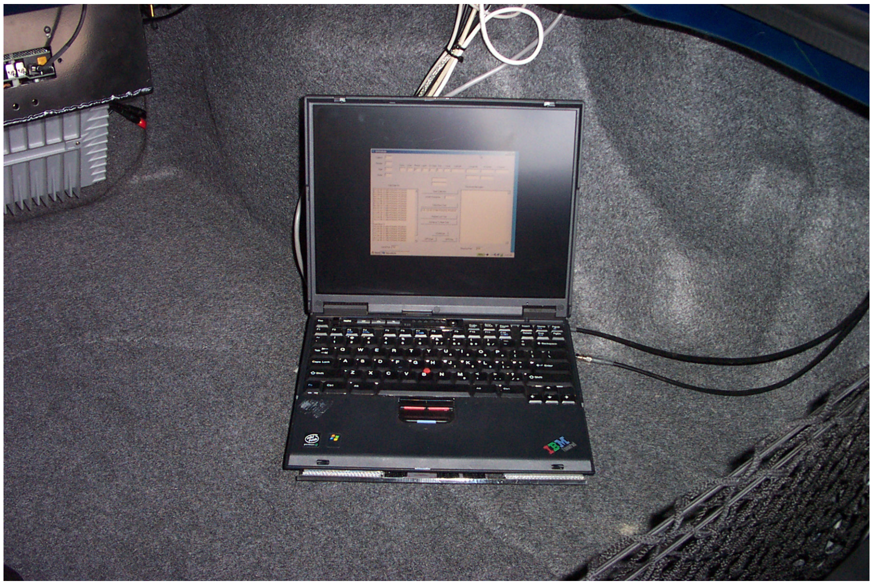

Figure 12: Experimenter DSRC laptop

The experimenter laptop, mounted in the trunk but controlled from the passenger sear, served three primary purposes First it used a prototype Atheros ® wireless board to interface with the DSRC system mounted at the intersection. This allowed the experimenter to communicate with the intersection for control of the experimental trial. In addition, the wireless link allowed the vehicle to receive information regarding light status and laser crossings from the intersection (Figure 14). The second purpose served was to collect position and speed information from the DGPS system (Figure 13). The DGPS system from Novatel calculated position and speed based on current GPS and the differential shift at a rate of 10Hz. In addition, speed data is further enhanced by using the doppler shift from the satellite units. Hardware testing demonstrated that position information from DGPS did not sustain the level of accuracy that the Hal Effect system did. However, speed information was significantly better due to sampling harmonic distortion of the Hal Effect. Thus DGPS is used for speed measurements while the Hal Effect is used for distance measurements.

Figure 13: Novatel DGPS

Figure 14: DGPS and DSRC Antennas

The third purpose application of the laptop was to serve as the experimenter interface. A small monitor was mounted on the floorboard just in front of the passenger seat. The monitor was not viewable from the driver's seat but easily glanced at by the experimenter. The laptop image was replicated on this monitor and controlled through an auxiliary keyboard and mouse (Figure 15). From the passenger seat the experimenter controlled the status of the data acquisition system and setup the next trial. This was accomplished with a custom software interface. The software was preloaded with the trial order that automatically advanced each time a trail was completed. Thus the experimenter need to interface with the system only to send the trial or skip/repeat a trial as needed.

Figure 15: Experimenter Interface

In order to preserve the integrity of data collection, the instrumented vehicle should appear ordinary. To this end, every effort was made to conceal instrumentation from the driver. For example, cameras were mounted behind mirrors, wires and other data recording equipment were hidden under interior panels and parts of the system that make noise were acoustically isolated from the passenger compartment.

J.5 EXPERIMENTAL PROCEDURE

J.5.1 Participant Screening

Participants underwent preliminary screening during initial phone contact. The screening ensured that only participants of the required age and gender were invited to participate (Appendix C). Additionally it provided an opportunity to eliminate subjects if they had any medical conditions that presented safety concerns. Participants that were qualified and willing to perform the study were scheduled for testing. Participants were instructed to arrive at VTTI at a mutually agreeable time. An experimenter met them in the main lobby and escorted them to a screening room. Subjects then completed an informed consent form (appendix D), health-screening questionnaire (appendix E), a W-9 tax form, a Snellen eye test, and the Ishihara color blindness test. The short health questionnaire is a safety measure to verify the driver 1) did not have any medical conditions that may be aggravated by rapid deceleration and 2) was not under the influence of any drugs or alcohol that could impair their ability to drive. The vision test ensured that all participants had a corrected acuity of at least 20/40 as prescribed by Virginia law. Once these procedures were completed, orientation began. The scripts used by experimenters for both orientation and the experiment are available in the appendices in Appendix F through H).

J.5.2 Participant Orientation

All participants underwent an identical orientation session prior to beginning the experiment. The first step was to provide the pre-driving questionnaires. These were administered in successive order beginning with the DDDI (Appendix A), followed by the DSI (Appendix B), and finally a sleep hygiene questionnaire. The DDDI and DSI focus on driving and in particular aggressive driving. The sleep hygiene question was a ruse designed to dissipate any expectation that resulted from the driving questionnaires.

The participant was then escorted to the experimental vehicle where they were instructed to adjust the seat, mirrors, and steering wheel positions to their comfort. The experimenter then sat in the passenger seat and began describing the experiment. Participants were invited to ask questions at several points throughout the description which included where the experiment would take place, the type of drive being simulated, how we were collecting information, speed limits, and legal intersection crossing behavior.

J.5.3 Block 1: On-Road Procedure

With the experimenter in the front seat, the participant was instructed to drive onto the Smart Road. The experimenter asked the participant to maintain 35mph as the roadway was entered. A trial was not sent for one complete loop around the test track. This provided the subject with a familiarization period prior to data collection. After the familiarization period data collection began by sending the first trial. Each subject experienced the experimental conditions in a pre-determined presentation order as outlined previously in the experimental design section.

J.5.3.1 Baseline Driver State

The baseline condition used the standard ITE intersection timing algorithm for the amber change interval. The condition should represent exactly what a driver would encounter on an actual roadway. That is, as the intersection is approached the signal changed from a green phase to an amber. After the standard change interval, the lamp switched to the red phase. For short TTIrp values the baseline driver typically traveled through the intersection toward the beginning of the amber change interval. For longer TTIrp values the baseline driver typically recognized the risk of violation associated with crossing the intersection was too high and decelerated to a stop prior to the stopbar.

J.5.3.2 Distracted Driver Sate

The simulation method for this condition, as described previously, was to shorten the amber change interval. The time in which the amber phase was shortened approximates the time of inattention. As a participant approached the intersection, the corresponding photo-gate sensed vehicle crossing. However, rather then immediately initiating the phase change, the TCD awaited a 1.6 second distraction delay. Once this delay had elapsed the amber phase change began; however the amber phase still ended at the same distance from the intersection as the baseline condition. The result is a shorter amber phase for the same TTIrp as the other driver states. The shorter interval increased the size of the dilemma zone (Equation 2) and thus increased the number of violations.

J.5.4 Block 2: On-Road Procedure

The second block counterbalanced the presentation of conditions for the willful driver state. In order to successfully modify participants intersection crossing cost/benefit ratio they had to be informed of the study's interest in the intersection.

J.5.4.1 Willful Driver State

When the first block was complete, participants were instructed to park along the roadway at the East end of the experimental loop. The experimenter then explained the second block in which they were asked to attempt to "beat the light". Participants were told that a second experimental portion was starting in which the focus was to examine the circumstances under which people choose to beat the red light. They were asked to imagine they were late for an appointment, or in a hurry to get to their destination. Thus, the scenario was developed in which a driver may be more likely to behave in a risky manner by attempting late crossings. The red-light-running behavior was further elicited from subjects by adjusting their cost-benefit ratio. That is, subjects were paid a bonus for each time they entered the intersection prior to the red light, and had money deducted each time they did not.

After the second orientation was complete, participants were instructed to begin driving the loop. The same TCD algorithm used during the baseline condition was repeated for this state. The only difference between the willful and baseline conditions is the extra motivation provided through the monetary incentives. Results show that for TTIrp values that compelled baseline drivers to stop instead resulted in a decision to go by the willful drivers. The shift towards risky driving also resulted in range-rate profiles that show acceleration as drivers attempt a late crossing. The entire experimental procedure including, participant greeting, orientation, and driving lasted approximately an hour and a fifteen minutes.

J.5.5 Debriefing

After completing all the experimental trials, subjects were instructed to return to the building, where they were debriefed. It was explained that the actual goal of the study was to analyze how stopping behavior changes across driving states and why they were not fully informed of it earlier. The experimenter answered any questions that arose and then asked the participant to sign a debriefing form (Appendix G). The debriefing acknowledged that they had been debriefed and acted as a receipt for their participation. Participants were then compensated and asked not to discuss the details of the study with anybody for the next three months.

The entire experimental procedure including, participant greeting, orientation, driving, and debriefing lasted approximately an hour and a fifteen minutes.

J.5.6 Data Reduction

After completion of the experiment, the generated data was downloaded to a server where it was accessible for data reduction. Most of the data reduction process used the Matlab environment (Release 12; Mathworks, Natick, MA). Although analysis was primarily based on data provided from vehicle sensors, the video files did have some utility for this study. First, it allowed for post-hoc visualization of scenarios affording insight into data trends. The data analyzers occasionally watched the driver actions that caused particular trends in the numeric data collected. This allowed the test condition parameters to be verified when needed.

C.0 Results and Discussion

Two primary software packages were used for analyzing data. Matlab Release12 by Mathworks, was used for data manipulation, reporting, and small-sample statistics. The Statistical Analysis System (SAS) Release 8.2 was used for all inferential analysis. ANOVAs, Chi-squares, and correlations were used to assess the effect of the independent variables on the surrogate driving performance measures. A Type I error of 0.05 was used to establish significance. When significant effects were identified, a Tukey-Kramer *post-hoc* test was performed.

A typical stopping intersection approach is demonstrated below (Figure 16). As the intersection is approached, the traffic signal changes phase, switching from a green to an amber indication when the vehicle is 185' from the intersection. Shortly after the amber light was presented the driver releases the accelerator pedal and subsequently pushes the brake pedal, as is shown by the brake and throttle position plots. Once the brake is applied, the vehicle begins to decelerate and eventually stops a few feet from the stopbar. In this instance the driver presses the brake to approximately 79% of its maximum travel. The signal switches to the red phase when the vehicle is approximately 25' from the intersection. Deceleration continues until the driver reaches a complete stop, approximately five feet from the stop bar.

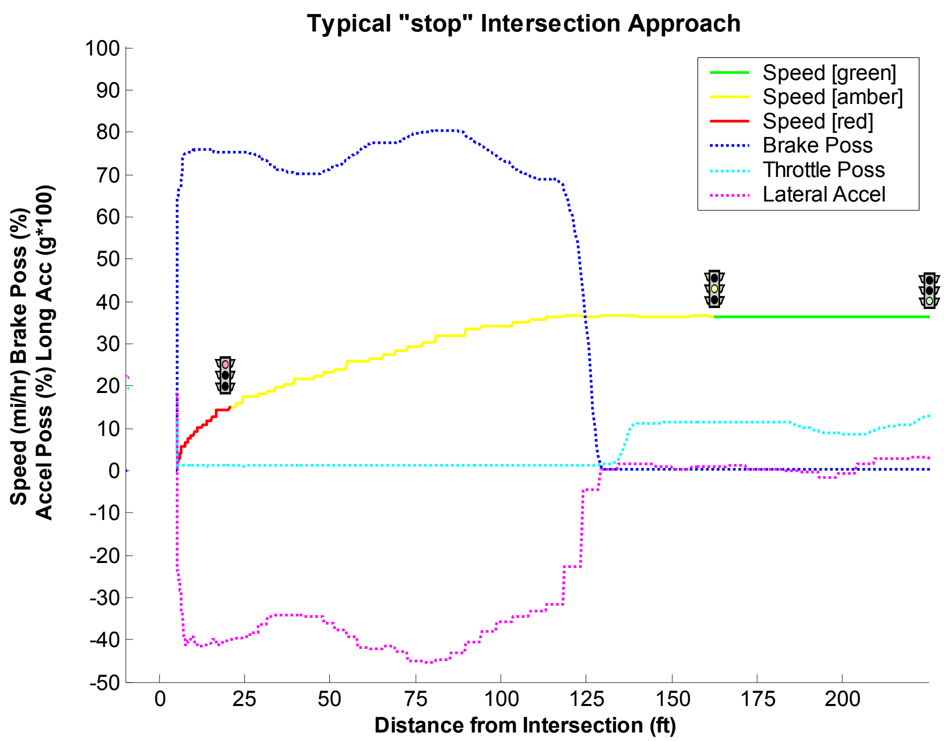

Figure 16: Typical intersection approach. The color of the solid line indicates the corresponding signal phase. Traffic signal icons indicate phase transition points.

The complete data set consisted of 28 participants each undergoing a unique combination of the twenty-one treatment conditions for a total of 588 intersection crossings. Four intersection crossings had to be removed from the data set due to hardware malfunctions caused primarily by wireless communication dropouts. The remaining data is shown in the scatter plot below (Figure 17). To create this scatter plot, as well as many of the subsequent plots, time based data was converted to the distance domain. Speed was averaged over five feet increments and subsequently centered over that increment (ie. an mean speed calculated from the stop bar to five feet from the stop bar was placed at 2.5 feet). This resulted in 45 speed samples taken every five feet from the stobar to 225 feet away. Having speed samples at equivalent ranges across all intersection approaches, allowed approach profiles to be averaged across all runs.

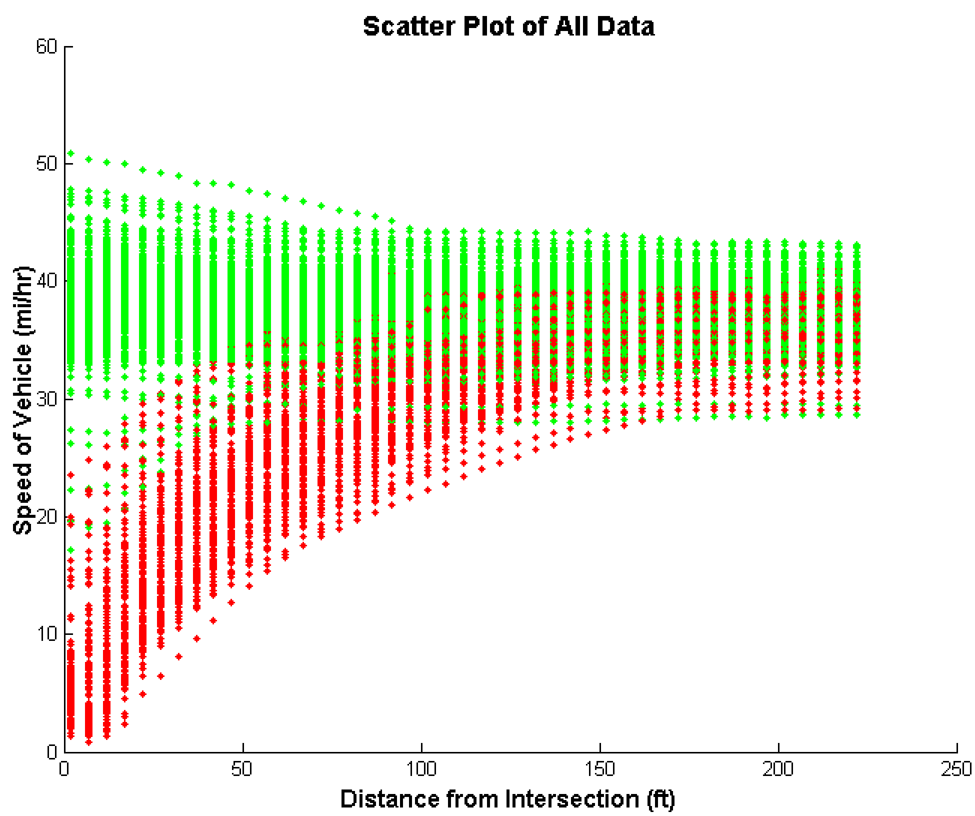

Figure 17: Scatter Plot of all speed data points collapsed across 5 foot distance increments

Drivers approaching the intersection were placed into two distinct groups, drivers who choose to stop, and drivers who choose to go (Figure 18). Typically a stopping driver begins decelerating as the intersection is approached while the go driver maintains the approach speed or accelerates slightly. This distinction between 'stop' and 'go' drivers will be used throughout the data analysis discussion.

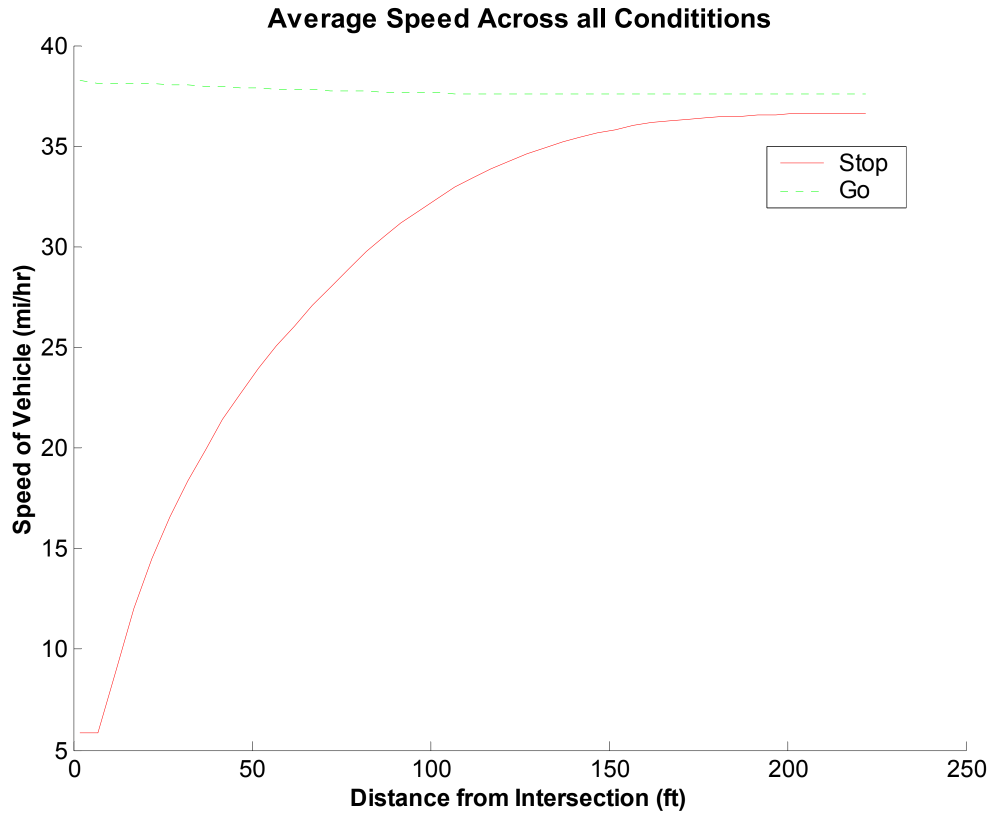

Figure 18: Mean vehicle speed approach profile across all conditions and divided into 'stop' and 'go' drivers

Note: A side effect of looking at data in a distance domain is the inflection point visible near the stop bar. When the signal phase returns to green, the vehicle drives away increasing the mean speed at that point and causing the inflection. Data in this region should be disregarded.

For a given distance from the intersection the distribution of speed is normal for either stop or go drivers. Meeting the assumption of normal data is required for several of the analyses described below. A series of box plots were created using the binned data shown in Figure 17. These plots demonstrated normal distributions and enabled the use of traditional inferential statistics for data analysis.

As discussed previously in section B.0J.1, the distances selected to initiate phase changes were based on an approximated distribution. To check the validity of this assumption, the 139 baseline approaches were analyzed for driver stop decision making. A distribution of driver stop decision by phase change distance was created (Figure 19). The expected vs. actual number of times drivers decided to stop varied from a 3% to 19% error (Table 1). With the exception of the smallest TTIrp, drivers tended to stop more often than predicted.

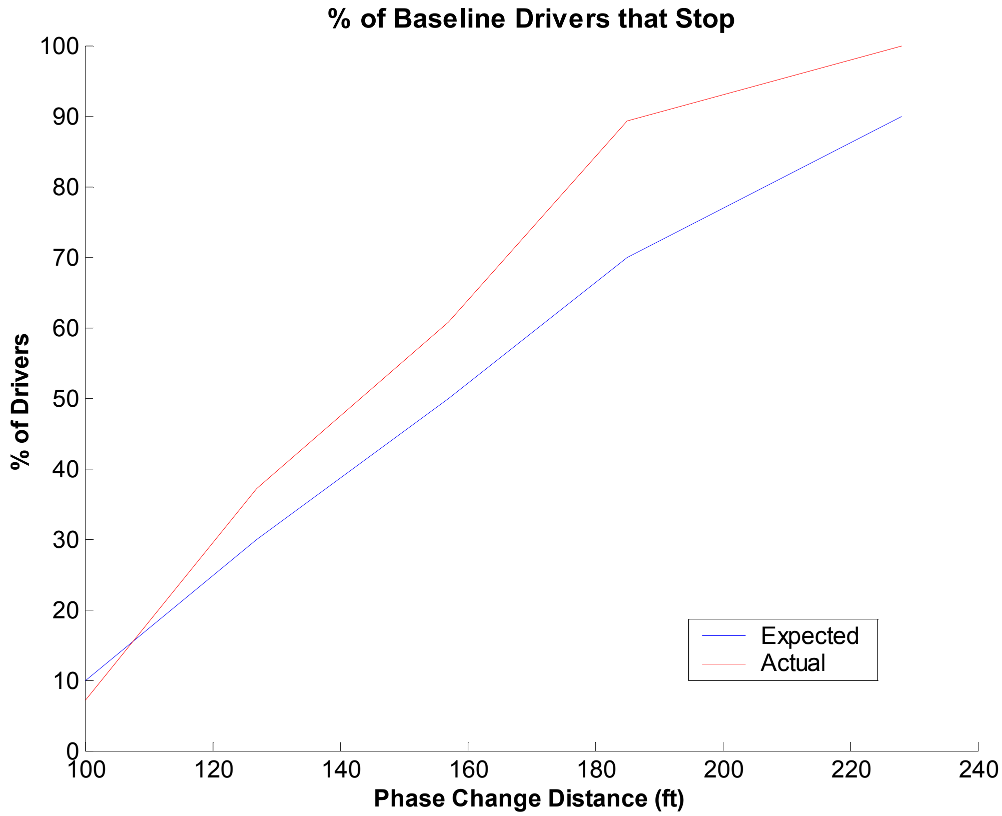

Figure 19: Driver stop vs go decision for the distance from intersection in which a phase change was initiated

Table 9: Expected Baseline Driver Decisions vs Actual Driver Decisions

TTIrp	Distance for Phase Change	% of Drivers Deciding to Stop	
		Expected	Actual
-1.62s	100ft	10 %	7.1 %
-1.09s	127ft	30 %	37.0 %
-0.51s	157ft	50 %	60.7 %
0.04s	185ft	70 %	89.3 %
0.87s	228ft	90 %	100 %

The remaining portion of the data analysis section will be devoted to addressing each of the research questions directly.

J.1 RQ 1: HOW DOES DRIVER STATE AFFECT INTERSECTION PERFORMANCE?

Driver state can affect the intersection approach in many ways. It may influence the drivers decision on whether or not to stop, when to brake, and how quickly to stop; or when to press the throttle, and how hard to accelerate. A top down approach will be used to discuss the effects of driver state. First, its influence on the driver's decision to stop will be analyzed using chi-square techniques. Then approach profiles will be discussed using summary statistics and subsequently decomposed with an inferential analysis of speed, reaction time, acceleration, and violation rate. Driver demographic (age and gender effects) will be briefly integrated throughout this discussion as well.

J.1.1 The stop or go decision – a Chi-Square Analysis

The Driver State factor significantly affected a driver's decision to stop. Results from a Chi-square analysis demonstrated a higher tendency for drivers to stop in the baseline condition rather than in the distracted condition ($\chi^2(2,N=582) = 71.77$, $p < 0.0001$) (Appendix E.0J.1.1). A total of 154 stops (out of 420 amber phase approaches) were made. Most of these stops (N=82, 59%) occurred in the baseline state; willful drivers performed 62 stops (44%), while distracted drivers stopped in only 10 (7%) instances. The large disparity of distracted drivers against baseline and willful driver states demonstrates that drivers with an inadequate amber phase, due to distraction, poor phase timing, or poor judgment are less likely to stop and may thus be more likely to violate the TCD.

Driver demographics also had an influence on a driver's decision to stop. A Chi-squared analysis of Age ($\chi^2[1,N=582] = 5.31$, $p = 0.021$) and Gender (χ^2 $[1,N=582] = 3.68$, $p = 0.055$) indicated a varying propensity for stopping for age with younger drivers topping less often (Table 10)(Appendix E.0J.1.2). While this propensity was not statistically significant for Gender, the results indicated a tendency for male drivers to stop less often.

Table 10: Stop Decision Frequency Counts for Age and Gender

Age		Gender	
Younger	Older	Male	Female
65	89	66	88

The age effect and gender trend agree with results of past research. Younger drivers are less likely than older drivers to stop at the traffic signal (Sivak et al., 1989). Similarly, research by Wang and Knipling (1994) suggests that males are more likely to collide with other vehicles during intersection crossings. It may be that the male's tendency to stop less frequently increases the number of opportunities for late crossings. These late crossings are likely to increase the potential for a collision, possibly explaining the results reported by Wang and Knipling. This trend was also reflected during the analysis of violation rates which will be discussed in a subsequent section..

Phase Change Distance and Driver State also interacted to effect a driver's decision to stop (Figure 20). For instance, at a phase change distance of 185', nearly 90% (25) of the drivers in the baseline condition stoped, while less than 5% (1) of distracted drivers do so. Distracted drivers exhibited a lower propensity to stop because the simulated distraction did not provide them with the opportunity to react to the full duration of the phase change.

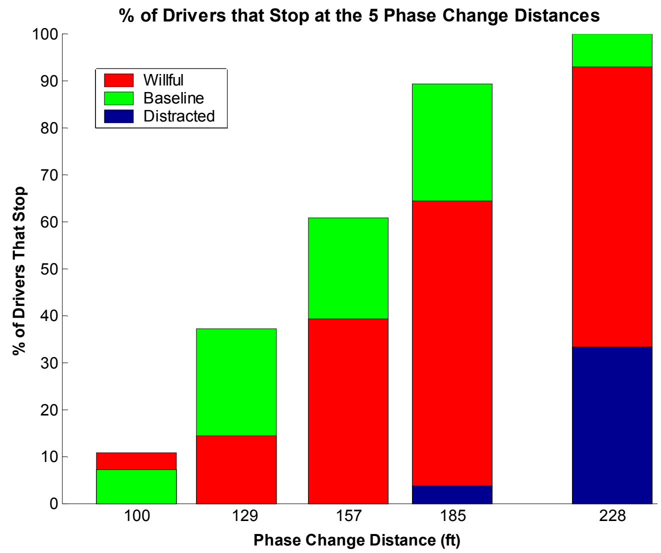

Figure 20: Percentage of baseline, willful and distracted drivers that choose to stop at the five phase change distances.

Figure 24 clearly demonstrates the decreased likelihood for distracted drivers to stop during the intersection approach. The TCD was timed such that in the distracted case, the amber phase was presented after the driver may have entered the intersection at phase change distances of 100' and 129'. At 157' the distracted driver would be required to stop at an uncomfortably high rate of deceleration. At phase change distances of 185' and 228' the distracted driver received the amber indication sufficiently close that most drivers expected to clear the intersection legally. The distribution of baseline to willful stops at the 100' phase change distance should be interpreted cautiously. This distribution is based on only five stops and lacks sufficient power to make any conclusions. It also demonstrates a unintended consequence of the bonus system. In a rare occasion, the bonus may have caused drivers to be over attentive to the signal, thus stopping when the normally would not. However, it is foreseeable that some drivers may act similarly when they are in a hurry outside the experimental environment. To better understand how drivers stop, approach profiles are discussed next.

J.1.2 The Intersection Approach

Much information can be gathered by looking at intersection approach profiles. By plotting speed over distance it is possible to get qualitative information about braking points, braking intensity, acceleration, and speed; as well as differences in these factors between driving groups. For drivers that stop, the baseline state exhibited the earliest brake application and the most relaxed deceleration profile (Figure 21). The willful state resulted in a slightly steeper profile than the baseline state for a region of the approach profile. This does not primarily appear to be a result of a later decision to brake. Rather, it seems to be caused by the higher initial speed of willful drivers. In contrast, the distracted driver state demonstrates a much later brake application with a steep deceleration profile. This is expected, given the nature of the simulated distraction.

Distracted drivers saw the amber later than their counterparts; accordingly, they reacted later. However, it is expected that a truly distracted driver that is not attentive to the signal change would respond similarly.

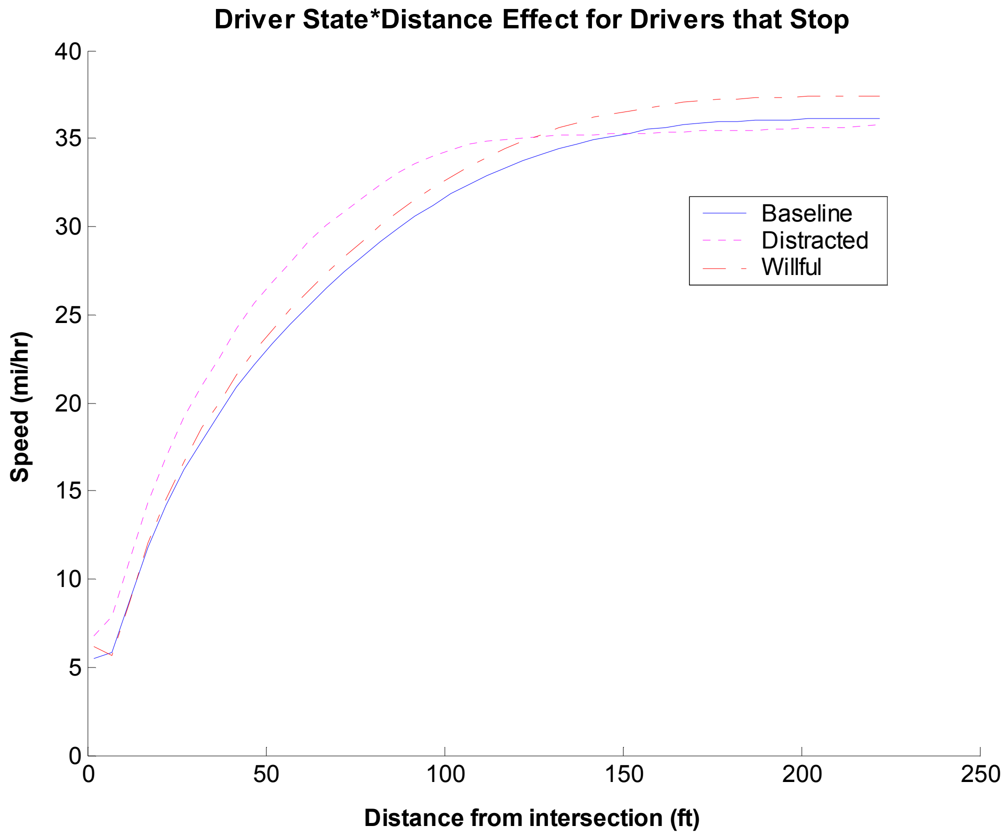

Figure 21. Mean 'Stop' profiles for baseline, distracted, and willful driver states.

For drivers that "Go," the willful driving state resulted in a tendency to drive faster and to accelerate through the intersection (Figure 22). This is likely a result of the driver trying to reduce the chance of a violation that would reduce their bonus pay. Willful drivers represented a group of individuals who are motivated to cross the intersection. A side effect of this motivation is an increased likelihood to speed in anticipation of the signal change. However, the effect size was small; willful drivers on average went 1.5mph faster than drivers in the baseline and distracted conditions (38.81 vs. 37.13mph & 37.28mph respectively).

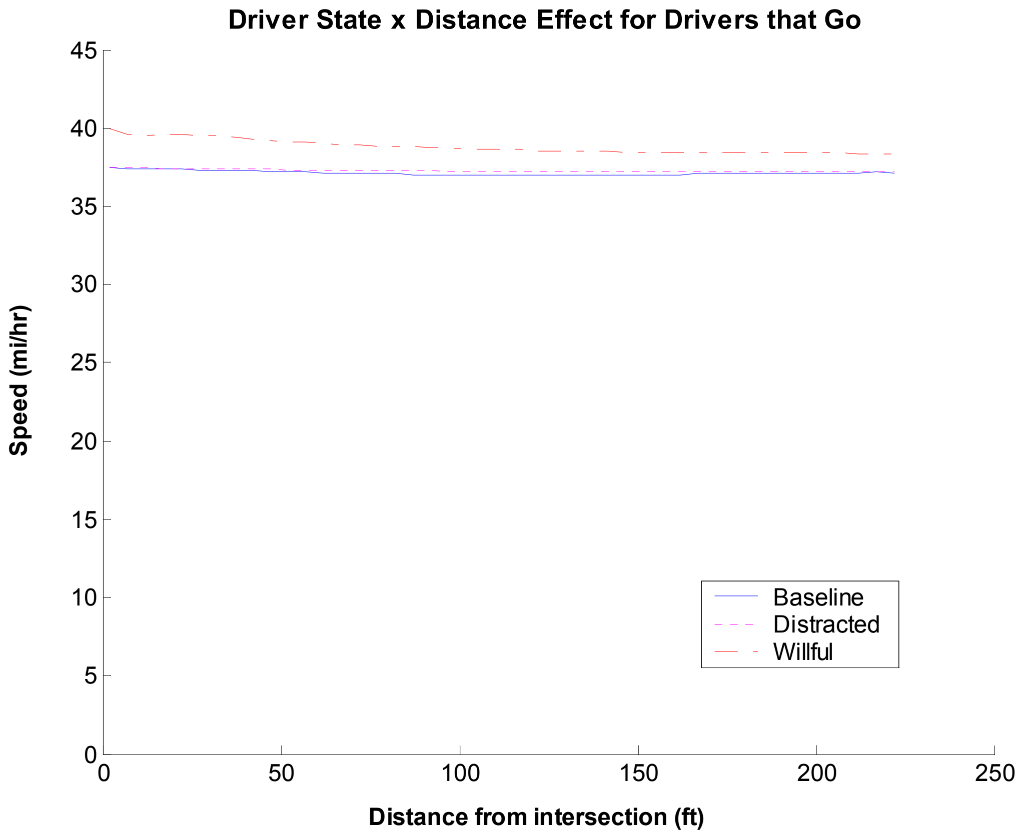

Figure 22. Mean 'Go' profiles for baseline, distracted, and willful driver states.

Differences in the approach profiles for both "Go" and "Stop" cases can be used to help develop IDS signal violation prevention algorithms. Assuming that the distracted driver approach represents the latest that a driver would be likely to stop, it may be reasonable to warn any driver that exceeds that approach profile (Figure 21). On the other hand, drivers whose approach falls near the baseline profile should not be warned. Warning drivers near the baseline profile would result in an unacceptable number of annoyance alarms and degrade the overall system performance by decreasing driver confidence on the system.

The algorithm may also need to identify the willful violator early in their approach. If the speed (and/or acceleration) profile of the willful driver is such that the intersection is likely to be entered prior to a conflict situation, the algorithm should not call for a warning. However, if the vehicle is not moving sufficiently fast (and/or accelerating to do so), the warning will need to be provided early during the approach to alter the willful driver's motivation and allow for sufficient time to stop the vehicle from a higher than average speed.

As demonstrated in the previous plots, driver state was expected to affect the intersection approach behavior of participants. To analyze this possibility, the intersection approach is decomposed into driver performance variables. The dependent performance variables analyzed combine to define the shape of the intersection approach (perception-reaction times, speed, deceleration, and violation rate). First, perception-reaction times are discussed.

J.1.2.1 *Reaction Time Analysis*

To further explore stopping behavior, the TAR and TB reaction times are compared with driver state. To test TAR and TB the data set was filtered to include instances in which the driver chose to stop and was contacting the throttle prior to stimulus presentation. The new data set consisted of 72 sample points. TAR was then operationally defined as the time interval between the amber signal presentation and when a 2.5% change in accelerator pedal position was recorded. TB was operationally computed as the time interval between the amber signal presentation and when a 2.5% change in brake pedal position was recorded. The 2.5% trigger a criterion was selected because it represents a very small change in pedal position and is large enough to overcome signal noise. Each of the reaction times was entered into ANOVAs with gender, age group, and driver state as the independent variables. In both analysis all factors failed to reach statistical significance.

This analysis indicates that although willful drivers stopped less frequently, when the stop decision was made they reacted in about the same time as baseline drivers. The fact that distracted drivers received the amber indication later in their approach did not appear to significantly change their perception reaction time. The TAR across driver states ranged from 0.01 seconds to 1.04 seconds with a mean of 0.37 seconds (SD=0.18). The TB across driver states ranged from 0.34 seconds to 1.43 seconds with a mean of 0.81 seconds (SD=0.16). This may indicate that assuming a constant value for reaction time measurements for the purpose of algorithm development is not unreasonable. However, it is possible that this analysis failed because of insufficient power. The reduced data set consisted of 39 baseline cases, 27 willful cases, and only 6 distracted cases. The reader should be aware of the weaknesses of this analysis when considering the following discussion.

J.1.2.2 *Speed Analysis*

The approach speed of drivers did result in significant effects for driver state. This analysis was completed twice, once for drivers that chose to go (n = 262), and once for drivers that chose to stop (n = 154). Both ANOVA analyses included the independent variables gender, age group, and driver state.

For drivers that "Go," only the driver state factor showed statistically significant speed effects ($F(2,45) = 17.65, p < 0.0001$) (Appendix J.3.1). A Tukey post-hoc test isolated the willful driver state from the other two ($p < 0.0001$). This is likely a result of the driver trying to reduce the chance of a violation that would reduce their bonus pay. Willful drivers represented a group of individuals that are motivated to cross the intersection. A side effect of this motivation is an increased likelihood to speed in anticipation of the signal change. However, as discussed previously, the effect size was small; willful drivers on average went 1.5mph faster than the baseline and distracted conditions (39.3mph vs. 37.29mph & 37.34mph respectively).

The distribution of significant speed effects by driver state changed when a driver decided to stop ($F(2,28) = 3.64, p = 0.0394$) (Appendix E.0J.3.3). The baseline state became statistically isolated from the willful and distracted states ($p < 0.001$). Baseline drivers received the amber phase in a timely fashion and did not have an elevated motivation to cross the intersection. This caused an earlier decision to stop and a reduction in speed at the furthest from the intersection; resulting in a lower mean speed. Again the effect size was small with baseline drivers traveling 1.3mph slower on average (28.7mph) compared with distracted and willful drivers (30.3mph 29.7mph respectively). Both the stop and go effects are apparent in the approach profiles discussed previously (Figure 21 & Figure 22). The plots also depict different slopes of the intersection approach plot during a stop. The slope of these lines is the deceleration rate drivers selected while stopping and will be discussed next.

J.1.2.3 Deceleration Analysis

To complete a deceleration analysis, the data set was filtered to include only instances in which drivers chose to stop (n = 154). Mean and peak deceleration attained during the approach were computed. The mean deceleration was calculated as a time-weighted average over the interval from when the vehicle began to slow until the time it stopped. The interval was initiated when deceleration exceeded 0.01g and continued until the vehicle came to a complete stop. Peak deceleration was identified as the highest rate of negative acceleration over that interval and averaged over five 10Hz cycles. Two ANOVAs (one for each dependent variable) were then constructed (Appendix E.0J.2). Statistical results are similar for both types of deceleration. Neither age nor gender attained significants for either peak or mean deceleration. Driver state did reach significants for mean, as well as peak deceleration ($F(2,33)=54.60, p=0.0002$ and $F(2,33)=31.74, p=0.0001$ respectively). A Tukey-Kramer *post-hoc* test demonstrated statistical differences in peak deceleration and time-weighted deceleration between the distracted driver state and the two other states, but no difference was noted between the baseline and willful driver states. (Appendix E.0J.2). Mean deceleration values are summarized in Table 11 below.

Table 11: Mean and Mean Peak Deceleration

Deceleration Type	Driver State			Average Across DS
	Baseline	Distracted	Willful	
Mean Peak Deceleration (SD)	0.46g (0.11g)	0.54g (0.08g)	0.48g (0.13g)	0.47g (0.12g)
Mean Deceleration (SD)	0.33g (0.07g)	0.39g (0.05g)	0.34g (0.09g)	0.34g (0.08g)

The deceleration trends demonstrated by this analysis are visible in the slope of the approach profiles shown in section J.1.2. The required rates of deceleration are highest for distracted, followed by willful, and then baseline drivers. Indeed, the late brake application of the distracted driver required that the driver brake harder. Willful drivers also appear to be willing to brake harder than baseline. This is likely due to a combination of later braking and higher initial speeds. Deceleration information such as this will help IDS designers during algorithm development. Several proposed algorithms encompass acceleration terms that are related to the values presented. The goal of any algorithm is to correctly identify violators. Thus, although the sample size is relatively small, it is appropriate to analyze violation rate as it relates to driver state.

J.1.2.4 Violations

Violations were identified when the vehicle crossed the stopbar after the light had switched to a red phase and crossed over the stop bar in excess of eight feet. The purposes of this eight foot allowance was to eliminate approaches which, although technically a violation, negligibly increased collision risk and were unlikely to elicit a ticket. This includes drivers that “creep” over the stopbar and late stoppers. Creeping occurs when a vehicle nearly stops and then slowly passes over the stop bar by a few inches or feet. This does not represent a driver who is likely to have increased risk of a collision or traffic ticket and thus would not need to be warned. Similarly, drivers that stop late by crossing over the stopbar without significantly entering the intersection are not likely to have increased collision risk nor receive a ticket. Eight feet was selected as the criteria because it represents approximately half the length of a typical vehicle crossing over the stopar. Late stoppers passing more than eight feet over the stopbar significantly enter the intersection and could potentially receive a ticket. Changing this allowance does effect how violations are distributed among the three driver states Table 12). If the allowance is removed ten violations occur due to creeping. At the other extreme, if the allowance is set at 15 feet or higher all stopping violators are removed. If the allowance is set at eight feet a total of 30 violations occur with 0 in the baseline state, 29 distracted, and 1 willful.

Table 12: Number of Violations by Driver State and Phase Change Distance at 0,5,8,10,&15 foot violation allowances

Driver State	Phase Change Distance	Number of Violations					Number of Violations by Driver State @ 8 ft
		0ft (0m)	5ft (1.5m)	8ft (2.4m)	10ft (3.0m)	15ft (4.6m)	
Baseline	100 ft (30.48m)	2	0	0	0	0	0
	127 ft (38.71m)	2	0	0	0	0	
	157 ft (47.85m)	4	1	0	0	0	
	185 ft (56.39m)	1	0	0	0	0	
	228 ft (69.49m)	1	0	0	0	0	
Distracted	100 ft (30.48m)	0	0	0	0	0	29
	127 ft (38.71m)	0	0	0	0	0	
	157 ft (47.85m)	1	1	1	1	1	
	185 ft (56.39m)	9	9	9	9	8	
	228 ft (69.49m)	19	19	19	19	18	
Willful	100 ft (30.48m)	0	0	0	0	0	1
	127 ft (38.71m)	0	0	0	0	0	
	157 ft (47.85m)	1	1	0	0	0	
	185 ft (56.39m)	0	0	0	0	0	
	228 ft (69.49m)	2	1	1	1	1	
Total Violations by Allowance		42	31	30	30	28	

To test if violation rate (number of violations/number of opportunities) was related to driver state an ANOVA analysis was used (n = 84). For the ANOVA analysis the data set was collapsed by driver state and subject. Violation rate was then treated as the dependent variable using driver state, age, and gender as the independent variables. Results demonstrated a significant effect for driver state ($F(2,28)=19.66, p=0.0008$) and gender ($F(1,28)=7.90 ,p=0.0483$).

A post-hoc Tukey test was executed on driver state to isolate the significant effects. This showed that the baseline and willful driver states are not statistically different from each other. However, distracted drivers do violate more frequently than either the baseline or willful drivers ($p < 0.0001$). The mean baseline violations were lowest with a rate of 0.000, followed by willful drivers at 0.017, and the statistically isolated distracted driver state with 0.211 violations per crossing.

Exploration of the significant gender main effect demonstrated that females tended to violate more often than males. Males violated the traffic control device 6.3% (13 instances) while females violated 8.6% (18 instances). This result in unexpected given that males in general stopped less frequently than females. In a study by Caird & Hancock (1994) it was indicated that males tended to make better judgments regarding the available time for making an intersection crossing. Perhaps male drivers were able to more accurately judge the remaining amber time such that fewer violations resulted.

J.2 RQ 2: WHERE SHOULD THE CRITICAL POINT OF DIVERGENCE BE LOCATED?

Across driver state, the range-rate distributions of compliant and violating drivers should diverge at some point upstream of the intersection (Figure 23). This critical point represents the distance at which a point detection IDS system can decide whether or not an approaching vehicle is likely to violate the TCD. Finding a point at which compliant drivers can be distinguished from violators is a difficult problem. It may seem as though an ANOVA analysis could be used to determine the point at which the stop and go profiles become significantly different. From this confidence intervals could be defined using least squares means. This would provide trigger information about the population rather than the sample. However, inferential statistics are based on means and the variance of those means. The goal of this analysis is to look at the behavior of all drivers, and in particular the relatively rare violating driver. For example, if an ANOVA is used on a data set using stop as the dependent variable a significant Stop*Distance interaction is identified. Tukey post-hoc analysis indicates that the means first become significantly different at 152 ft (46.3m) +5.5 ft (1.7m) /-1.5ft (0.5m) with 99.99% confidence. However, if this trigger is overlaid on the data collected from this study many misses and false alarms would result. Thus small sample statistics are used to explore the trigger point.

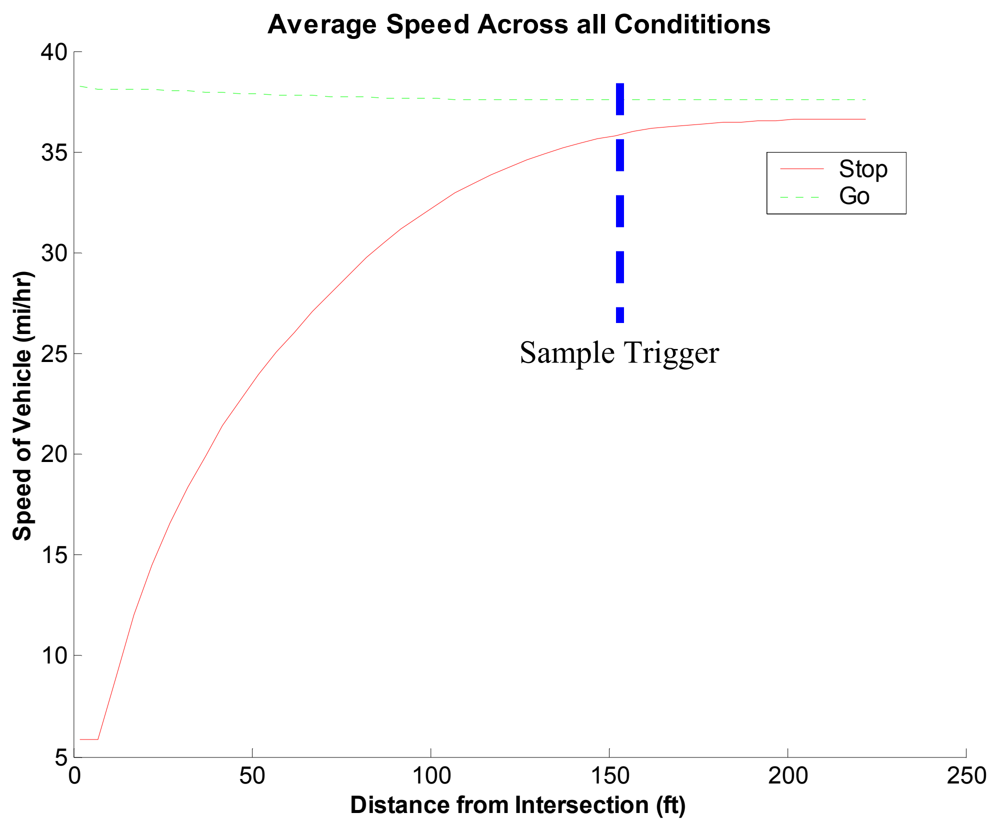

Figure 23: Range-rate distribution for violators and non-violators

The problem of locating the critical point is much like a controls problem using signal detection theory. Depending on the location of the critical point there will be a certain percentage of correctly identified violator (hits) and correctly identified compliant (correct rejections) drivers. However, there will also be violators who were not warned (misses) and compliant drivers who were warned (false alarms). This relationship is demonstrated by the normal curves for violator and compliant drivers (Figure 24).

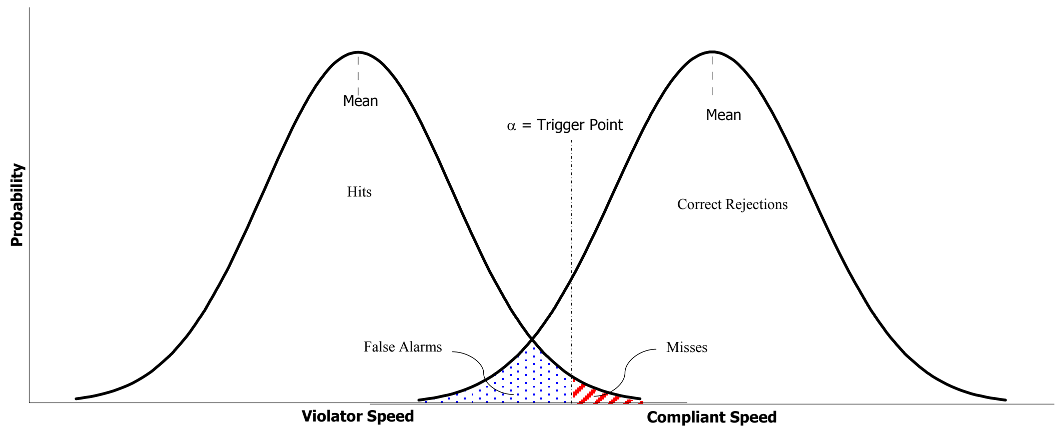

Figure 24: Probability distribution for rate of violator and compliant drivers at critical point

A miss represents the condition in which a violating driver was not warned and inappropriately entered the intersection. It is assumed that if a violator had received a warning he/she could have modified his/her behavior and avoided the violation. Thus an IDS system should minimize the number of misses as they have a higher probability of causing a conflict. Therefore to control the number of allowable misses alpha values of 0.2, 0.1, 0.05, and 0.01 are selected. This correlates to correctly identifying violators 80%, 90%, 95% and 99% respectively. However, while this controls the percentage of misses, the number of false alarms will vary as the critical distance moves.

If a critical distance is selected very close to the intersection the two normal curves will be non-overlapping resulting in no false alarms or misses. However, the alarm would be too late for the driver to perceive, react and stop. As distance increases the curves will move towards each other; overlap will increase until the two are completely confounded. The percentage of false alarms will rise with increasing overlap. From signal detection theory we know false alarms create problems such as decreased user confidence and annoyance. Thus, there is a tradeoff between the number of false alarms and maximizing the distance to the critical point. Determining the number of acceptable false alarms is not in the scope of this research project. Rather the output of this analysis is a plot of false alarms vs. distance for each of the alpha values. This will allow future designers to determine where to set the critical point based on the acceptable false alarm rates and misses.

The critical point was determined using an analysis of range-rate data. All drivers who chose to go were separated from those who chose to stop. It was then assumed that all drivers that chose to go were violators. In other words, it is assumed that the approach profile of a violating driver is not different that a driver that decides to go. Mean speed and confidence intervals were calculated by distance for drivers that opted to go. Thus, depending on the value of alpha, 80%, 90%, 95% or 99% of the drivers that chose to go will fall above the lower confidence interval. The lower confidence interval tended to oscillate within 0.5mph indicating that the use of a constant speed rather than as a function of distance was appropriate (a negligible impact on false alarms was noted). The constant speed trigger was calculated by averaging the lower confidence limit data across distance. This resulted in the trigger speeds as indicated in Table 13 and overlaid on a scatter plot in Figure 25.

Table 13: Trigger speeds for five alpha levels

Alpha	(1-Alpha) *100	Trigger Speed
0.2	80%	37.53 mi/hr (60.40 km/h)
.15	85%	35.22 mi/hr (56.68km/h)
.1	90%	34.64 mi/hr (55.75 km/h)
.05	95%	33.76 mi/hr (54.33 km/h)
.01	99%	32.16 mi/hr (51.76 km/h)

Questions about the level of appropriateness arise when considering the trigger speeds. High alpha values create trigger speeds that exceed the 35mph speed limit. This assumes that any violating driver is exceeding the speed limit when a trigger distance is crossed. While speeding is more likely for a willful driver (based upon previously presented results) it is not necessarily more likely for a distracted driver. A system that measures speed at multiple discrete points may be able to use a different alpha value for each distance. This design option will be discussed in further detail later in this section.

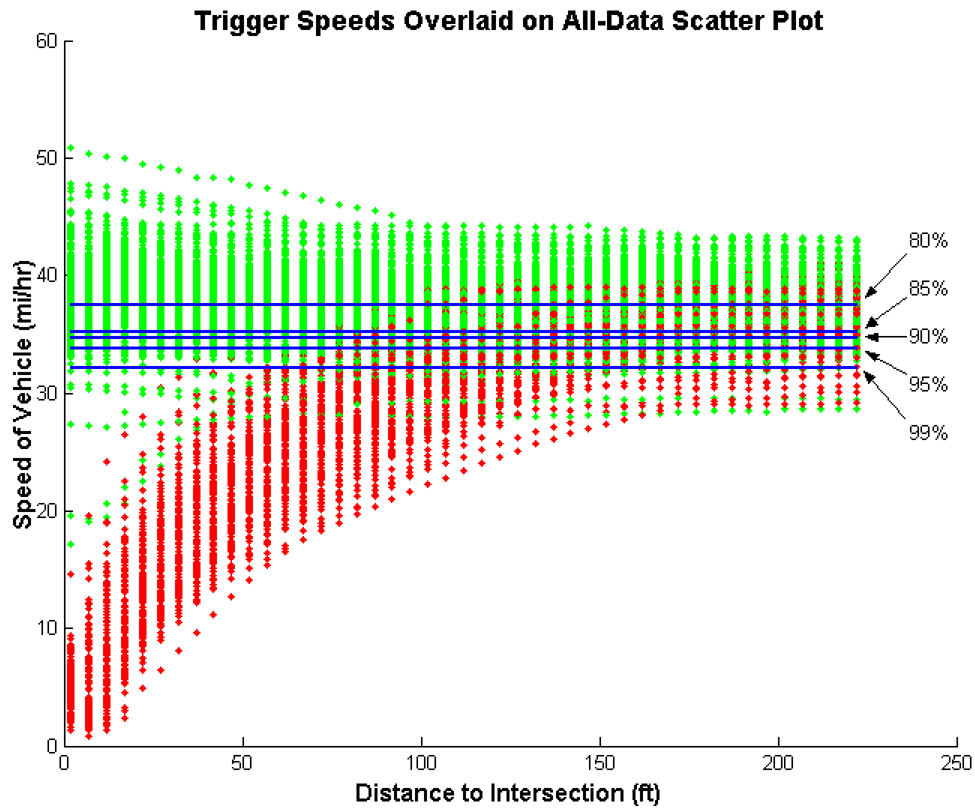

Figure 25: Trigger speeds overlaid on scatter-plot of drivers who chose to go and drivers who chose to stop.

When a "will-be" stopper's approach lies above the trigger line at the critical distance in Figure 28 an unnecessary alarm has occurred. That is, the driver would have been alerted despite the fact that they would have stopped without the warning. These are not necessarily inappropriate alarms as these drivers perhaps should have been warned even though they stopped. For instance, in the distracted driver case the driver received the amber indication late. Thus, although they did react and stop the vehicle, a late reaction time and high deceleration relative to a baseline driver occurred. Thus, the profile was sufficiently aggressive to initiate the alarm. Since the driver was indeed distracted this should not be considered a false alarm; the system functioned as intended. Thus the term unnecessary alarm will be used to describe conditions in which the alarm would have initiated even though the driver stopped without its assistance.

For a given critical distance the number of unnecessary alarms is the sum of the stop profiles lying above the trigger line. A few assumptions can be made to reduce the number of unnecessary alarms that occur. The first assumption involves ignoring any driver that can safely pass through the intersection if they simply maintain 35mph. Safely passing through the intersection doesn't necessarily indicate that a violation did not occur. Rather, it indicates that ample time is available for a driver to clear the intersection before cross traffic has entered the path of a violator. In this experiment the first four phase change distances are sufficiently close to the intersection such that drivers could cross safely without significant acceleration. Indecision could lead to a decrease in speed such that a violation does occur. However, it is unlikely that this indecision will lead to a sufficiently late intersection crossing to result in an accident. Thus for the false alarm analysis only intersection crossings in which the phase change initiated at the furthest distance (228ft) are considered. As expected the number of unnecessary alarms increases with distance from the intersection (Figure 27). The number of unnecessary alarms can be further reduced if the distance from the stopbar to the pathway of the adjacent vehicles is added to the intersection distance. This assumes that drivers will continue to brake after they have crossed the stopbar (an assumption that must be verified in future work). For the intersection used in this study an extra 30 feet can be added which will slide the curves in Figure 27 to the right by 30 feet.

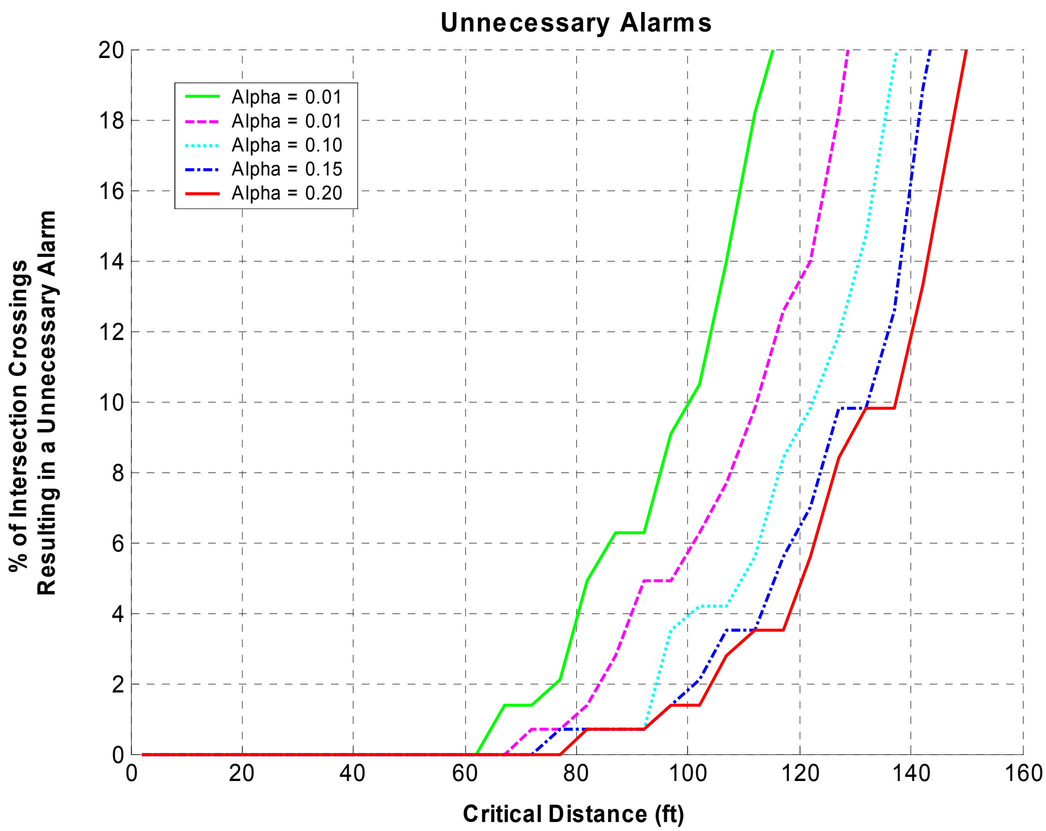

Figure 26: The percentage of unnecessary alarms as a function of critical distance and alpha (corresponds to trigger speed) for all driver states.

The data set was skewed to represent overly aggressive and distracted drivers. It has been shown that these drivers tend to brake later than baseline drivers. The late braking requires a rate of deceleration that is higher than a typical driver performs. Thus, it is foreseeable that it would be appropriate to warn these drivers even though they would have stopped without a warning. To determine the true false alarms the plot above is repeated for the baseline drivers only Figure 27. Drivers in the baseline condition do not need a warning as they intended to stop. Thus, drivers that are warned in the baseline condition are almost certainly true false alarms. IDS designers should work to minimize the number of these false alarms.

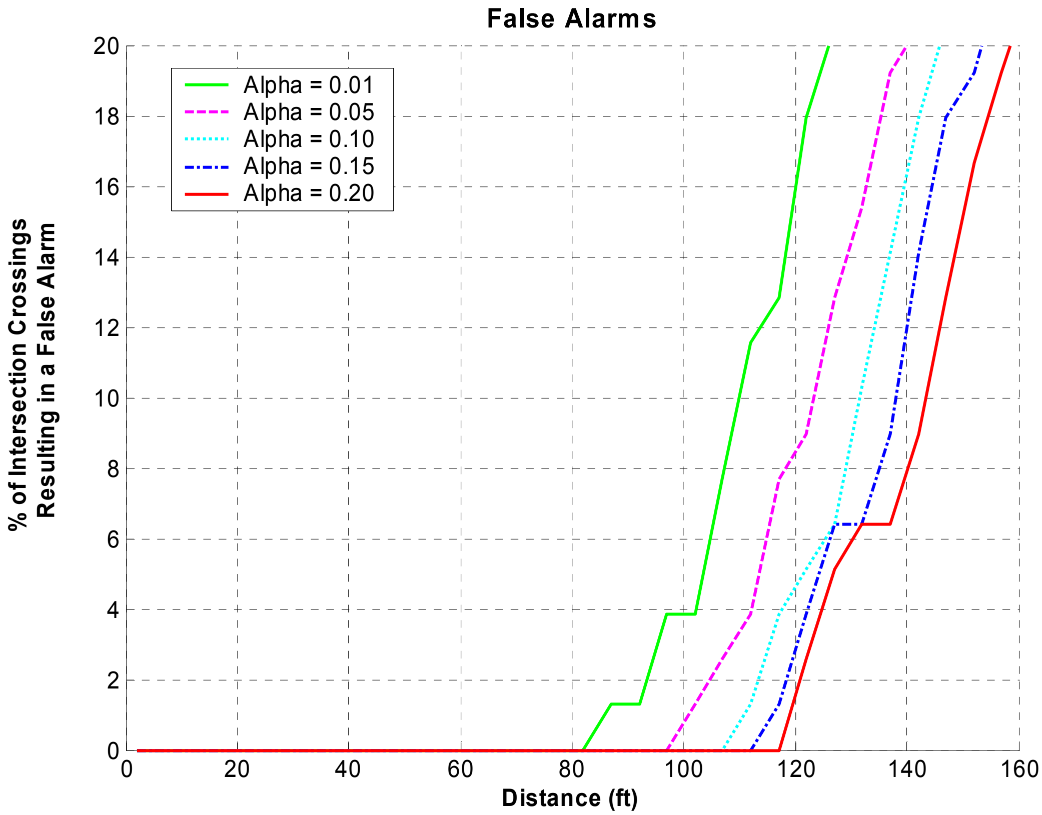

Figure 27: The percentage of false alarms as a function of critical distance and alpha (corresponds to trigger speed) for baseline drivers only.

The above plot suggests that with an alpha value of 0.01 (32mph) a trigger distance set at 80 feet is the furthest point from the intersection that will result in no false alarms. At this point 4% of the drivers will receive unnecessary alarms. The drivers receiving this alarm are primarily in the distracted condition due to the late braking profile. To further consider the implications of setting the critical distance at 80 feet a required braking rate plot is provided (Figure 28). This plot was generated using basic the basic kinematics equations of motion. It displays the mean rate of deceleration required to stop depending on the distance at which the warning is initiated and assuming a 0.5, 1, or 1.5 second reaction time. At a trigger distance of 80 feet a mean deceleration rate of near 1g is required to stop. Deceleration rates in this range will not be acceptable to drivers much less in the capability of the vehicle. If it is assumed that a driver will continue to stop after the stopbar has been crossed an additional 30 feet can be added to the distance available for stopping. This provides 110 feet of stopping distance rather than 80 feet corresponding to a still unrealistic .7g assuming a rather optimistic one second reaction time.

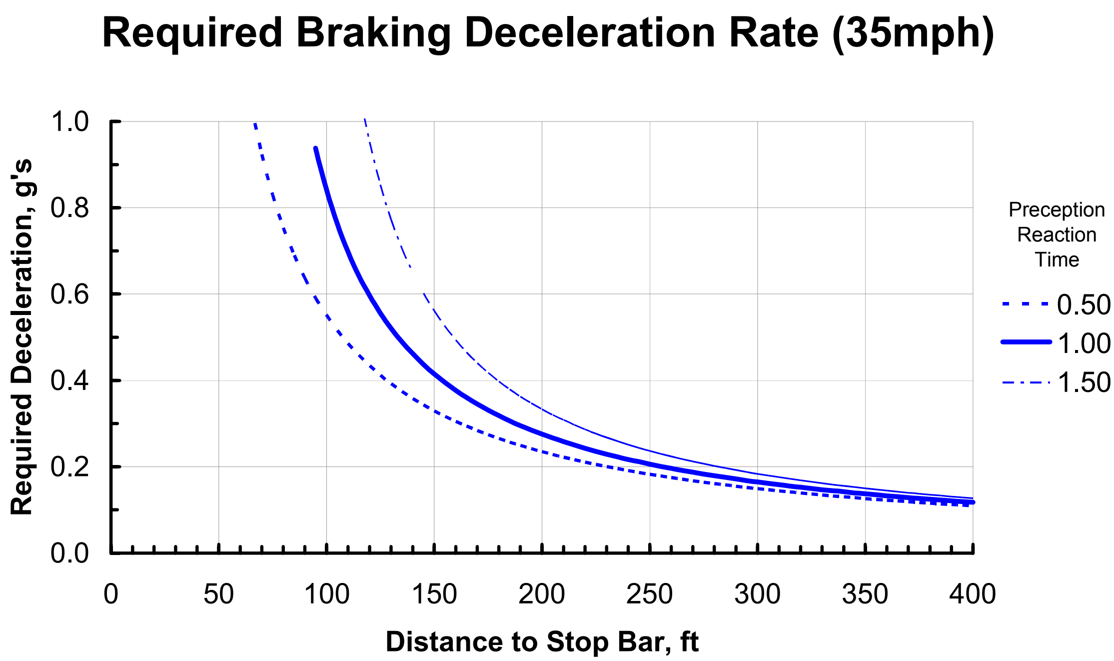

Figure 28: Required deceleration rate as a function of distance at which the alarm is initiated for perception reaction times of .5, 1, and 1.5 seconds and assuming an initial speed of 35mph

If it is decided that missing some violators is acceptable the trigger speed (alpha) can be increased. Or, if it is decided that a certain percentage of false alarms is acceptable the trigger distance can increase. For instance, if alpha is increased to 0.05 (34mph) and we accept a 2% false alarm rate, a triggering distance of 130 feet is selected. With an assumed one second reaction time this corresponds to a sub 0.5g mean deceleration rate. As indicated during the acceleration analysis it is reasonable to assume drivers are willing to brake at this level. However, it is not unusual for a distracted driver to demonstrate significantly higher perception reaction times. If a 1.5 second reaction time is assumed the required mean deceleration rate is once again an unreasonable 0.8g (though if the 30 allowance is assumed to be valid a 0.5g average is needed). Continuing to increase alpha creates trigger speeds that exceed the speed limit. This would miss any driver that is not speeding negating the safety enhancement for law-abiding drivers. Such an approach seems an unacceptable compromise. Compounding of the triggering problem occurs when speeders are considered. The required mean rate of deceleration increases substantially with increased approach speed (Figure 29).

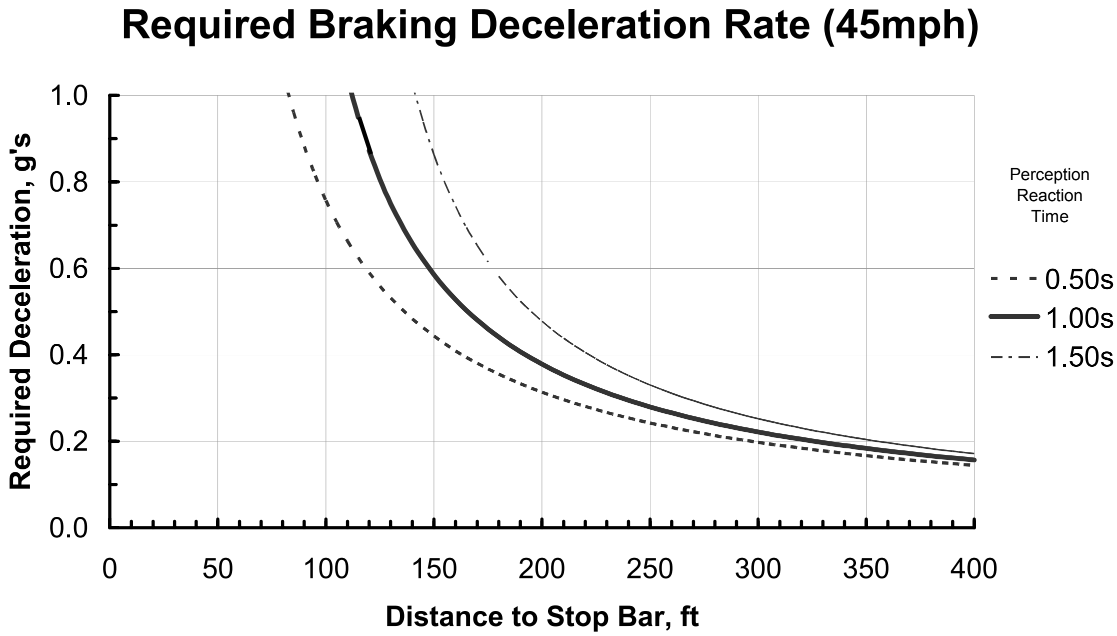

Figure 29: Required deceleration rate as a function of distance at which the alarm is initiated for perception reaction times of .5, 1, and 1.5 second and assuming an initial speed of 45mph

It is not unusual for drivers to exceed the posted speed limit in excess of 10mph. Speeders can substantially impact the performance of a single point detection intersection algorithm. For instance, in the last scenario described the critical distance was 130 feet which corresponded to a realistic 0.5g mean deceleration with an assumed one second reaction time. For the speeding driver, this once again corresponds to an unrealistic 0.75g deceleration. Yet the speeding driver represents the highest potential for severe injury and thus should not be disregarded. Several factors have been shown to negatively impact single point detection such that it doesn't appear feasible. However, this doesn't preclude the use of a multiple point detection system.

A multiple point detection system would take several discrete speed samples at various distances from the intersection. Detection points far from the intersection would use speed triggers that may be set higher than the speed limit to warn speeding drivers. As the intersection is approached the speed triggers will decrease corresponding to the distance needed for drivers to stop. In this way the trigger alpha values can be kept sufficiently low to minimize misses. Trigger distances may also be selected to minimize false alarms. Unfortunately as this analysis is based only on 35mph drivers, the information necessary to construct a multipoint algorithm is not yet available. This analysis can be used to define a single point in the multipoint detection using the information provided previously. The selection of this critical point will depend on the number and characteristics of the other points selected in the multipoint array. The array will need to be developed as a system by integrating this information with data from future studies.

J.3 RQ 3: Can potential violators be predicted using the questionnaire - based measures of aggressiveness

To explore the utility of the questionnaire data in an intersection violation scenario, a Pearson Correlation analysis was performed. To do this, the total-scores as well as subscale partial-scores for each questionnaire were first tallied. The driving performance measures were then independently averaged across all stops for each participant. This resulted in a data set with 28 observations (one for each participant) with scores for the questionnaires total-scale and subscales; and the driving variables TB, TAR, peak deceleration, and mean declaration. The correlation demonstrated several significant relationships between both the driving variables and the questionnaires, as well as between the questionnaires themselves (Appendix J.6.2). For clarity the relevant correlations are separated into two tables, one for comparing the questionnaires scores to the classification and driving performance variables and the other for comparing the two questionnaires (Table 14 & Table 15 respectively).

Table 14: Correlation matrix of pre-driving questionnaires with performance measures

.	Subscale	TB	TAR	Peak Accel	Avg Accel
DDDI (p-value)	Aggressive Driving	-0.360 (.060)	-0.202 (.303)	0.110 (.579)	0.127 (.521)
	Negative Emotions	0.339 (.078)	0.206 (.293)	0.340 (.077)	0.190 (.333)
	Risky Driving	0.148 (.519)	0.148 (.454)	**0.411* (.030)**	0.330 (.087)
	Total Score	0.187 (.350)	0.210 (.294)	**-0.411 (.030)**	0.362 (.063)
DSI (p-value)	Aggression	0.356 (.063)	0.256 (.188)	0.291 (.133)	0.273 (.289)
	Dislike of Driving	0.195 (.320)	0.232 (.235)	0.219 (.264)	0.120 (.542)
	Hazard Monitoring	**-0.387* (.042)**	**-0.478* (.010)**	0.076 (.700)	0.076 (.700)
	Fatigue Proneness	-0.044 (.8230	0.0650 (.743)	-0.180 (.360)	-0.262 (.178)
	Thrill Seeking	0.253 (.195)	0.242 (.215)	**0.377* (.048)**	**0.388* (.041)**
	Total Score	-0.051 (.798)	0.030 (.881)	-0.197 (.315)	-0.273 (.159)

The correlation analysis did not demonstrate particularly strong relationships between the questionnaires and intersection approach behavior. Age group had the highest number of significant correlations with both driving questionnaires. For the DDDI younger drivers tended to score higher on the total-score and the Aggressive Driving subscale. Past research has demonstrated a tendency for younger drivers to be more aggressive at intersections (Sivak, Soler, & Trankle, 1989). This trend is further verified by the DSI in which younger drivers tended to be more aggressive, show a lower regard for hazard monitoring and a have high tendency for thrill seeking. Interestingly, unlike the DDDI, the total DSI score was not significant and had a low correlation with age group. This is likely due to differences in the measures of the two scales. The DDDI subscales measure dangerous driving in a consistent direction (i.e. dangerous drivers tend to score low on all subscales). The DSI switches direction in that high scores on measures such as Thrill Seeking are more dangerous while high scores on Hazard Monitoring indicate a safer driver. Thus it is likely inappropriate to use the total DSI score, as indicated by the lack of correlation across all measures. A search of past studies using the DSI indicated that only the subscales are typically evaluated, whereas the authors of the DDDI recommend using the total score as well as the subscales.

The literature review demonstrated mixed results for gender differences in intersection behavior. Although males are often categorized by society as tending to be more risky drivers, results of the correlation did not typically support this belief. The exception is with males tending to be thrill seekers as defined by the DSI. Previous analysis showed males were more likely to decide to go when faced with a changing signal phase, which may reflect this thrill seeking measure.

Both reaction time variables are correlated with the Hazard Monitoring subscale of the DSI. This may indicate that drivers who carefully observe the driving environment to identify hazards also react faster. That is these drivers have a defensive driving style in which they may be more prepared to react to a hazardous situation. To these drivers the changing signal may be viewed as a hazard such that the driver is prepared to react faster.

Peak deceleration is correlated with Risky Driving and the total DDDI scales. Both peak deceleration and mean deceleration are correlated with Thrill Seeking under the DSI. As discussed previously, Thrill Seeking and Risky Driving are defined similarly. Drivers who tend to be more aggressive or thrill seeking also appear to be willing to decelerate at higher rates than those who score lower on those scales.

From an applied standpoint none of the correlations are high enough to represent good predictors of signal approach behavior. It may be that the experimental conditions, or surrogate measures used during this study were not sufficiently sensitive to the scales. However, it is more likely that the dangerous driving characteristics measured by the questionnaires were not highly reflected during the course of this experiment. The experimental setting and duration may inherently cause drivers to drive in a more cautious manner than they would typically do. Thus there may have been a less dramatic difference in driving performance measures of dangerous verses safe drivers. A longer, naturalistic type driving experiment may demonstrate higher correlations between intersection approach performance and the questionnaire measures.

The DDDI is a relatively recent scale that has been validated with several other behavioral scales (Dula & Ballard, 2003). These scales included the Propensity for Angry Driving scale, the Trait Anger Expression Inventory, and the Interpersonal Behavior Survey Short Form. However, to date the DDDI has not been validated with a robust time-tested driving questionnaire such as the DSI. To explore the relationship between the two scales, a correlation of the two was computed (Table 16).

Table 15: Correlation matrix of pre-driving questionnaires

Questionnaire		DSI (p-value)					
	Subscale	Aggression	Dislike of Driving	Hazard Monitoring	Fatigue Proneness	Thrill Seeking	Total Score
DDDI (p-value)	Aggressive Driving	**0.528 (.005)**	**0.517 (.006)**	**-0.420 (.029)**	0.337 (.092)	**0.405 (.036)**	**-0.407 (.040)**
	Negative Emotions	**0.665 (<.001)**	0.343 (.074)	-0.253 (.213)	0.160 (.425)	0.324 (.092)	-0.039 (.845)
	Risky Driving	**0.408 (.031)**	0.225 (.225)	-0.224 (.253)	0.090 (.654)	**0.490 (.008)**	0.282 (.154)
	Total Score	**0.630 (<.001)**	**0.441 (.021)**	-0.311 (.114)	0.249 (.220)	**0.448 (.012)**	**0.421 (.032)**

Results from the Person Correlation indicate that the DDDI is weighted toward the DSI's definition of aggression. All of the DDDI subscales are correlated with Aggression, several of which show relatively high correlations. The DDDI's definition of Aggressive Driving also tends to be correlated with most of the subscales of the DSI. As stated by Dula and Geller (2002), aggressive driving is difficult to define and may thus be measured to some extent by other subscales. Thrill Seeking also correlates well with aggressive and risky driving. It is logical that a thrill seeking driver would tend to drive in a more aggressive or risky manner.

Overall the pattern of correlation indicates that the two scales measure different but complimentary attributes of the driver behavior. Both scales appear to measure an overall level of aggressiveness towards driving. However, the lack of correlation among most pairs of the subscales indicates uniqueness between the scales. In particular, the DSI subscale Fatigue Proneness is uncorrelated with all DDDI scales. Because of the significant correlation between many of the factors, future researchers should consider selecting the scale that more directly measures the attributes of interest; rather than using both questionnaires. This simple correlation was not intended to be a complete comparative analysis of the two questionnaires. Researchers wishing to do further comparisons should consider other explorative methods such as cluster analysis.

D.0 Conclusions

The design of IDS systems requires knowledge about driver behavior during the intersection approach. The primary use of the information provided herein is to help decide when and how a countermeasure should be deployed. However, prior to designing an IDS prediction algorithm, engineers must first understand the characteristics of the intersection approach that result in a violation. Thus, it was necessary for this experiment to collect data about intersection approaches that were likely to result in a violation.

It is difficult to gather data with regard to intersection violations. Signal violation is a relatively rare event that is complex to recreate on a test-track. Historically, the first signalized intersection was installed in London over 120 years ago--before the automobile was even invented. Over time traffic engineers have refined the original design such that, based upon vehicle kinematics, a violation should never occur. Traffic signals are designed to allow sufficient time for drivers to make a correct decision each time they approach the intersection. However, variation in human behavior precludes the realization of a perfect system. The problem arises when drivers either allocate insufficient attention to the TCD or believe that the benefit of crossing the intersection overrides the penalty of violating it.

To understand how violations occur, drivers in this experiment had to be placed in situations that recreated the approaches of imprudent and aggressive drivers. To do this, the present study induced willful and distracted behaviors that represented drivers with a high risk for violation. For the distracted condition, the driver had a long simulated distraction that reduced their ability to make a correct decision while approaching the signal. Complementing this was the willful driver state that provided a high motivation to violate in the form of monetary bonuses. As was expected, the results indicated that drivers in the willful and distracted states were more likely to violate the signal. The approaches of these drivers were compared with baseline approach behaviors to better understand how drivers violate TCDs. In this regard, the information presented can be considered as a tool for designers of IDS solutions.

The IDS algorithm must be capable of identifying a driver that is likely to violate the signal. However, the system does not need to know if the approaching driver is distracted or willful. Rather, the system must only be sensitive to characteristics of the approach that imply an impending violation. The data from this research indicates that this is an important distinction to make. While distracted and willful drivers do violate more often, there are instances in which their approaches are indistinguishable from a baseline approach. The variation in human behavior during an intersection approach is larger than the average differences between driver states. For instance, a baseline driver that has a hard-braking driving style will exhibit the same deceleration level as a driver that typically brakes lightly but was distracted and, thus, had to brake hard in order to stop.

The IDS designer should consider the differences between the driver states, while realizing that the algorithm itself will not be capable of discriminating between these groups. It is important to consider the differences between driver states because they do indicate a likelihood of violation: the tendency of a distracted driver to brake late increases the chance that a violation will occur but does not guarantee it. Triggering on a driver that applies the brakes late would create a system that is responsive to the distracted driver. However, it would also provide a false alarm for the occasional baseline driver who simply has an aggressive stopping style. The data suggests that there is better separation between violator and compliant drivers than there is between driver states. Thus, an algorithm should judge an approaching vehicle on likelihood of violation without predicting driver state.

The following discussion begins by first describing how the driver states differ and what makes distracted and willful drivers the targets of violation detection systems. Further detail on how to discriminate between violators and compliant drivers is also discussed. Using this knowledge the discussion will continue into the theoretical construct of situational awareness and its implications to the design of an IDS system. Finally, the study's limitations as well as its implications for future research are reviewed.

J.1 ALGORITHM DEVELOPMENT

Knowledge of intersection approach profiles will allow designers of IDS systems to tailor device sensitivity towards criteria that indicate a probability of violation. There are characteristics of the approach that occur more frequently under some driver states that provide information on the likelihood of violation. For instance, an appropriately designed algorithm may recognize the early beginning deceleration of a baseline driver and assume that driver will stop even if their speed is high. Results of this research demonstrated that a distracted driver will decelerate later and has the highest risk for violation. Consequently, distracted drivers also likely represent the highest intersection collision risk. Similarly, the willful driver tends to exhibit speeding and early acceleration as well as increased violation risk. The tendency for willful drivers to speed and accelerate through the intersection may result in more severe injuries if collisions occur. An appropriately designed algorithm will discern these behaviors and deduce increased likelihood of a violation.

In addition, these trends have implications for the design of the overall IDS system. For instance, in the case of a willful driver, the IDS system may need to convince drivers that their intention to drive through the intersection is incorrect and that they must instead choose to stop to avoid violating the signal. For the distracted driver, the IDS system must decrease the size of the dilemma zone by shortening the driver's reaction time. This will require quickly attaining their attention and effectively conveying the stop message.

As discussed previously, the data from this study suggests that a deployed algorithm will only be capable of predicting a violation and not the mental state of the driver. This is because there is insufficient separation between driver states to reliably make a categorical decision at a reasonable distance from the intersection. Although there were many statistically significant driver state effects, baseline drivers sometimes exhibited similar approaches to their distracted and willful counterparts. This is because of the statistical emphasis on capturing differences in means rather than outer limits. Given that an IDS system is only interested in the rare violation case, statistical differences between groups, while informative and useful in developing algorithm ideas, will not be applicable to a deployed algorithm.

This suggests that to develop an algorithm, the three driving states should not be viewed as independent driver groups, but rather, should be combined into a single data set that encompasses the entire range of intersection approaches. Within this single data set, some drivers will stop, some will maintain their speed, and others will accelerate at various distances from the intersection. In the end, some of these drivers will violate the signal; the remaining drivers will either legally stop or legally go. Once data is gathered, it is more prudent to view it only in terms of violators, and non violators. Algorithms can then be evaluated solely in terms of how well they predict violations and not how well they predict the state of the driver. This is difficult given the rare occurrence of violations. Even in this controlled study, in which attempts to elicit violations were made, only 30 out of 588 intersection approaches resulted in an illegal crossing. For this reason, a simplifying assumption was made during the point-detection algorithm test. This assumption classified all drivers who chose to go, regardless of actual legality, as violators. As discussed previously, this method provided a sufficient sample size to draw conclusions about the abilities of a single-point algorithm. This assumption has been used previously in intersection collision avoidance research to determine the feasibility of point detection in the field (BMI, 2003). At the current state of the art, this is still a reasonable assumption to make. It provides researchers with the ability to efficiently gather information and to test various system concepts. However, as this technology moves forward, field operational tests will be required to validate this assumption and to analyze violations as they occur.

Results presented during the exploration of the single-point detection method indicated that point detection is an insufficient violation-prediction method. In order for the single-point system to correctly identify violators upstream of the intersection, an unacceptable number of false alarms would be produced. These false alarms would likely annoy drivers, thus causing them to disregard the alarm.,deflating any potential safety benefit (Wickens & Hollands, 2000). Point detection is ineffective because of the difficulty in identifying a violator based on a single measure. The range-rate approach profile of a violating vs. compliant driver may look identical at 100 feet but completely different at 90 feet. The point at which they diverge is not consistent and depends on the individual driving style of each driver. Complicating the issue is the need to warn drivers at differing locations depending on the initial speed of the vehicle. Drivers approaching the intersection at higher rates (i.e., willful speeder) must receive the warning earlier in order for them to have sufficient time to react and stop the vehicle. This suggests that the location of the critical detection point is dependent on initial speed. It will be important for an IDS system to warn vehicles that approach the intersection in excess of the speed limit, given that speeding is not uncommon and may contribute to the intersection crash problem. In addition, it appears as though range-rate may not be the best predictor of violation. Rather, measures such as deceleration could be more sensitive to the intentions of the approaching driver.

The shortcomings of point detection suggest that other types of predictive algorithms should be considered. Continuous and multi-point detection algorithms are in development. Unlike point detection, these types of algorithms will not contain a single "critical point." For the multi-point algorithm, there will be several critical points, and for continuous detection, the number of critical points will be limited only by the system's ability to process information. The current iteration of these algorithms makes use of basic kinematic equations of motion, which require several assumptions. While it is not the intent of this document to provide final design guidelines for these algorithms, some preliminary considerations are worth noting.

Predicting an imminent violation will require knowledge of the dynamic environment, including, though not limited to, range, range-rate, and possibly acceleration. In addition to these real-time variables, the algorithms make assumptions regarding the driver's ability to react to the countermeasure in terms of reaction time and perceived maximum deceleration rate. The data collected suggests some initial inputs into developing this type of algorithm.

Interestingly, the results of this study indicated that the difference in the urgency of the stop was only reflected in the deceleration level and not in reaction time. In other words, drivers who elected to stop closer to the intersection applied the brake harder but not faster than drivers who elected to stop far from the intersection. On occasions when a stop decision was made, drivers also reacted in about the same time, regardless of their mental state (recall the nature of the simulated distraction did not induce higher TB values). This finding suggests that a mean reaction time parameter can be implemented into an algorithm without considerable negative effects on accuracy. For algorithm use, reaction time is typically defined as the time from when the warning is initiated until the brake is depressed. Since a warning was not available to drivers during this study, the TB variable can be used in its place. Recall that TB was operationally defined as the time from the amber presentation until the initial brake depression. The TB measured during this study may underestimate the perception reaction time of a driver to an actual warning. This is primarily due to the nature of the experiment. Drivers were aware of the intersection and the elevated occurrence of phase changes. It is possible that drivers allocated extra attentional resources to the signal and prepared to take some form of action. In particular, the simulated distraction did not increase reaction time as one would expect from an actual secondary task. With these limitations in mind, designers should use the 0.37 second mean TB as an initial algorithm input. As further studies are undertaken, this value will undoubtedly change as it will also be dependent on the effectiveness of the countermeasure or warning used.

Average deceleration rate is also a likely input into continuous kinematic algorithms. For instance, this study indicated that drivers will not stop at a deceleration rate higher than 0.5g. Therefore, the algorithm should initially assume a 0.5g maximum average deceleration. That is, drivers need to be warned at a distance-to-intersection that requires 0.5g or less to stop. At 35 mph with an assumed reaction time of 0.37 sec, this translates to a warning distance of approximately 100 feet.

These parameters should provide good initial values for IDS algorithms. New algorithms may use additional variables or methods to which these scalar values will not be applicable. For instance, an algorithm may use a real-time acceleration rate that is dependent on intersection range and range-rate. While the data collected is capable of producing such an equation, additional analysis will need to be completed as novel algorithms are invented.

J.2 IMPLICATIONS OF SITUATIONAL AWARENESS

It is of interest to note the relevance of situational awareness (SA) to the intersection approach scenario.   Proponents of SA will identify differences in approach profiles as the result of unequal SA between driver states. A frequently accepted definition of situational awareness is presented by Endsley (1988): "Situational Awareness is the perception of the elements in the environment within a volume of time and space, the comprehension of their meaning, and a projection of their status in the near future." A decision making process in a dynamic environment, such as that of the approaching driver, requires an understanding of the current and future situation (Wickens & Hollands, 2000). In general, a driver with a higher awareness of the situation should be able to execute a choice more rapidly and accurately than a driver who is less aware. Endsley (1995) developed a three-level model of SA which included: Level 1) perception of the elements in the environment, Level 2) comprehension of the current situation, and Level 3) prediction of future status. The level of situational awareness exhibited by a person increases as an understanding of each level is obtained. Awareness acquired in levels two and three depends on the accuracy and grasp of the information obtained during lower levels.

In Endsley's three-level framework, the approach profiles of drivers in each state can be contrasted for both the experimental setup used in this study and the naturalistic environment (a driver on the open roadway outside the experimental environment). The following discussion will individually consider the implications of SA during the intersection approach for each driver state. Within each driver state, the implications of SA are further broken down into the experimental and naturalistic contexts.

The baseline driver, whether in the experiment or naturalistically, has the highest SA. This driver should have a complete perception of the elements in the environment (Level 1 SA) and a good comprehension of the current situation (Level 2 SA). The relatively simple driving environment encountered in the experiment (i.e., no traffic and low visual clutter) probably increased SA in these levels over that of the naturalistic driver. It is also likely that baseline drivers in the experiment had a higher SA in Level 3 than their naturalistic counterparts. This is because of an expectation that developed while drivers repeatedly crossed the intersection. Repetition allowed drivers to better predict future events based on their past experience.

A driver in the willful state should have a similar level of SA to that of the baseline driver. The largest difference between these driver states, and a probable reason for increased violations in the willful state, is the reliance on Level 3 SA. A baseline driver is more likely to err on the side of caution when the prediction of future events is not certain (i.e., when the light will turn red relative to vehicle position). In contrast, the highly motivated willful driver is more likely to assume that the Level 3 data is sufficiently reliable to make a go judgment, even if its accuracy is uncertain. The experimental and naturalistic contexts differ in the motivation that stimulates the aggressive go decisions. For example, motivations such as being late to work may be different than the monetary incentive used in this study. As with baseline drivers, there may be some differences across Level 1 and Level 2 SA due to the controlled nature of the experiment.

Alternatively, the distracted driver demonstrates a lapse in SA across all three levels. At Level 1, the naturalistic distracted driver may have incorrectly and/or incompletely perceived the elements in the situation. They may have neglected to notice surrounding traffic, signal-ahead signs, current signal phase, and possibly the signal itself. This is in contrast to the experiment in which a simulated distraction was used. In the simulation, only one cue was missing from the driver's perceptual field. That is, the reduction in amber phase length represented a driver who only missed the signal phase change but had a good perception and comprehension of the overall environment (i.e., not focusing on internal thoughts, looking off the roadway, etc). The simulation essentially delayed Level 2 comprehension of the signal phase in order to elicit incorrect Level 3 predictions. Thus, it was difficult for distracted drivers in the experiment to forecast where their vehicle would be located when the signal became red. Once information was provided in the form of an amber signal, a comprehension of the situation was gained. However, since the amber phase was short, the comprehension had a high probability of being incorrect; resulting in frequent Level-3 errors (violations).

Recall that the naturalistic distracted driver initially lacks both sufficient perception (Level 1) and compression (Level 2). In order to decide whether or not to go (Level 3), the information at Level 1 and Level 2 must be attained once sufficient attentional resources have been focused on the driving scenario (the distraction has ended). Thus, relative to the simulated distraction, the naturalistic driver may spend more time at Level 2, attempting to comprehend the situation once sufficient Level-1information has been gathered. The implication of this is that the time necessary to obtain Level-1 and Level-2 information may result in longer reaction times for naturalistic drivers than for drivers in this experiment. This would explain the lack of significant differences in TB between distracted and baseline drivers found in this experiment.

Future researchers may consider using the SA framework while developing IDS countermeasures. It may be that the decreased SA of the willful and distracted drivers does lead to increased violations. In this case, the countermeasure should be designed to provide the missing pieces of SA to those drivers in the most efficient manner possible. For a willful driver, the system should provide accurate information on the future state of the intersection. This will enhance Level-2 comprehension, allowing the diver to make an informed decision. In the case of a distracted driver, the countermeasure must first provide enough Level-1 information to allow comprehension and prediction. This means that the countermeasure should first grab the driver's attention, but simultaneously allow them to gather information about the entire situation. For instance, a visual countermeasure should be placed in an area that still allows the driver to see the intersection and surrounding traffic. The information included in the countermeasure should be simple and directive so that the distracted driver can quickly comprehend the situation. It should also provide the sense of urgency required such that the driver knows an immediate action should be taken to avoid future consequences. The countermeasure will likely need to accomplish all of these goals each time it is initiated, as discriminating between driver states is not likely going to be plausible in a deployed IDS system.

J.3 QUESTIONNAIRE BASED MEASURES OF AGGRESSIVENESS

Results of the questionnaire and driving performance correlation demonstrated insufficient relationships to predict red-light behavior. The correlations did show predictive validity in that most of the correlations were interpretable. Research scientists who wish to use an existing measure of aggressiveness should consider using only one of the two measures presented. While comparing participant responses to the DDDI with those of the DSI, convergent validity was noted. Most of the measures appear to be replicated within both scales and thus do not provide orthogonal information. The only exception to this was with regard to the DSI fatigue scale, which demonstrated the only notable discriminate validity.

J.4 DATA PRESENTATION AND ANALYSIS METHODOLOGY

The graphical analysis tools presented in this report are novel for intersection approach research. The graphical methods presented provide an intuitive picture of the interactions between multiple variables during an intersection approach. In particular, plots of intersection approaches over distance, rather than time, provide compatibility across multiple intersection approaches. Adding several dependent measures to the plot affords verification and selection of measures such as TB and TAR that rely on the interaction of multiple measures (i.e., amber presentation to brake or throttle movement). This is very useful when setting operational definitions and when deciding where to measure variables such as acceleration during peculiar events such as double clutching. Methods for presenting scatter-plots of range-rate over range and divided by stop and go, are also innovative. The scatter-plot displays the range of intersection approach styles while conveying a sense of density distribution. This helps to identify outliers throughout the intersection approach and better understand the interaction between drivers that opt to go and those that opt to stop. Finally, the scatter-plot is an excellent graphical tool to test potential algorithms. This is done by overlaying the algorithm - independent of whether it is continuous, point, or multipoint - on the scatter plot. Performance is then graphically determined by counting the number of data points that exceed the algorithm threshold. The data presented in this study may be used to create and evaluate algorithms as they are produced.

J.5 LIMITATIONS OF CURRENT STUDY

While this study provides a basis for the development of IDS algorithms, it is preliminary in nature and, therefore, has limitations. These limitations should be considered when using the information presented and when designing future studies.

Perhaps the largest gap in the results of this study concerns speed. Because all of the trials were competed at only 35mph, it is unknown how speed affects driver behavior. Obviously, speed will affect the distances at which the decision to stop is made, but it may not affect the TTI of these decisions. Issues such as this have implications to IDS systems that must be resolved prior to constructing a robust algorithm.

The nature of the distraction also has significant implications towards the external validity of this study. It was assumed that for an intersection approach, the true distracted driver will act similarly to a driver in the simulated distraction. Nonetheless, the method applied was the best available to control for the timing, duration, and physical location of the distraction.

The bonus system was an effective method for eliciting more aggressive behavior at the intersection. However, the extent to which this external motivation represents the internal motivation a driver may feel is unknown. The cost/benefit ratio provided may have inappropriately altered a driver's motivation such that irregular behavior was observed.

The behavioral states used may lack sufficient levels to fully identify all of the potential states assumed by drivers. The distracted behavior state represented both true distracted drivers, as well as drivers making an inappropriate decision on the remaining amber time. The willful state represented drivers with a high motivation, but it did not necessarily capture the behavior of drivers who intentionally run a red light. Thus, the groupings selected may not embody the full range of approaches an algorithm must recognize.

Finally, the environment in which this test was performed may affect the results. The experiment took place on a test track, with no traffic, perfect weather, an experimenter present, and a provided experimental vehicle. These attributes of the study will likely have an effect on the way people approach intersections. For instance, outside the test track environment, with traffic, and in the presence of an IDS system, drivers may be willing to stop at rates over 0.5g. Furthermore, drivers may have been aggressive due to the lack of traffic and penalties for breaking the law.

The elicited driver states and test-track environment do limit the generalizability of the results presented. The reader should recognize that the results presented may not represent the typical driver as accurately and reliably as necessary to fully understand driving behavior. The results presented are a useful tool for beginning to understand how drivers act when navigating a changing signal. The results will also provide initial values for designing IDS systems; however, further research will be needed to gather the information needed to create a deployable IDS system.

J.6 Implications for Future Research

The present study is viewed as a first iteration in a series of studies that will need to be completed in order to fully understand and predict intersection TCD violation. Additional studies need to expand upon the results presented. It is necessary to repeat the design for various speeds ranging up to 60mph and higher (to compensate for speeding traffic). While it is expected that the experimental setup is sufficient for the development of IDS algorithms, future experimenters must test their systems in a higher fidelity field operational test prior to full deployment.

The study also failed to consider intersection approaches under an enduring red phase. Further experimentation is needed to better understand how drivers approach the intersection under all other circumstances to optimize triggering algorithms. The environment, including weather, location, and geometric intersection design should be varied. The good-weather test track used for this study can influence driver behavior due to factors such as the lack of traffic, in-vehicle experimenter, dry roadway, good visibility, unfamiliar vehicle and relatively short testing time. Future studies should supplement the efforts of this study with naturalistic data and/or a field operational test.

In the context of developing an IDS system, several more experiments will be necessary. The parameters needed for the algorithms must be measurable by the infrastructure-mounted devices. This requires significant hardware testing and validation, particularly for continuous detection systems in which novel sensing technologies are necessary. In addition, these devices must be able to reliably discriminate the violator sufficiently upstream to provide a useful warning. That warning must also be salient to elicit the desired driver response. These and other system IDS parameters will need to be experimentally tested. Further research may also be necessary to determine why violations occur.

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Appendix A – The Dula Dangerous Driving Index

Please answer each of the following items as <u>honestly</u> as possible. Please read each item carefully and then circle the answer you choose on the form. If none of the choices seem to be your ideal answer, then select the answer that comes <u>closest</u>. THERE ARE NO RIGHT OR WRONG ANSWERS. Select your answers quickly and do not spend too much time analyzing your answers. If you change an answer, erase the first one as well.

1. **I drive when I am angry or upset.**

   A. Never B. Rarely C. Sometimes D. Often E. Always

2. **I lose my temper when driving.**

   A. Never B. Rarely C. Sometimes D. Often E. Always

3. **I consider the actions of other drivers to be inappropriate or "stupid"**

   A. Never B. Rarely C. Sometimes D. Often E. Always

4. **I flash my headlights when I am annoyed by another driver.**

   A. Never B. Rarely C. Sometimes D. Often E. Always

5. **I make rude gestures (eg., giving "the finger"; yelling curse words) toward drivers who annoy me.**

   A. Never B. Rarely C. Sometimes D. Often E. Always

6. **I verbally insult drivers who annoy me.**

   A. Never B. Rarely C. Sometimes D. Often E. Always

7. **I deliberately use my car/truck to block drivers who tailgate me.**

   A. Never B. Rarely C. Sometimes D. Often E. Always

8. **I would tailgate a driver who annoys me.**

   A. Never B. Rarely C. Sometimes D. Often E. Always

9. **I "drag race" other drivers at stop lights to get out front.**

   A. Never B. Rarely C. Sometimes D. Often E. Always

10. **I will illegally pass a car/truck that is going <u>too</u> slowly.**

    A. Never B. Rarely C. Sometimes D. Often E. Always

11. **I feel it is my right to strike back in some way, if I feel another driver has been aggressive toward me.**

    A. Never B. Rarely C. Sometimes D. Often E. Always

12. **When I get stuck in a traffic jam I get <u>very</u> irritated.**

    A. Never B. Rarely C. Sometimes D. Often E. Always

13. I will race a slow moving train to a railroad crossing.

A. Never B. Rarely C. Sometimes D. Often E. Always

14. I will weave in and out of slower traffic

A. Never B. Rarely C. Sometimes D. Often E. Always

15. I will drive if I am only <u>mildly</u> intoxicated or bussed.

A. Never B. Rarely C. Sometimes D. Often E. Always

16. When someone cuts me off, I feel I should punish him/her

A. Never B. Rarely C. Sometimes D. Often E. Always

17. I get impatient and/or upset when I fall behind schedule when I am driving.

A. Never B. Rarely C. Sometimes D. Often E. Always

18. Passengers in my car/truck tell me to calm down.

A. Never B. Rarely C. Sometimes D. Often E. Always

19. I get irritated when a car/truck in front of me slows down for no reason.

A. Never B. Rarely C. Sometimes D. Often E. Always

20. I will cross double yellow lines to see if I can pass a slow moving car/truck.

A. Never B. Rarely C. Sometimes D. Often E. Always

21. I feel it is my right to get where I need to go as quickly as possible.

A. Never B. Rarely C. Sometimes D. Often E. Always

22. I feel that <u>passive</u> drives should learn how to drive or stay home.

A. Never B. Rarely C. Sometimes D. Often E. Always

23. I will drive in the shoulder lane or median to get around a traffic jam.

A. Never B. Rarely C. Sometimes D. Often E. Always

24. When passing a car/tuck on a 2-lane road, I will barely miss on-coming cars.

A. Never B. Rarely C. Sometimes D. Often E. Always

25. I will drive when I am drunk.

A. Never B. Rarely C. Sometimes D. Often E. Always

26. I feel that I may lose my temper if I have to confront another driver.

A. Never B. Rarely C. Sometimes D. Often E. Always

27. I consider myself to be a risk-taker.

A. Never B. Rarely C. Sometimes D. Often E. Always

28. I feel that most traffic "laws" could be considered as suggestions.

A. Never B. Rarely C. Sometimes D. Often E. Always

Appendix B – Driver Stress Inventory

Office use only

Please check one box only unless otherwise indicated (do not write in boxes at right margin).

Section A

1. Please state your age in years: ____________

2. Please state your gender: Male ☐ Female ☐

3. What is your highest educational qualification?_______________________________________

4. Please state your occupation:__________________________________

5. Please state the year when you obtained your full driving license: 19____

6. About how often do you drive nowadays?

Everyday ☐ 2-3 days a week ☐ About once a week ☐ Less often ☐

7. Estimate roughly how many miles you personally have driven in the past year:

Less than 5000 miles ☐ 5000-10,000 miles ☐ 10,000-15,000 miles ☐

15,000-20,000 miles ☐ Over 20,000 miles ☐

8. Do you drive to and from your place of work?

Everyday ☐ Most days ☐ Occasionally ☐ Never ☐

9. Please state which of these types of road you use frequently (check one or more boxes as appropriate):

Freeways ☐ Other main roads ☐ Urban roads ☐ Country roads ☐

10. During the last three years, how many minor road accidents have you been involved in?
(A minor accident is one in which no-one required medical treatment, AND costs of damage to vehicles and property were less than $800).

Number of minor accidents ____ (if none, write 0)

11. During the last three years, how many major road accidents have you been involved in?
(A major accident is one in which EITHER someone required medical treatment, OR costs of damage to vehicles and property were greater than $800, or both).

Number of major accidents ____ (if none, write 0)

12. During the last three years, have you ever been convicted for:

(a) Speeding	Yes No	☐ ☐
(b) Careless or dangerous driving	Yes No	☐ ☐
(c) Driving under influence of alcohol or drugs	Yes No	☐ ☐
(d) Other moving violation - please specify:	Yes No	☐ ☐

____

Section B

Please answer the following questions on the basis of your usual or typical feelings about driving. Each question asks you to answer according to how strongly you agree with one or other of two alternative answers. Please read each of the two alternatives carefully before answering. To answer, mark the horizontal line at the point which expresses your answer most accurately. Be sure to answer all the questions, even if some of them don't seem to apply to you very well: guess as best you can if need be.

Example: Are you a confident driver?

The more confident you are, the closer to the 'very much' alternative you should mark your cross. If you are quite a confident driver you would mark it like this:

not at all | 0 1 2 3 4 5 6 7 8 9 10 | very much

1. Does it worry you to drive in bad weather?

very much | 0 1 2 3 4 5 6 7 8 9 10 | not at all

2. I am disturbed by thoughts of having an accident or the car breaking down

very rarely | 0 1 2 3 4 5 6 7 8 9 10 | very often

3. Do you lose your temper when another driver does something silly?

not at all | 0 1 2 3 4 5 6 7 8 9 10 | very much

4. Do you think you have enough experience and training to deal with risky situations on the road safely?

not at all | 0 1 2 3 4 5 6 7 8 9 10 | very much

5. I find myself worrying about my mistakes and the things I do badly when driving

very rarely | 0 1 2 3 4 5 6 7 8 9 10 | very often

6. I would like to risk my life as a racing driver

not at all | 0 1 2 3 4 5 6 7 8 9 10 | very much

7. My driving would be worse than usual in an unfamiliar rental car

not at all | 0 1 2 3 4 5 6 7 8 9 10 | very much

8. I sometimes like to frighten myself a little while driving

very much | 0 1 2 3 4 5 6 7 8 9 10 | not at all

9. I get a real thrill out of driving fast

very much | 0 1 2 3 4 5 6 7 8 9 10 | not at all

10. I make a point of carefully checking every side road I pass for emerging vehicles

very much | 0 1 2 3 4 5 6 7 8 9 10 | not at all

11. Driving brings out the worst in people

not at all | 0 1 2 3 4 5 6 7 8 9 10 | very much

12. Do you think it is worthwhile taking risks on the road?

very much | 0 1 2 3 4 5 6 7 8 9 10 | not at all

13. At times, I feel like I really dislike other drivers who cause problems for me

very much | 0 1 2 3 4 5 6 7 8 9 10 | not at all

14. Advice on driving from a passenger is generally:

useful | 0 1 2 3 4 5 6 7 8 9 10 | unnecessary

15. I like to raise my adrenaline levels while driving

not at all | 0 1 2 3 4 5 6 7 8 9 10 | very much

16. It's important to show other drivers that they can't take advantage of you

not at all 0 1 2 3 4 5 6 7 8 9 10 very much

17. Do you feel confident in your ability to avoid an accident?

not at all 0 1 2 3 4 5 6 7 8 9 10 very much

18. Do you usually make an effort to look for potential hazards when driving?

not at all 0 1 2 3 4 5 6 7 8 9 10 very much

19. Other drivers are generally to blame for any difficulties I have on the road

not at all 0 1 2 3 4 5 6 7 8 9 10 very much

20. I would enjoy driving a sports car on a road with no speed-limit

very much 0 1 2 3 4 5 6 7 8 9 10 not at all

21. Do you find it difficult to control your temper when driving?

very much 0 1 2 3 4 5 6 7 8 9 10 not at all

22. When driving on an unfamiliar road do you become more tense than usual?

very much 0 1 2 3 4 5 6 7 8 9 10 not at all

23. I make a special effort to be alert even on roads I know well

very much 0 1 2 3 4 5 6 7 8 9 10 not at all

24. I enjoy the sensation of accelerating rapidly

not at all 0 1 2 3 4 5 6 7 8 9 10 very much

25. If I make a minor mistake when driving, I feel it's something I should be concerned about

very much 0 1 2 3 4 5 6 7 8 9 10 not at all

26. I always keep an eye on parked cars in case somebody gets out of them, or there are pedestrians behind them

not at all 0 1 2 3 4 5 6 7 8 9 10 very much

27. I feel more anxious than usual when I have a passenger in the car

not at all 0 1 2 3 4 5 6 7 8 9 10 very much

28. I become annoyed if another car follows very close behind mine for some distance

very much 0 1 2 3 4 5 6 7 8 9 10 not at all

29. I make an effort to see what's happening on the road a long way ahead of me

not at all 0 1 2 3 4 5 6 7 8 9 10 very much

30. I try very hard to look out for hazards even when it's not strictly necessary

not at all 0 1 2 3 4 5 6 7 8 9 10 very much

31. Are you usually patient during the rush hour?

very much 0 1 2 3 4 5 6 7 8 9 10 not at all

32. When you pass another vehicle do you feel in command of the situation?

not at all 0 1 2 3 4 5 6 7 8 9 10 very much

33. When you pass another vehicle do you feel tense or nervous?

not at all 0 1 2 3 4 5 6 7 8 9 10 very much

34. Does it annoy you to drive behind a slow moving vehicle?

very much 0 1 2 3 4 5 6 7 8 9 10 not at all

35. When you're in a hurry, other drivers usually get in your way

not at all 0 1 2 3 4 5 6 7 8 9 10 very much

36. When I come to negotiate a difficult stretch of road, I am on the alert

very much 0 1 2 3 4 5 6 7 8 9 10 not at all

37. Do you feel more anxious than usual when driving in heavy traffic?

not at all 0 1 2 3 4 5 6 7 8 9 10 very much

38. I enjoy cornering at high speed

not at all 0 1 2 3 4 5 6 7 8 9 10 very much

39. Are you annoyed when the traffic lights change to red when you approach them?

very much 0 1 2 3 4 5 6 7 8 9 10 not at all

40. Does driving usually make you feel aggressive?

very much 0 1 2 3 4 5 6 7 8 9 10 not at all

41. Think about how you feel when you have to drive for several hours, with few or no breaks from driving. How do your feelings change during the course of the drive?

a) More uncomfortable physically (e.g. headache or muscle pains) 0 1 2 3 4 5 6 7 8 9 10 No change

b) More drowsy or sleepy 0 1 2 3 4 5 6 7 8 9 10 No change

c) Maintain speed of reaction 0 1 2 3 4 5 6 7 8 9 10 Reactions to other traffic increasingly slow

d) Maintain attention to road-signs 0 1 2 3 4 5 6 7 8 9 10 Become increasingly inattentive to road-signs

e) Normal vision 0 1 2 3 4 5 6 7 8 9 10 Your vision becomes less clear

f) Increasingly difficult to judge your speed 0 1 2 3 4 5 6 7 8 9 10 Normal judgement of speed

g) Interest in driving does not change 0 1 2 3 4 5 6 7 8 9 10 Increasingly bored and fed-up

h) Passing becomes increasingly risky and dangerous 0 1 2 3 4 5 6 7 8 9 10 No change

---

Office use only a) b) c) d) e) f) g) h)

Appendix C – Initial Screening Questionnaire

Initial Contact Participant Screening Questionnaire

Note to Researcher:
Initial contact between participants and researchers may take place over the phone. If this is the case, read the following Introductory Statement, followed by the questionnaire. Regardless of how contact is made, this questionnaire must be administered verbally before a decision is made regarding suitability for this study.

Introductory Statement:
After prospective participant calls or you call them, use the following script as a guideline in the screening interview.

Hello. My name is _____ and I'm a researcher with the Virginia Tech Transportation Institute in Blacksburg, VA. The project involves participation in a driving study to help researchers understand how people drive.

This study involves coming to the Transportation Institute one time for approximately 2 hours. During this session you would help us analyze driving behavior by completing tasks in one of our test vehicles on the Smart Road. The vehicle will be equipped with data collection equipment. Does this sound interesting to you?

Next, I would like to ask you several questions to see if you are eligible to participate.

Questions

1. Do you have a valid driver's license?

   Yes _____ No _____

2. How often do you drive each week?

   Every day ____ At least 2 times a week___ Less than 2 times a week_____

3. How old are you? ______ (stop if not 18-25 years old or 55+ years old.)

4. What type of vehicle do you usually drive?_________________________

5. Have you previously participated in any experiments at the Virginia Tech Transportation Institute? If so, can you briefly describe the study?

   Yes _____ ____
   No _____

6. How long have you held your drivers' license? ________________________________

7. Are you able to drive an automatic transmission without assistive devices or special equipment?

   Yes _____ No _____

8. Do you have a history of any of the following? If yes, please explain.

Stroke	No____	Yes___
Brain tumor	No____	Yes___
Head injury	No____	Yes___
Epileptic seizures	No____	Yes___
Respiratory disorders	No____	Yes___
Motion sickness	No____	Yes___
Inner ear problems	No____	Yes___
Dizziness, vertigo, or other balance problems	No____	Yes___
Diabetes	No____	Yes___
Migraine, tension headaches	No____	Yes___

9. (Females only, of course) Are you currently pregnant?

Yes _____ No _____ (If "yes" then read the following statement to the subject: "*It is not recommended that pregnant women participate in this study. However, female subjects who are pregnant and wish to participate must first consult with their personal physician for advice and guidance regarding participation in a study where risks, although minimal, include the possibility of collision and airbag deployment.*"

12. Are you currently taking any medications on a regular basis? If yes, please list them.

    Yes _____ ____

    No _____

13. Do you have normal or corrected to normal hearing and vision? If no, please explain.

Yes _____
No _____ ____

I would like to take your name, phone number or phone numbers where you can be reached and hours/days when it's best to reach you.

Name ____ Male/Female

Phone Numbers ____

Best Time to Call ____

When contacting subjects for scheduling purposes, the following statement must be included in the conversation. "*We ask that all subjects refrain from drinking alcohol and taking any substances that will impair their ability to drive prior to participating in our study.*"

Criteria For Participation:

1. ***Must hold a valid driver's license.***
2. ***Must be 18-25 or 55+ years of age.***
3. ***Must drive at least 2 times a week.***
4. ***Must have normal (or corrected to normal) hearing and vision.***
5. ***Must be able to drive an automatic transmission without special equipment.***
8. ***Cannot have lingering effects of brain damage from stroke, tumor, head injury, recent concussion, or infection. Cannot have had epileptic seizures within 12 months, respiratory disorders, motion sickness, inner ear problems, dizziness, vertigo, balance problems, diabetes for which insulin is required, chronic migraine or tension headaches.***
9. ***Cannot currently be taking any substances that may interfere with driving ability (cause drowsiness or impair motor abilities)..***

Appendix D – Informed Consent

VIRGINIA POLYTECHNIC INSTITUTE AND STATE UNIVERSITY

Informed Consent for Participants of Investigative Projects

Title of Project: Influence of driver characteristics on driving performance

Investigators: Mr. Zachary Doerzaph, Industrial and Systems Engineering, Graduate Research Assistant, Virginia Tech Transportation Institute.

Dr. Vicki Neale, Leader of the Human Factors Engineering Group, Virginia Tech Transportation Institute.

I. The Purpose of this Research Project

This study will collect driver performance data to better understand the way people drive. Every person has their own unique driving style, however, most of us tend to follow the same general patterns in our daily drives. The goal of this study is to better define those general patterns.

II. Procedures

For this study you will be asked to drive on the Smart Road with an experimenter for about an hour and a half. There will be a few instances in which the experimenter may want you to change your driving behavior. However, in general we want you to drive as you normally would on any roadway, following the typical laws and regulations of the road.

This vehicle contains sensors and data processing equipment that will capture aspects of your driving behavior. Small video cameras are also mounted in the vehicle. One of these cameras will be directed toward your face while you are driving. The equipment has been installed in such a way that you will hardly be able to notice its presence. It will not interfere with your driving, and there is nothing special that you will need to do in regard to the equipment.

III. Risks

Anytime you operate a motor vehicle there are certain risks involved, this study is no different. However, every effort has been made to ensure your safety such that any risk toward you and others is minimized. If at any point in the session the experimenter believes that continuing the session would endanger you or the equipment, she will stop the testing.

IV. Benefits of this Research Project
The information collected from this project will generalize how people tend to drive. This information will be used to design and develop intelligent transportation systems that will eventually be installed on open roadways. These devices should enhance safety and efficiency by better accommodating the driver.

V. Extent of Anonymity and Confidentiality
The results of this experiment will be kept strictly confidential. Your name and personal information will be separated from the data collected and replaced by a naming convention (ie participant #).

As indicated, video will be recorded while you are driving. The video includes an image of your face, so that we can determine where you are normally looking. The video will be treated with confidentiality and kept secure. It will be shared only with other qualified researchers, and not published except as noted in the following paragraph.

If at a later time we wish to use the video information for other than research purposes, say, for public education, or if we wish to publish (for research or for other purposes) your likeness or other information from the study that identifies you either directly or indirectly, we will only do so after we have obtained your permission.

VI. Compensation
You will be paid a minimum of $10 per hour for the time you actually spend in the experiment. Additional payment for a second part of this study is performance dependent. Thus, it will be possible to receive bonuses in excess of the per hour rate. The bonus system will be explained to you in detail prior to beginning that part of the study. Payment will be made immediately after you have finished your participation.

VII. Freedom to Withdraw
You should know that at any time you are free to withdraw from participation in this research program without penalty. Circumstances could arise in which you or the experimenter opts to end the study early. These could include, but are not limited to unforeseen health problems, safety concerns, and/or equipment malfunctions. You will still be compensated for the duration of time in which you participated.

VIII. Medical Treatment and Insurance

If you should become injured in an accident, the medical treatment available to you would be that provided to any driver or passenger by emergency medical services in the vicinity where the accident occurs. The vehicle you will be driving is insured for automobile liability and collision/comprehensive through Virginia Tech and the Commonwealth of Virginia. There is medical coverage for you under this policy. The total policy amount per occurrence is $2,000,000. This coverage would apply in case of an accident, except as noted below.

Under certain circumstances, you may be deemed to be driving in the course of your employment, and your employer's worker's compensation provisions may apply in lieu of the Virginia Tech and Commonwealth of Virginia insurance provisions, in case of an accident. The particular circumstances under which worker's compensation would apply are specified in Virginia law. If worker's compensation provisions do not apply in a particular situation, the Virginia Tech and Commonwealth of Virginia insurance provisions will provide coverage.

Briefly, worker's compensation would apply if your driving for this research can be considered as part of the duties you perform in your regular job. If it is not considered as part of your regular job, then the insurance policy would apply.

IX. Approval of Research
This research project has been approved, as required by the Institutional Review Board for Research Involving Human Participants at Virginia Polytechnic Institute and State University, and the Virginia Tech Transportation Institution.

X. Participant's Responsibilities
I voluntarily agree to participate in this study. I have the following responsibilities:

(1) I will not volunteer to participate in this research if I am younger than 18 years of age, or if I do not have a valid driver's license, or if I am not in good health.
(2) I will not take part in the experiment if I have taken any drugs, alcoholic beverage, or medication within the previous 24 hours that might affect my ability to safely operate a truck. It is my responsibility to inform the experimenters of any additional conditions that might interfere with my ability to drive. Such conditions would include inadequate sleep, hangover, headache, cold symptoms, depression, allergies, emotional upset, visual or hearing impairment, seizures (fits), nerve or muscle disease, or other similar conditions.
(3) As the driver of the research vehicle, I must obey all traffic regulations and maintain safe operation of the vehicles at all times. I will treat the driving task as the primary task and perform the other instructed tasks only when it is safe to do so.
(4) I should answer all questions truthfully

X. Participant's Permission
I have read and understand the Informed Consent and conditions of this research project. I have had all my questions answered. I hereby acknowledge the above and give my voluntary consent for participation in this project.

If I participate, I may withdraw at any time without penalty. I agree to abide by the rules of this research project.

______________________________	______________________________
Signature	Date

Should I have any questions about this research or its conduct, I may contact:

Mr. Zachary Doerzaph Principal Investigator	231-1536
Dr. Vicki Neale Faculty Advisor	231-1514
Mr. David Moore Chair, IRB	231-4991

Appendix E - Health Screening Questionnaire

Health Screening Questionnaire

1. Are you in good general health? Yes No

   If no, list any health-related conditions you are experiencing or have experienced in the recent past.

   ____
   ____
   ____

2. Have you, in the last 24 hours, experienced any of the following conditions?

Inadequate sleep	Yes	No
Hangover	Yes	No
Headache	Yes	No
Cold symptoms	Yes	No
Depression	Yes	No
Allergies	Yes	No
Emotional upset	Yes	No

3. Do you have a history of any of the following?

   Visual Impairment Yes No

   (If yes, please describe.)

   ____
   ____
   ____

   Seizures or other lapses of consciousness Yes No

   (If yes, please describe.)

   ____
   ____
   ____

   Any disorders similar to the above or that would impair your driving ability Yes No

   (If yes, please describe.)

   ____
   ____

4. List any prescription or non-prescription drugs you are currently taking or have taken in the last 24 hours.

5. List the approximate amount of alcohol (beer, wine, fortified wine, or liquor) you have consumed in the last 24 hours.

6. Are you taking any drugs of any kind other than those listed in 4 or 5 above?

Yes No

8. Have you ever had whiplash?

Yes No

(If yes, please describe.)

Signature

Date

Appendix F - Debriefing Form

Participant Name: _________________________

Virginia Tech 1872

TRANSPORTATION INSTITUTE

Thank you for your participation and time that you have taken to help us gather information about the way people drive through intersections. The results of this study will help enhance intersection safety. We also appreciate your cooperation in keeping the details of this study confidential.

If you have any questions please do not hesitate to contact us. Zac Doerzaph or Vicki Neale will be glad to answer all your questions related to this evaluation process.

Date	___/___/___
Time In:	_____:_____
Time Out:	_____:_____
Total	$_________

TOTAL TIME:______________________

TOTAL PAYMENT:_________________

VTTI Staff Signature:_________________

Appendix G – Apparatus Setup

System Setup & Takedown

1. Setup Isabel

- Clean interior/exterior as needed, always wash windshield
- Start Isabel and pull outside
- Plug in monitors
- Turn on cooling fan
- Plug in and turn on Inverter
- Plug in GPS unit
- Initialize Laptop
  - Startup Laptop (be sure USB keyboard is unplugged), remember to hit escape when wireless warning message appears on screen
  - Open "shortcut to IDS vehicle.exe"
  - Plug in USB keyboard
  - Switch to front monitor (fn+F7)
- Initialize 100-car Box
  - Press on button and wait for it to light up
  - Verify systems loads 100car.exe
  - Move any data contained in c://data to the folder c://data/completed
- From passenger seat initiate a fake data collection
- Verify that the 100-car system created files, delete them once verified
- Check to see that all vehicle cameras are operating and focused correctly
- Verify GPS and DSRC antennas are mounted and positioned correctly

2. Setup Intersection

- Open controller cabinet and plug in yellow extension cord
- Start intersection computer
  - Turn on monitor
  - Be sure power supply is on and press black on switch
  - Enter password "IDS" to log in
  - Open "controller.exe" program
- Close controller cabinet but do not lock latch
- Setup Lasers
  - Place each laser in appropriate location and plug in
  - Focus laser by make the indicator on top a steady green light with a red light that only activates when the beam is interrupted

3. Verify System Operation

- Drive Isabel through intersection to see that every laser is tripping twice as vehicle passes
- Run a couple of trails and verify correct signal change
- Drive Isabel to front of building and await first participant

Appendix H – In-Building Experimenter

IN – BUILDING EXPERIMENTER

4. **Set up the conference room**
    - Make sure to have pens
    - Make sure to have a watch to know when the participant arrives
    - Binder with all the necessary forms
    - Close all the shades
    - Turn on all overhead lights
    - Turn off halogen lamps

5. **Make sure the participant packets include the following:**
    - Time In/Out Receipt Form
    - Informed Consent (2 copies)
    - Tax Forms
    - Vision Test Forms
    - Pre-Drive Questionnaires (health screening & Dula Index)
    - Experimenter Log

6. **Greet Participant**

7. **Record the participants arrival time on the in/out receipt form**

8. **Show driver's license**
    - Must be a valid Class A driver's license. Out of state is fine.
    - Check to make sure it has not expired

9. **Informed consent**
    - Give the participant the form- Encourage them to read it before signing it!
    - Answer questions
    - Have participant sign and date the form and the copy
    - Give the participant a copy of the informed consent

10. **Tax Forms**

To complete the W-9, the participant must fill out the following in the box:
- Name
- Address
- Tax ID number (social security number)
- Sign and date at the bottom

If the participants make more than $500.00 doing studies from Jan 1 to Dec 31, this will be reported to the IRS as income.

Back side of tax form- Print the participants name at the top. If they question what this is for….
This says we are not hiring them full time. There won't be any health benefits or paid vacation etc. We can not fire them because we are not really hiring them. They can quit at any time without being held liable for services by the University. They are a one-time contractor. If they already work for Tech, this is completely separate from their job, and their performance will not have any affect on their employment with Tech.

11. Vision Tests

Record the results for the 2 vision tests on the Vision Test Form

a) The first test is the Snellen eye chart test.

Take the participant over to the eye chart test area.
Line up their toes to the line on the floor (20 feet).
Participants can leave on their glasses if they wear them for driving.

Procedure: *Look at the wall and read aloud the smallest line you can comfortably read.*

If the participant gets every letter on the first line they try correct have them try the next smaller line. Continue until they miss a letter. At that time, record the one that they were able to read in full (line above).
If they get the first line they attempt incorrect, have them read the previous line. Repeat as needed until they get one line completely correct. Record this acuity.
Participant must have 20/40 or better vision using both eyes to participate in the study.

b) Vision Test for Color Blindness.

Procedure:
Take the participant back to his/her desk.
Place the book containing the plates on the testing apparatus

Please hold the red end of this handle to your nose and read the number on the following plates.

Record the participants answers on the Vision Tests Form

12. Pre drive Questionnaires

- Ask participant to fill out questionnaires
- Answer any questions

13. Exchange Participants with In-Vehicle Experimenter

- Introduce new participant to in-vehicle experimenter
- Provide in-vehicle with experimenter log and blank data disk
- Take completed experimenter log and data disk from in-vehicle experimenter
- Walk old participant back to conference room

14. Debrief Participant

- Show participant the debriefing form and explain actual intent of research
- Have participant read and sign debriefing form
- Answer any questions

15. Pay the participant $10 per hour plus any bonus/deduction received

- Fill out the time in/out form and give it to them
- Fill out payment log with participants name and amount paid
- Ask participant to sign and write their SSN in the payment log

16. Download data

- Move data from zip disk to network drive
- Rename files to represent subject number (ie "IDS_Subject_5")
- Delete files from zip disk

Appendix I – In-Building Experimenter

IN - VEHICLE EXPERIMENTER

17.Exchange Participants with In-Vehicle Experimenter

- Introduce yourself to new participant
- Provide in-building experimenter with completed log and data disk
- Retrieve new experimenter log and blank disk

18.Orient driver to the vehicle

- Seat Adjustment
- Mirror Adjustment
- Gear Shift
- Tell them they can control the HVAC, but that we won't be using any of the other buttons on the center stack.
- Tell them not to turn the vehicle off

19.Describe the Block I Experiment

Read the following to the participant

Today we will be taking a drive out on the smart road. It is a controlled access facility; this means there will be no other traffic or pedestrians on the roadway during the time we are out there. This car is specially equipped with instruments that collect information about vehicle performance such as speed and acceleration. The purpose of this study is to gather information about urban environments and use it to develop new technologies that help engineers design safer transportation systems. As such we want you to drive as you would if we were out on any actual roadway driving to a typical destination such as work or the grocery store. With this in mind, we also want you to abide by all typical traffic regulations as you normally would. On the roadway you will see a standard signalized intersection identical to the type you encounter on your daily drives. The intersection uses a typical control system which means the light will be changing phase as you drive. Thus, you may have to make decisions on whether you should stop or go through the intersection. Your decision should reflect the same choice you would normally make, do not behave more conservative or risky than you normally would.

Show Participant the "intersection crossing law description" and describe each scenario

I will be riding in the passenger seat overseeing the experiment as you drive. However, for the most part you should drive as though I am absent from the vehicle. You are welcome to ask questions if necessary, however, try to avoid unneeded conversation. As *always, our first priority is your safety. If at any time you feel uncomfortable please inform me so that I can make any necessary adjustments while you take a break.*

Once you have been driving for about a half-hour, I will have you pull off the roadway for a short break in which I will explain a second portion of the study to you.
Do you have any questions I can answer at this time?

Data Collection

---

1. Give directions

- To the Smart Road
- Around the entire loop
- Provide 35 mph, maintenance reminders as needed

2. Complete First Block

- Make periodic checks to see that the data acquisition is functional
- Check that signal response matches trial
- If problem arises re-run trial on following loop
- Make notes of all discrepancies and re-runs in experimenter log

3. Take a break

After completing the first block of trials have the subject have the participant pull off the roadway on the lower turnaround. Give them a minute to relax and get out of the vehicle to stretch.

4. Describe the Block II experiment

Read the following to the participant

That completes the first portion of this experiment; it is time to start the second and final part. We are now particularly interested in your intersection crossing behavior during times when you are in a hurry to reach your destination. For instance, you may pretend you are running a little late to a very important meeting and need to make up time.

In order to provide extra motivation we are going to incorporate a bonus system for the remainder of our time on the road. In fact, right now you have an extra $5 bonus over your hourly pay. We will continue to drive loops around the smart road again driving as though we were on the open roadway. As you approach the intersection, the signal may change. Each time you successfully enter the intersection while the light is amber, I will pay you a $3bonus. However, each time you enter the intersection when the light is red I *take $1 away from you. Entering the intersection is defined as any portion of the car crossing over the stopbar. Thus it is not a violation if you have already crossed the stopbar when the light turns red. The only exception to this is if you stop in the intersection. If you pass through while it is green, or if you stop on the red, you do not get any additional money, nor do we take any away. I will track your earnings and deductions each time we pass through the intersection.*

In a moment we will re-enter the roadway and continue driving loops through the intersection. Be aware that the speed limit is 35 mph, however, you may increase your speed while crossing the intersection to the extent that you normally would while trying to "beat the light". Your goal is to get through the intersection as many times as possible while minimizing violations. A violation occurs if any part of your vehicle enters the intersection after the signal has changed to red.

Do you have any questions before we begin?

Answer any questions they may have, then instruct them to once again start driving loops.

5. Complete Second Block

- Make periodic checks to see that the data acquisition is functional
- Check that signal response matches trial
- If problem arises re-run trial on following loop
  - Make notes of all discrepancies and re-runs in experimenter log

6. Return to the building

- Have participant wait in the vehicle
- Copy new files to a Zip disk and then move them into the "completed" directory
- Escort participant back to building and exchange with in-building experimenter

Appendix J – Data Analysis Results

J.1 CHI-SQUARED ANALYSIS OF STOP

J.1.1 Driver State Chi-Squared

Table 16: Driver_State by Stop frequency counts

Frequency / Percent / Row Pct / Col Pct	go	stop	Total
Baseline	113 19.42 57.95 26.40	82 14.09 42.05 53.25	195 33.51
Distracted	182 31.27 94.79 42.52	10 1.72 5.21 6.49	192 32.99
Willful	133 22.85 68.21 31.07	62 10.65 31.79 40.26	195 33.51
Total	428 73.54	154 26.46	582 100.00

Statistics for Table of Driver_state by stop

Statistic	DF	Value	Prob
Chi-Square	2	71.7746*	<.0001

J.1.2 Gender Chi-Squared

Table 17: Gender by Stop frequency counts

Gender stop

Frequency / Percent / Row Pct / Col Pct	go	stop	Total
Male	222	66	288
	38.14	11.34	49.48
	77.08	22.92	
	51.87	42.86	
Female	206	88	294
	35.40	15.12	50.52
	70.07	29.93	
	48.13	57.14	
Total	428	154	582
	73.54	26.46	100.00

Statistics for Table of Gender by stop

Statistic	DF	Value	Prob
Chi-Square	1	3.6795	0.0551

J.1.3 Age Group Chi-Squared

Table 18: Age_Group by Stop Frequency Counts

Frequency / Percent / Row Pct / Col Pct	go	stop	Total
Young	227 39.00 77.74 53.04	65 11.17 22.26 42.21	292 50.17
Old	201 34.54 69.31 46.96	89 15.29 30.69 57.79	290 49.83
Total	428 73.54	154 26.46	582 100.00

Statistics for Table of AgeGroup by stop

Statistic	DF	Value	Prob
Chi-Square	**1**	**5.3129**	**0.0212***

J.2 ANALYSIS FOR REACTION TIME

J.2.1 Time-to-Accelerator-Release ANOVA

Table 19: ANOVA summary table for TAR as the dependent variable

Source	Df	F	Pr > F
Between subjects factors			
AgeGroup	1	2.04	0.1684
Gender	1	1.55	0.2276
SUB(Gender*Age_Group)	20	3.06	
Within subject factors			
Driver_State	2	0.99	0.4094
SUB*Driver_State(Gender*Age_Group)	9	0.69	

J.2.2 Time-to-Brake ANOVA

Table 20: ANOVA summary table for TB as the dependent variable

Source	Df	F	Pr > F
Between subjects factors			
Age_Group	1	3.15	0.0911
Gender	1	1.55	0.2278
SUB(Gender*Age_Group)	20	6.35	
Within subject factors			
Driver_State	2	1.28	0.2174
SUB*Driver_State(Gender*Age_Group)	9	0.30	

J.3 Analysis for Speed

J.3.1 For drivers that go

Table 21: ANOVA summary table for Mean Speed as the dependent variable for drivers that decide to go

Source	Df	F	Pr > F
Between subjects factors			
Age_Group	1	1.17	0.1684
Gender	1	1.37	0.2276
Gender*Age_Group	1	0.00	0.9801
SUB(Gender*Age_Group)	24	580.71	
Within subject factors			
Dstate	**2**	**17.65***	**<0.0001**
AgeGroup*Driver_State	2	2.00	0.1471
Gender*Driver_State	2	0.25	0.7782
Gender*Age_Group*Driver_State	2	0.60	0.5547
SUB*Driver_State(Gender*Age_Group)	45	113.66	

J.3.2 Post-hoc Tukey Test

```
                    Least Squares Means
    Adjustment for Multiple Comparisons: Tukey-Kramer

                                        LSMEAN
            Dstate     Speed LSMEAN      Number

            Baseline       54.6926745         1
            Distracted     54.7634436         2
            Willful        57.5571576         3


             Least Squares Means for Effect Dstate
           t for H0: LSMean(i)=LSMean(j) / Pr > |t|

                   Dependent Variable: Speed

      i/j              1              2              3

         1                     -1.39254      -51.4646*
                                 0.3448        <.0001
         2      1.392536                     -60.7414*
                  0.3448                       <.0001
         3      51.46458        60.7414
                  <.0001         <.0001
```

J.3.3 For drivers that Stop

Table 22: ANOVA summary table for Mean Speed as the dependent variable for drivers that decide to stop

Source	Df	F	Pr > F
Between subjects factors			
Age_Group	1	0.01	0.9119
Gender	1	0.09	0.7621
Gender*Age_Group	1	0.32	0.5764
SUB(Gender*Age_Group)	24	6.11	
Within subject factors			
Driver_State	**2**	**3.64***	**0.0394**
Age_Group*Driver_State	2	0.51	0.6051
Gender*Driver_State	2	0.33	0.7224
Gender*Age_Group*Driver_State	2	0.07	0.7885
SUB*Driver_State(Gender*Age_Group)	28	2.23	

J.3.4 Post-hoc Tukey Test

```
                Adjustment for Multiple Comparisons: Tukey-Kramer

                                          LSMEAN
                Dstate     Speed LSMEAN    Number

                Baseline    42.0740546          1
                Distracted  44.3821333          2
                Willful     43.5396138          3


                  Least Squares Means for Effect Dstate
                 t for H0: LSMean(i)=LSMean(j) / Pr > |t|

                     Dependent Variable: Speed

        i/j              1              2              3

           1                      -3.31169*      -4.16662*
                                    0.0027         <.0001
           2       3.311695                      1.188686
                     0.0027                        0.4599
           3       4.166623       -1.18869
                     <.0001         0.4599
                Driver State for All Participants
```

J.4 ANALYSIS FOR DECELERATION

J.4.1 Mean Acceleration

Table 23: ANOVA summary table for Deceleration as the dependent variable

Source	Df	F	Pr > F
Between subjects factors			
AgeGroup	1	0.17	0.6813
Gender	1	0.00	0.9971
SUB(Gender*AgeGroup)	25	5.14	
Within subject factors			
Dstate	**2**	**54.60***	**<0.0001**
SUB*Dsta(Gend*AgeGr)	45	113.66	

J.4.2 Post-hoc Tukey Test

```
Adjustment for Multiple Comparisons: Tukey-Kramer

                 AvgTimeAccel      LSMEAN
      Dstate           LSMEAN      Number

     Baseline     -0.33268780           1
     Distracted   -0.39352300           2
     Willful      -0.34395161           3


            Least Squares Means for Effect Dstate
         t for H0: LSMean(i)=LSMean(j) / Pr > |t|

             Dependent Variable: AvgTimeAccel

  i/j              1             2             3

     1                    4.861107      1.791324
                            <.0001        0.1891
     2      -4.86111                    -3.89339
              <.0001                      0.0014
     3      -1.79132       3.89339
              0.1891        0.0014
            TB for Drivers that stop
```

J.4.3 Peak Deceleration

Table 24: ANOVA summary table for Peak Deceleration as the dependent variable

Source	Df	F	Pr > F
Between subjects factors			
Age_Group	1	0.71	0.4073
Gender	1	0.36	0.5566
SUB(Gender*Age_Group)	25	3.84	
Within subject factors			
Driver_State	**2**	**31.74***	**<0.0001**
SUB*Driver_Sta(Gend*Age_Group)	45	1.08	

J.4.4 Post-hoc Tukey Test

```
Adjustment for Multiple Comparisons: Tukey-Kramer

                PeakAccel      LSMEAN
        Dstate      LSMEAN      Number

        Baseline   -0.45691707       1
        Distracted -0.54499000       2
        Willful    -0.47984516       3


       Least Squares Means for Effect Dstate
     t for H0: LSMean(i)=LSMean(j) / Pr > |t|

         Dependent Variable: PeakAccel

  i/j           1            2            3

    1                    4.449*     2.305135
                         0.0003       0.0699
    2       -4.449                -3.23457*
            0.0003                    0.0079
    3     -2.30513      3.23457
            0.0699       0.0079
```

J.5 ANALYSIS FOR VIOLATION RATE

J.5.1 ANOVA Analysis

Table 25: ANOVA summary table for Violation Rate as the dependent variable

Source	Df	F	Pr > F
Between subjects factors			
AgeGroup	**1**	**7.90**	**0.0483***
Gender	1	0.39	0.5652
Gender*Age_Group	1	1.19	0.3372
SUB(Gender*Age_Group)	24	580.71	
Within subject factors			
Driver_State	**2**	**19.66***	**0.0008**
Age_Group*Driver_State	2	0.04	0.9577
Gender*Driver_State	2	2.00	0.1969
Gender*Age_Group*Driver_State	2	0.83	0.4722
SUB*Driver_State(Gender*Age_Group)	45	113.66	

J.5.2 Post-hoc Tukey Test

```
                Least Squares Means
     Adjustment for Multiple Comparisons: Tukey

                      Violation      LSMEAN
         Dstate          LSMEAN      Number

         Baseline   -0.00000000           1
         Distracted  0.21099402           2
         Willful     0.01661051           3


           Least Squares Means for Effect Dstate
         t for H0: LSMean(i)=LSMean(j) / Pr > |t|

              Dependent Variable: Violation

   i/j              1             2             3

      1                   -11.0131*      -0.86701
                            <.0001         0.6630
      2      11.01309                    10.14608*
               <.0001                      <.0001
      3      0.867006     -10.1461
               0.6630       <.0001
```

J.6 PERSON CORRELATION

J.6.1 Variable Definitions

J.6.1.1 Classification Variables

Gender = Gender of participant
AgeGroup = Age group of participant

J.6.1.2 Driving Performance Variables

TB = Time to brake
TAR = Time to accelerator release
PeakAccel = Mean maximum rate of deceleration achieved for each stop run
AvgAccel = Mean of mean deceleration rate achieved for each stop run

J.6.1.3 Dula Dangersous Driving Questionaire

DDDI_Total = Total score
DDDI_AD = Aggressive driving subscale
DDDI_NE = Negative emotions subscale
DDDI_RD = Risky driving subscale

J.6.1.4 Driver Stress Inventory

DSI_Total = Total score
DSI_A = Aggression subscale
DSI_DD = Dislike of driving subscale
DSI_HM = Hazard monitoring subscale
DSI_FP = Fatigue proneness subscale
DSI_TS = Thrill seeking subscale

J.6.2 Pearson Correlation Table

First line = Person Correlation
Second line = P-value
Third line = Sample Size

	Gender	AgeGroup	TB	TAR	Peak Accel	AvgAccel	DDDI_Total	DDDI_AD	DDDI_NE	DDDI_RD	DSI_Total	DSI_A	DSI_DD	DSI_HM	DSI_FP	DSI_TS
Gender	1	0	0.06302	0.0797	-0.19643	-0.33506	0.03443	0.03553	0.09726	-0.15369	-0.19294	0.11115	0.17455	0.2477	0.10303	-0.52846
		1	0.75	0.6868	0.3164	0.0813	0.8646	0.8603	0.6225	0.4349	0.335	0.5734	0.3743	0.2038	0.6091	0.0038
	28	28	28	28	28	28	27	27	28	28	27	28	28	28	27	28
AgeGroup	0	1	-0.16692	-0.31899	-0.18375	-0.24395	-0.38885	-0.40904	-0.3404	-0.32447	0.11447	-0.48721	-0.4631	0.37694	-0.313	-0.51474
	1		0.3959	0.098	0.3493	0.2109	0.045	0.0341	0.0763	0.0921	0.5697	0.0086	0.0131	0.048	0.1119	0.0051
	28	28	28	28	28	28	27	27	28	28	27	28	28	28	27	28
TB	0.06302	-0.16692	1	0.4857	-0.12753	-0.22423	0.18745	0.16257	0.3384	0.12704	-0.00883	0.3561	0.19527	-0.38724	0.07394	0.25253
	0.75	0.3959		0.0088	0.5178	0.2514	0.3491	0.4179	0.0782	0.5194	0.9651	0.0629	0.3193	0.0418	0.714	0.1948
	28	28	28	28	28	28	27	27	28	28	27	28	28	28	27	28
TAR	0.0797	-0.31899	0.4857	1	-0.19614	-0.23297	0.20976	0.30028	0.20619	0.14759	-0.31745	0.2563	0.23191	-0.47767	0.07075	0.24207
	0.6868	0.098	0.0088		0.3172	0.2328	0.2937	0.128	0.2925	0.4536	0.1066	0.188	0.235	0.0102	0.7258	0.2146
	28	28	28	28	28	28	27	27	28	28	27	28	28	28	27	28
Peak Accel	-0.19643	-0.18375	-0.12753	-0.19614	1	0.91736	0.47046	0.34131	0.33966	0.41135	-0.04623	0.29138	0.21848	0.07608	0.17463	0.37714
	0.3164	0.3493	0.5178	0.3172		<.0001	0.0133	0.0814	0.077	0.0297	0.8189	0.1325	0.264	0.7004	0.3837	0.0479
	28	28	28	28	28	28	27	27	28	28	27	28	28	28	27	28
AvgAccel	-0.33506	-0.24395	-0.22423	-0.23297	0.91736	1	0.36254	0.31742	0.18988	0.32915	-0.01774	0.20754	0.1203	0.07618	0.13309	0.38788
	0.0813	0.2109	0.2514	0.2328	<.0001		0.0631	0.1067	0.3331	0.0872	0.93	0.2893	0.542	0.7	0.5081	0.0414
	28	28	28	28	28	28	27	27	28	28	27	28	28	28	27	28
DDDI_Total	0.03443	-0.38885	0.18745	0.20976	0.47046	0.36254	1	0.79981	0.82503	0.90401	-0.42121	0.62988	0.44099	-0.31102	0.24918	0.47786
	0.8646	0.045	0.3491	0.2937	0.0133	0.0631		<.0001	<.0001	<.0001	0.0321	0.0004	0.0213	0.1143	0.2196	0.0117
	27	27	27	27	27	27	27	27	27	27	26	27	27	27	26	27
DDDI_AD	0.03553	-0.40904	0.16257	0.30028	0.34131	0.31742	0.79981	1	0.43166	0.68074	-0.40672	0.52811	0.51774	-0.42015	0.33714	0.40504
	0.8603	0.0341	0.4179	0.128	0.0814	0.1067	<.0001		0.0246	<.0001	0.0392	0.0046	0.0057	0.0291	0.0921	0.0361
	27	27	27	27	27	27	27	27	27	27	26	27	27	27	26	27
DDDI_NE	0.09726	-0.3404	0.3384	0.20619	0.33966	0.18988	0.82503	0.43166	1	0.61313	-0.03937	0.66502	0.34258	-0.24277	0.16013	0.32429
	0.6225	0.0763	0.0782	0.2925	0.077	0.3331	<.0001	0.0246		0.0005	0.8454	0.0001	0.0743	0.2132	0.425	0.0923
	28	28	28	28	28	28	27	27	28	28	27	28	28	28	27	28
DDDI_RD	-0.15369	-0.32447	0.12704	0.14759	0.41135	0.32915	0.90401	0.68074	0.61313	1	-0.28229	0.40803	0.23685	-0.22358	0.09032	0.48968
	0.4349	0.0921	0.5194	0.4536	0.0297	0.0872	<.0001	<.0001	0.0005		0.1537	0.0311	0.2249	0.2528	0.6541	0.0082
	28	28	28	28	28	28	27	27	28	28	27	28	28	28	27	28
DSI_Total	-0.19294	0.11447	-0.00883	-0.31745	-0.04623	-0.01774	-0.42121	-0.40672	-0.03937	-0.28229	1	-0.09283	-0.05684	0.35547	0.17638	-0.24039
	0.335	0.5697	0.9651	0.1066	0.8189	0.93	0.0321	0.0392	0.8454	0.1537		0.6451	0.7783	0.0688	0.3788	0.2271
	27	27	27	27	27	27	26	26	27	27	27	27	27	27	27	27
DSI_A	0.11115	-0.48721	0.3561	0.2563	0.29138	0.20754	0.62988	0.52811	0.66502	0.40803	-0.09283	1	0.48159	-0.32344	0.42627	0.51933
	0.5734	0.0086	0.0629	0.188	0.1325	0.2893	0.0004	0.0046	0.0001	0.0311	0.6451		0.0095	0.0932	0.0266	0.0046
	28	28	28	28	28	28	27	27	28	28	27	28	28	28	27	28
DSI_DD	0.17455	-0.4631	0.19527	0.23191	0.21848	0.1203	0.44099	0.51774	0.34258	0.23685	-0.05684	0.48159	1	-0.50368	0.57951	0.20352
	0.3743	0.0131	0.3193	0.235	0.264	0.542	0.0213	0.0057	0.0743	0.2249	0.7783	0.0095		0.0063	0.0015	0.2989
	28	28	28	28	28	28	27	27	28	28	27	28	28	28	27	28
DSI_HM	0.2477	0.37694	-0.38724	-0.47767	0.07608	0.07618	-0.31102	-0.42015	-0.24277	-0.22358	0.35547	-0.32344	-0.50368	1	-0.2007	-0.46359
	0.2038	0.048	0.0418	0.0102	0.7004	0.7	0.1143	0.0291	0.2132	0.2528	0.0688	0.0932	0.0063		0.3155	0.013
	28	28	28	28	28	28	27	27	28	28	27	28	28	28	27	28
DSI_FP	0.10303	-0.313	0.07394	0.07075	0.17463	0.13309	0.24918	0.33714	0.16013	0.09032	0.17638	0.42627	0.57951	-0.2007	1	0.23205
	0.6091	0.1119	0.714	0.7258	0.3837	0.5081	0.2196	0.0921	0.425	0.6541	0.3788	0.0266	0.0015	0.3155		0.2441
	27	27	27	27	27	27	26	26	27	27	27	27	27	27	27	27
DSI_TS	-0.52846	-0.51474	0.25253	0.24207	0.37714	0.38788	0.47786	0.40504	0.32429	0.48968	-0.24039	0.51933	0.20352	-0.46359	0.23205	1
	0.0038	0.0051	0.1948	0.2146	0.0479	0.0414	0.0117	0.0361	0.0923	0.0082	0.2271	0.0046	0.2989	0.013	0.2441	
	28	28	28	28	28	28	27	27	28	28	27	28	28	28	27	28