AN INVESTIGATION OF LOW-LEVEL STIMULUS-INDUCED MEASURES OF DRIVER DROWSINESS

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(ABSTRACT)

Few attempts have been made to use physical and physiological driver characteristics to predict driver drowsiness. As a result, a reliable drowsy driver detection system has yet to be devised. Thus, the primary objectives of this research were to determine whether driving characteristics and response variables could be used to detect eyelid closure associated with drowsiness, and to provide potential measures of driver drowsiness. In the study, eyelid closure was defined as the measurement standard of drowsiness. Eyelid closure, in studies conducted at Duke University, was a reliable measure of drowsiness.

A computer simulated nighttime driving task introduced 90 minutes of typical highway driving to twenty driver/subjects seated in a moving-base driving simulator. Each driver/subject drove under two conditions--rested and

after 19 hours of being awake. During the 90 minutes of driving, two types of low-level stimuli, steering wheel torque and front wheel displacement, were applied to the simulation. Responses to these stimuli as well as driving measures from the intervals between stimuli were analyzed for variations associated with eyelid closure. Seventeen dependent variables were investigated.

In the data analyses, several dependent variables consistently varied with time-on-task, driving condition, and eyelid closure. Lane lateral deviation and yaw deviation increased with increased eyelid closure for both the intervals between stimuli and for the intervals immediately following the introduction of stimuli. These variables were also significantly correlated with eyelid closure.

Since a number of individual dependent variables provided measures associated with eyelid closure, predictive analyses combining multiple variables were attempted. A linear optimization model only slightly improved the correlation of the single best variable correlation with eyelid closure. A discriminant analysis, on the other hand, was relatively successful in classifying the individual driving observations as either 'alert' or 'drowsy'. The discriminant analysis provided the most optimistic technique for future developments in drowsy driver algorithms.

In post hoc analyses, driver population blocking factors were identified. The identification of drowsy driver variables and blocking factors should be pursued further, because multiple dependent variable models show promise in predicting driver drowsiness.

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INTRODUCTION

For safe automobile operation, a driver must continuously monitor the road, traffic, and atmospheric conditions to provide proper control. However, the safe operation of a vehicle becomes impossible with the onset of drowsiness. Drowsiness or intrusive sleep is operationally defined as "an undesirable decrease in arousal level to the point that satisfactory performance is no longer possible" (Erwin, 1976, p. i). Thus, an automobile driver who suffers from a bout of drowsiness while driving becomes inattentive to the dynamic control-process that an automobile requires.

Although it is difficult to attribute the cause of a traffic accident to drowsiness, the number of accidents determined to be a result of falling asleep at the wheel or driver fatigue are reported. In 1982, Virginia traffic statistics reported that 3% of all fatal driving accidents (32 deaths) were attributed to falling asleep or driver fatigue. This statistic may seem low, but of the state's fatal accidents, 20% were reported without a cause being stated (Virginia, Department of State Police, 1982). Perhaps a portion of these unclassified fatal accidents may in fact be due to driver drowsiness.

Through data obtained in a driver's survey by Duke University in Durham, North Carolina, there is evidence that a significant portion of the driver population experiences drowsiness while driving. (Tilley, Erwin, and Gianturco, 1973). In the Duke survey, a questionnaire was administered to 1500 licensed drivers at a Department of Motor Vehicles licensing station in Durham. Two project technicians assisted successful license renewal applicants in completing the questionnaire. The results of the questionnaire tallies indicated that 64% of the surveyed drivers had experienced drowsiness while driving. Additional support of this response was associated with the respondents' report of the qualifying characteristics of their experience: 69% said drowsiness while driving was associated with eating; 70% were able to identify a diurnal pattern of drowsiness while driving; and 91% reported that the phenomenon was associated with sleep loss (Tilley et al., 1973). Of the drivers who reported difficulty with drowsiness, 10% reported that "I have had near auto accidents because of drowsiness or falling asleep", while more than 10% of the group reported that they had experienced one or more accidents that resulted from drowsiness or sleeping at the wheel.

One of the more relevant results of the Duke University study was the awareness of the drivers to their state of drowsiness. Of the group that reported having difficulty with drowsiness while driving, 31.2% indicated that drowsiness occurred before they were aware of it. These drivers were alerted to their condition by driving off the road or due to some other arousing event. Also, those that recognized their progression toward drowsiness while driving reported that "they could alert themselves without stopping the automobile". That is, 93.7% of the respondents felt that drowsiness was a reversible process if recognized prior to the onset of actual sleep.

In view of the data obtained from the population survey by Tilley et al. (1973), it appears that driver drowsiness is an immediate and impending danger in highway safety. The fact that 64% of the respondents openly admitted that they experienced drowsiness while driving supports the need for research in the areas of driver drowsiness and preventive safety measures. This point is further supported when it is considered that 31.2% of the respondents who suffered from bouts of drowsiness were not aware of their progressive state of drowsiness.

Additional support for the Tilley et al. (1973) drowsiness data was provided after an extensive emissions (exhaust) experiment conducted at the GM Proving Ground in 1975 (Jones, Kelley, and Johnson, 1978). Jones et al.

(1978) reported that of 219 respondents in their driving study 87% indicated that they became drowsy while driving. Of those who suffered from drowsiness, 37.5% were not aware of their drowsiness onset. Again, 88.3% of the subjects felt that they could alert themselves without having to stop their vehicle, if warned of their drowsiness.

Existing Drowsiness Countermeasure Devices

Some safety measures which have been developed to alleviate the dangers associated with driver drowsiness include federal regulations for professional drivers, simple suggestions, and mechanical devices. None of these methods have shown much merit. The main problem associated with the federal regulations for professional drivers lies in the fact that the regulations are only as effective as how well they are observed and enforced. There is evidence suggesting that the federal regulations in effect are not obeyed (McDonald, 1981).

Other countermeasures which have been developed to deter driver drowsiness or provide a warning signal to the drowsy driver are commented on by Harris (1967):

> Drivers have been faced with the problem of drowsiness for a long time and apparently no 'solution' has been found. Some methods for the alleviation of drowsiness that have been suggested are: singing, chewing a pack of gum, taking off the right shoe, and sitting on something hard. It

> is a simple and tempting matter to suggest solutions for a common problem such as drowsiness and the suggested solution may serve for some people thus providing evidence for them (and for others) that it has merit. It is very difficult, however, to collect reliable evidence to substantiate the general value of some method. There may, in fact, be no reliable method for most people. Nevertheless, the problem is sufficiently serious in its consequences in the driving situation to call for continued research (Hulbert, 1972, p. 292).

Harris's comment projects little hope for providing a truly reliable drowsiness countermeasure that most people could use successfully. However, many of the countermeasures developed at that time did not provide an adequate assessment of the physical and physiological aspects of drowsiness nor did they consider the individual differences of the drivers.

Some of the mechanical devices which were available in the mid 60's are presented below with a brief description and commentary regarding their use. A few of these devices are still on the commercial market today.

1. The Electronic Transistor Safety Alarm was a lightweight plastic device that curled around the driver's ear and buzzed when the driver's head nodded. This device ignored the fact that the driver loses alertness before his head begins to nod (Hulbert, 1972).

2. The Button Steering Wheel Alarm plugged into the car radio and was mounted on the steering wheel. An alarm would sound anytime the button was released. This device was very awkward to use due to the unnatural pressures required by the finger or thumb to hold the button down. In addition, when the driver turned the steering wheel to execute a turn, the button would need to be released, therefore sounding the alarm. The device was very impractical (Hulbert, 1972).
3. The ALERTMASTER by Williams (1966) was a pedal similar to an accelerator pedal, which was positioned on the floor to the left of the clutch pedal for use with the left foot. Anytime the pedal pressure was released a horn would sound. The basis of this device relied on an assumption of the inventor-- that when a driver begins to experience drowsiness, his left foot naturally relaxes, thereby causing the horn to sound (Hulbert, 1972).
4. The Alert-O-Matic by Frederik (1966) provided three alerting signals which increased in severity. The first signal was a light presented every sixty seconds. Upon observing the light, the driver would need to respond by tapping lightly on the horn, which

the Alert-O-Matic was wired to, within five seconds of the initial light activation. If the five seconds passed, a second signal, the car horn, would be set off. If the driver did not respond within three seconds to the horn, the device would turn the car ignition on and off rapidly for five seconds. Should the driver continue to doze, the device shuts off the ignition completely. The driver can stop the system at any time by depressing the horn. The major concern with this device is that no validation attempt was made regarding the variable times assigned to each of the system stages. A driver could doze off anytime between the sixty second intervals in stage one of the system. Also, the system was easy to adapt to since the sixty second interval was consistent (Hulbert, 1972).

These are only a few examples of the methods offered to alert a driver of drowsiness or sleep. The necessity of developing a reliable drowsiness countermeasure becomes increasingly apparent when faced with the existing techniques. The devices which have been developed to date appear to simplify a complex design problem and as a result they tend to overlook much of the research data available in the physical and psychological components of driver drowsiness.

Recently, however, NISSAN has introduced a countermeasure device, safety driver advisor (SDA), which relies specifically on the steering velocity of the driver to detect driver drowsiness. NISSAN hypothesizes that erratic steering behaviors result "when the driver becomes drowsy, or falls in a short but dangerous lapse into sleep". The erratic steering behaviors which NISSAN defines as being characteristics of driver fatigue or drowsiness are "more frequent steering maneuvers, and no steering correction for a prolonged period followed by a jerky motion, the latter being repeated in a drowsy state" (Automotive Engineering, 1984).

In operation, the SDA studies and memorizes the driver's normal steering habits in the first ten minutes of driving. The input sources to the device include a photo-optical steering angle and velocity sensor built into the steering wheel. The SDA device ignores control movements which coincide with braking, declutching, gear shifting, turn signal activating, and cornering. It classifies the steering associated with these actions as conscious efforts.

When erratic steering behaviors are detected SDA provides both visual and auditory warning cues to the driver. The SDA device is the result of ten years of research efforts by NISSAN. The device appears promising, but further research may be warranted. Three design concerns immediately come to mind regarding the appropriateness of the SDA. They are: (1) the environmental and road conditions of the ten minute baseline may seriously influence the effectiveness of the SDA, (2) the usefulness of steering velocity as a drowsiness indicator has not been validated, and (3) the removal of steering inputs during cornering by SDA may be defeating the purpose of the device.

Since many of the drowsy driver countermeasures presented above lack experimental foundations, the report which follows is a review of the current research being conducted in driver drowsiness, driver fatigue, and related topics in vigilance. Perhaps by reviewing the current driving literature, a new approach to the development of drowsy driver warning devices may become apparent.

STUDIES ON DROWSINESS AND DRIVING

Although the phenomenon of drowsiness while driving is a well-known occurrence, little attention has been directed towards drowsiness in the research literature. Many studies have dealt with drowsiness in a contemplatory fashion but few attempts have been made to study the phenomenon in rigid scientific research (Wertheim, 1978). Currently drowsiness research has been related to several topics including fatigue, prolonged driving, diurnal variation, sleep deprivation, low-event monotonous driving, and highway hypnosis. Few explanations of drowsiness have been offered.

A factor which contributes to the lack of literature on drowsiness is that some of the medical studies which have been conducted involve subjects with pathological drowsiness disorders, such as narcolepsy and hypersomnia (e.g., Fagerstrom and Lisper, 1978, among others). Typically, narcoleptics are characterized by sleep attacks, while hypersomniacs, "sleepy normals", are characterized by slowly progressive sleep onset. Unfortunately, the majority of people who encounter intrusive sleep while driving do not have these pathological conditions. The general driver population has been largely neglected by the medical profession in drowsiness research (Erwin, 1976).

One group of studies on drowsiness which tends to be an exception to the general drowsiness literature is a series of drowsiness related studies conducted by Duke University. Ten laboratory studies were devoted specifically to drowsiness using both narcoleptics and the general population. A final report of the studies was presented by Erwin in February of 1976. Since the Duke University studies are the most comprehensive in the drowsiness research literature, an overview of their findings is presented here.

In general, the purpose of the Duke University studies was to achieve a greater understanding of the phenomenon of intrusive sleep. Intrusive sleep, as mentioned earlier, may be defined as an undesirable decrease in arousal level to the point that satisfactory performance is no longer possible (Erwin, 1976). Through the population survey by Tilley *et al*. (1973), presented in the introduction, evidence was obtained that a significant portion of the population suffers from onsets of intrusive sleep during driving. As a result, there has been large loss of life, health, and property.

A major controversy which has resulted from the study of intrusive sleep is defining the physiological state. Researchers generally accept that there is a continuum of decreasing arousal from the fully alert state, through drowsiness, to finally, sleep (Erwin, 1976). Using the electroencephalogram (EEG), which is universally accepted as the most precise measure of the arousal states of the sleep-wake continuum, at least five stages of sleep have been recognized. Of the five stages of sleep, the most difficult stage to identify is Stage I sleep, light sleep. There is little distinction between being awake (Stage W) and encountering light sleep (Stage I). This is the region in which drowsiness occurs. Aside from the fact that Stage I sleep is difficult to recognize, there is debate as to whether Stage I represents sleep or not. However, a resolution to this problem for the purpose of studying intrusive sleep is provided. Intrusive sleep is presented as being "that moment when persistent eyelid closure occurs" (Erwin, 1976, p. ii). This physiological definition of intrusive sleep is used since successful driving requires the appropriate responses to the dynamic nature of visual cues. The driver cannot respond properly if his/her eyes are closed.

Using the description of intrusive sleep given above, the Duke studies investigated a collection of psychophysiological measures to determine their correlation with the onset of drowsiness. Eight physiological variables and one performance measure were analyzed. These measures were obtained in laboratory studies, not on-the-road. Some of the measures may seem impractical for field research, but they may be applicable in the future with advancements in the measurement technologies. The nine measures investigated were: plethysmography, respiration rate, electroencephalography, skin resistance level, skin potential level, electromyography, heart rate variability, eyelid position, and steering wheel reversals. Each are discussed below relative to their usefulness in drowsiness research:

1. Plethysmography - Plethysmography was unsuccessful in obtaining stable long term (>30 minutes) measures even in optimal laboratory conditions. The long term measurements contained a large amount of uninterpretable noise related to body movements and changes in position (Erwin, 1976).
2. Respiration rate - No direct correlation between respiration rate and drowsiness onset and/or sleep was obtained. Only in Stage II sleep was there a

significant correlation and Stage II sleep occurs 10 to 15 minutes after the onset of Stage I sleep (Erwin, 1976).

3. Electroencephalography - EEG changes occur following eye closure (very rapid shift, within 0.05 seconds, with eyelid closure is identified as Stage I sleep), but no significant alterations are indicated prior to eyelid closure (Erwin, Hartwell, Volow, and Alberti, 1976; Erwin, Volow, and Gray, 1973).

4. Skin electrical characteristics - Skin resistance level (SRL) and skin potential level (SPL) may measure lowered autonomic arousal, but not necessarily sleep or drowsiness. As valid measures for determining drowsiness, the measures result in too much variability, both between and within-subjects over time. Although, Kousmens, Tursky, and Solomon (1968) suggest "that the SPL measure may have more discriminate power in delineating sleep from the wake state", than the SRL measure (Erwin, et al., 1972; Erwin, et al., 1973; Volow, Erwin, Cipolat, and Hartwell, 1976; Erwin, 1976).

5. Electromyography - Essentially, the EMG offers no predictive characteristics. Significant sleep can

occur for several minutes prior to any real EMG changes (Erwin, 1976).

6. Heart Rate Variability - The variance of the interbeat interval indicates no significant changes with the onset of sleep (Volow and Erwin, 1973).

7. Eyelid Position - In a low demand tracking task, Erwin (1976) found eyelid position measures to be physiologically "the cleanest and most stable signal" examined in the Duke studies. (Erwin, 1976, p. xii). The eye aperture in the open position measures 13 mm $\pm$ 1.5mm. This measure remains stable across subjects. That is, there is relatively little between subject variation in the aperture of the opened eyelids and no within-subject variation over time. Also, unique characteristics of the eye closure may be detected in the state of drowsiness. The eyelids are lowered at a much slower rate than can be demonstrated when an individual is alert. An explanation for this is that there is an alteration in the relative balance between the skeletal and smooth muscles controlling the upper eyelid position. The slow ramp closures which result can be used as an index of drowsiness.

Two types of measurement techniques which are used to measure eyelid position are infrared photoreflective technique and DC recording.

1) In the infrared photoreflective technique, modulated infrared light is focused upon the upper eyelid. The contrast between the lid and pupil is detected by a photo-diode. With this method, stable results are obtainable in laboratory settings.

2) In DC potential recording, the eye serves as a dipole; negative at the retina, and positive at the cornea. Eyelid closure results in an upward rotation of the eyeball that changes the orientation of the dipole of the eye through which eye position is recorded. (Erwin, 1976; Erwin, Wiener, Hartwell, Truscott, and Linnoila, 1975).

8. Control Reversal - A reduction in the number of micro-control reversals occurs prior to the onset of sleep, indicating a lowered level of arousal. Movements of the control become quiescent one to five seconds after eyelid closure. This measure, however,

is a relatively "late" early warning system (Erwin, 1976).

In conclusion, Erwin (1976) recommends the use of eyelid data in drowsiness research. Two important reasons for using the eyelid position data were presented. First, severe drowsiness can be induced in many subjects by a simulated driving task. Secondly, highly significant changes in eyelid behavior can be monitored which correlate with drowsiness and deteriorating performance in simulated driving. Even though these assets provide merit for the use of eyelid data, there is still some question regarding how well this type of measure will work on-the-road. Further research is needed to develop this measure for practical use in field research.

An automatic measure of eyelid droop or slow closure which has been used in the normal driving situation is a device developed by Technology Associates. It requires the driver to wear a special pair of eyeglass frames containing a sensor assembly and an amplifier-detector unit (Technology Associates, Inc., 1978). For general population use this type of equipment causes several problems. First, a driver who wears prescription glasses cannot wear the special eyeglass frames without removing his/her own glasses. Second, the driver who is not accustomed to wearing glasses is not comfortable wearing the special eyeglasses. And finally, the eyeglass frames require no less than eight fine adjustments to measure eyelid closure accurately. As a result, the automatic measurement of eyelid droop and closure is at present impractical for actual highway use. However, eyelid closure data if obtainable for research may lead to the discovery of indirect measures of intrusive sleep.

A drowsiness-related study which supports the use of eye movement measures in driving research is a highway hypnosis study by Wertheim (1978). The study investigates a theory concerning the occurrence of drowsiness and inattention while driving. Wertheim contends

> that some of our mental abilities are related to the activity of the oculomotor system (the neurological system responsible for the initiation of eye movements). Accordingly, the need for eye movement patterns specifically required in driving performance has such a bearing on our oculomotor system that several other physiological functions are influenced (Wertheim, 1978, p. 112).

To investigate his hypothesis, Wertheim dichotomizes oculomotor control into an <u>attentive</u> component and an <u>intentive</u> component. The attentive component refers to the situation in which the retinal information serves as the main input for the oculomotor neurons, while the intentive component refers to oculomotor activity which is governed by information from other sources (primarily internal). (This dichotomy was validated with the visual system functions in an earlier paper by Wertheim (1974)).

The results of the study indicate that in driving tasks when the road situation is highly predictable (e.g., during prolonged driving on long unchanging stretches of highway or prolonged single-file driving), the intentive component of the oculomotor control increases at the expense of the attentive component. Wertheim associates the intentive oculomotor control with a certain degree of mental relaxation or lowered alertness, which may be detected in the physiological functions of the body.

Support for the success of EEG measures in monitoring the level of driver arousal was documented by Lemke (1982) in a monotonous prolonged driving task. Lemke (1982) used EEG measures to predict states of decreased vigilance. Through the investigation of five physiological signals including EEG, ECG, pulse rate, blood pressure, and flicker fusion frequency; the EEG parameter confirmed a decrease in vigilance over time. Both mechanical and EEG signals were recorded simultaneously for one 3-minute period in the middle of a one-hour driving task. In the analysis of this data, the redundancy of the EEG signals against the mechanical signals provided evidence that the mechanical signals of the vehicle may be used to predict decreased driver performance and decreased vigilance. In fact, Lemke indicated that the EEG measures may be of use as a criterion measure in a warning device for detecting decreased levels of vigilance.

Although, the studies mentioned above support the investigation of physiological measures in association with driver drowsiness, there are also drowsy driver studies which support the use of driver performance characteristics. One such study was conducted by Atwood and Scott (1981). The aim in their investigation was to examine "driver performance measures to predict whether a driver was suffering from sleep loss and/or excessive driving time" (Atwood and Scott, 1981, p. 726). Based on the performance measures obtained a multivariate criterion for detecting drowsy drivers was developed.

The experimental period over which the drivers performed their tasks was 27 hours. During the first 3 hours of day one of the study, the subjects drove around a closed 7.2 km oval track at approximately 80 kph. For the next 21 hours to impose sleep deprivation, each of the subjects remained awake. During this time period, the subjects performed batteries of behavioral tests at regular intervals. After the 21 hour period passed, each subject drove a second 3-hour scenario. The sleep-deprived driving period took place on day two of the study (after a 24 hour period). Each of the subjects listened to music transmitted through earphones during both of the driving tasks. Four subjects, three males and one female, drove in the study.

The performance variables which were obtained and analyzed were descriptive statistics (means, standard deviations, minimum and maximum values, ranges, percentile ranges, interquartile ranges, etc.) for vehicle velocity (kph), steering wheel position (degrees relative to center), lane position (meters of left-hand wheels from centerline), and accelerator position (percent of full-scale deflection). The statistics were computed for 30, 45, and 70 seconds of data.

To develop a multivariate model for drowsy driving, discriminant analyses were employed. The analyses attempted to identify the smallest n-variable set that best assigned a driver to an 'awake' and a 'drowsy' condition. A second week of data collection was obtained to determine how well each discriminant function predicted when the driver was becoming drowsy (an on-board computer loaded with the algorithm monitored the driver's performance). Only one subject/driver was utilized in the validation procedure.

In building the discriminant functions, data from only the first trail of day one and data from the next to the last trial of day two were used. Each trial contained six observations. The discriminant functions which resulted from the data of one subject for the 30, 45, and 70 second data intervals all included lane position in at least one form. The 30 second function used the mean and maximum values, while the others used median/range and mean/standard deviation, respectively. The other variables which entered the discriminant functions varied. They included measures of steering wheel position and accelerator position.

Since the data reported in this study was only from one subject, it was difficult to evaluate the procedure used to validate the discriminant functions. But, based on the reported results, the driver was declared drowsy on day two in a significantly greater number of trials than on day one. The results using the 30 second function (the best predictor) indicated that performance changed after sleep-loss and with time-at-the-wheel. As stated by Atwood and Scott (1981), 'Moreover, there is good reason to believe that this change in performance can be detected and used to warn the driver that he/she is falling asleep at the wheel' (p. 730).

The important contributions which Atwood and Scott made to the drowsy driver literature was a methodology for building algorithms and promise that algorithms may be developed using driver performance variables.

RESEARCH IN DRIVER FATIGUE

Since not many driving studies have been devoted to the phenomenon of drowsiness, this portion of this review presents research findings which may be of value in the investigation of drowsiness. Included are reviews on driver fatigue involving prolonged driving, sleep deprivation, diurnal rhythms, and low-event monotonous driving. These studies utilize driving performance measures, physiological measures, and subjective measures. Measures suggested for use in the assessment of driver fatigue include steering wheel reversals; velocity changes; average speed; number of brake, clutch, and accelerator reversals; reaction time; subsidiary task performance; heart rate; EEG; EMG; skin response characteristics; blood pressure; critical flicker fusion frequency; eye movement frequency and amplitude; and eyelid position. Some of the studies may include one or more of the topics mentioned for review. Because the study appears under a specific research heading does not imply that the study is solely concerned with that topic. The format was selected to indicate the research emphasis of the study. Finally, a few remarks are made in regard to the validity issues of simulation versus real world driving research.

Prolonged Driving

Prolonged driving as an independent variable is the most frequently used variable in driving research.

In a 24-hour driving study conducted by Safford and Rockwell (1967), seven subjects were instructed to drive for 24 hours or as long as they could maintain satisfactory performance. Of the seven subjects, all but two were able to complete the prescribed 24 hours of driving; and they drove for approximately 21 hours. During the study, four dependent variables were collected -- velocity means, velocity variances, steering wheel reversals, and accelerator reversals. The analysis of these data indicated that there were no universal trends across the subjects in driving performance relative to fatigue. No one variable was an indicator of fatigue for all seven subjects. Thus, the measures could not be generalized over time. Without knowing the specific characteristics of an individual subject driver, the means of the dependent variables could either increase or decrease.

In a second stage of this study, the seventh subject repeated the driving task under two additional conditions.

The first condition and the second condition were both performed after 24 hours of sleep deprivation.

Under the 24 hours of sleep deprivation in the first condition, the subject was only able to drive for 12 hours. The regression line constructed for this condition accounted for more of the total variation than any of the other regression lines of the other subjects in the first stage of the study. This suggests that the four dependent variables cannot be accepted as a universal measure of fatigue (Safford and Rockwell, 1967).

In the second condition of the second stage, the seventh subject was examined by a physician who prescribed 5 mg tablets of dextroamphetamine sulfate to keep the subject alert while driving. One tablet was administered one hour before driving, then every four hours thereafter. The subject, under the effects of sleep deprivation, was able to drive twice as long under the influence of the drug than when not, as in the first condition. Also, the subject claimed that he felt much better driving in the second condition as compared with the first condition. The usage of drugs by the subject resulted in a positive effect on the steering wheel reversals over time. With the drugs, the subject maintained a higher level of vigilance performance.

One consideration which was emphasized in this study was that when 24 hours of driving was specified as a requirement for the driving duration, the subjects tended to use the 24 hour mark as a goal. Since, the goal was adopted by the subjects, the effects of fatigue were not displayed until the later stages of the 24 hours. In the future, Safford and Rockwell (1967) recommend that a specific length of time not be prescribed to the subjects prior to a prolonged driving experiment.

Another opinion held by Brown (1967) with regards to prolonged driving is that

> If anything, performance tended to be better than on the control day and the findings were considered to support the hypothesis that prolonged driving leads to greater automatization of control skills, which increases the time available for the perceptual requirements of the driving task (Brown, 1967, p. 665).

This conclusion was arrived at after data were analyzed from a 12-hour virtually continuous driving task. Measures were obtained for both control skills and subsidiary vigilance task performance. The control skill measures included the number of brake, clutch, and accelerator reversals; pedal activations; wheel reversals; lateral and longitudinal accelerations; and driving time. The vigilance task involved the detection of light signals. The study resulted in no statistically-significant adverse effects due to prolonged driving (Brown 1966).

This study was later repeated by Brown (1967) to overcome some experimental inadequacies and contamination. Two specific inadequacies were pointed out. First, there was reason to believe that the subsidiary task was insensitive to the possible changes in the reserve capacity of the drivers due to prolonged driving. The sequence of responses to the task could be pre-programmed when the demands of driving were low and were then reproducible when the driving demand was high. Secondly, all the scores were obtained in highly stimulating city traffic which had a tendency to offset the effects of prolonged driving deterioration.

The results of the follow-up investigation, which was also conducted in city traffic, generally supported the results of the initial study. Virtually continuous driving for 12 hours need not affect driving performance. The original hypothesis regarding the automatization of prolonged driving remained a viable hypothesis.

Sleep Deprivation

Two studies which investigate driver fatigue and the effects of sleep deprivation are discussed below. A major problem which plagues many of the studies in driver fatigue is that there are truly no valid indicators of fatigue. None of the physiological or performance variables have been related to hours of driving, nor has fatigue been related to specific measures of driving performance.

One performance measure which has shown promise in relation to driver fatigue is reaction time (RT) (Lisper, 1966; Lisper, Dureman, Ericsson, and Karlsson, 1968; Lisper, Dureman, Ericsson, and Karlsson, 1971). Reaction time has been shown to increase over driving time in all three studies by Lisper (1966) and Lisper _et_ _al_. (1968, 1971). In the Lisper _et_ _al_. (1971) four hour on-the-road driving study, three driving conditions were examined: driving in daylight, driving in darkness, and driving in daylight after one night of sleep deprivation. The results indicated that there were no significant differences in RT between daylight and darkness driving. However, there was an increase in RT with hours of driving in all three driving conditions. The test hypothesis that a night without sleep relative to a night with sleep deteriorated driving performance resulted in no statistically-significant differences. This result contradicted previous findings by Wilkinson (1965) and Williams, Lubin, and Goodnow (1959); that RT performance deteriorated after sleep loss. Lisper _et_ _al_. (1971) attributed this contradiction of results to an unapparent stimulating effect in the sleep deprivation condition. The arousal level of the subjects may have been increased. As stated by Lisper _et_ _al_. (1971),

> the failure of sleep deprivation to have an effect on performance will make sense if it is assumed that performance is related only to level of arousal, which in turn is related mainly to sensory and cortical input to the arousal system. Consequently, if sleep deprivation influences performance only via the arousal system, sleep deprivation can be balanced by variation in sensory or cortical input. This theoretical position, implicitly taken by Duffy (1962), Wilkinson (1965), and Corcoran (1964), can be considered as explaining why sleep deprivation does not necessarily deteriorate performance, why the sensory variation component seems to be of great significance in the driver-fatigue problem, and why the test-driving-retest design fails to demonstrate fatigue from driving even of considerable duration (Lisper et al. 1971, p. 340).

Another point worth mentioning concerning the Lisper et al. (1971) study is that a large variation in RT performance from subject to subject occurred across the experiment. This result was expected, for it is well-documented that there are great individual differences in impairment from sleep loss (Wilkinson, 1965).

The second study involving the effects of sleep deprivation is by Huntley and Centybear (1974). Huntley and Centybear (1974) investigated the effects of alcohol and sleep deprivation (29 hours) singularly and jointly on driver control. Sleep deprivation alone had no statistically-significant effects upon driving performance (number of control movements). But, in combination with alcohol usage, sleep deprivation reduced the coarse steering control-rate initially found when only the alcohol influences were investigated; sleep deprivation counteracted the effects of alcohol. It should be noted that this counteracting effect was only found in control-use behavior. The result may not be transferable to other task settings.

Diurnal Variations

A driving phenomenon which is rarely investigated but shows a pattern effect in traffic accidents is diurnal rhythms (Lisper, Eriksson, Fagerstrom, and Lindholm, 1979). A diurnal pattern in traffic statistics remains even when traffic volume differences are taken into account. A critical period appears to be between the hours of 2 and 6 AM. These accidents are typically connected with falling asleep behind the wheel (Lisper *et al.*, 1979).

Studies by Hoffman, Mayer, Grundei, and Meier (1971-72) and Harris and Mackie (1972) found significant evidence that during the time period suggested by Lisper *et al.* (1979) there is a marked decrease in the physiological arousal in highway driving. A major point regarding these studies was that neither study dealt with circadian rhythm as a single factor. The circadian performance measure was confounded with one or more additional factors (e.g., driving in daylight and darkness, driving in different traffic volumes and intensities, or number of hours since last sleep period).

However, in the Lisper _et_ _al_. (1979), critical confounding factors were considered. Four driving sessions which lasted three hours each beginning at 0300, 0900, 1500, and 2100 were used. During each of these trials, a subsidiary reaction time task was used to measure driving performance. The results indicated that there were small variations in performance among the four sessions. But, differences in the rate of performance deterioration among the sessions was not indicated. Lisper _et_ _al_. (1979) concluded that biological rhythm as a single factor has only minor effects on a subsidiary reaction time task. Therefore, other factors must contribute to the diurnal rhythm of traffic accidents. One possible factor may be that drivers in the early morning (2 to 6 AM) have too many continuous hours behind the wheel, with a consequent lack of sleep (Lisper _et_ _al_., 1979).

Low Event Driving

It has been reported subjectively by driving subjects that the main cause of drowsiness while driving is the monotony of the road (Riemersma, Sanders, Wildervanck, and Gaillard, 1977). Whenever the driving environment offers little variation and few stimuli the driving condition is said to be 'low event driving'.

Many studies allude to the idea that when few stimuli are in the driving environment, that the driver is more apt to suffer from performance decrements (Brown, 1966; 1967). In fact, in a simulator study by Sussman, Sugarman, and Knight (1971), the ability of the driver to maintain the vehicle on the road decreased linearly over 4 hours of low-event driving. There was a significant decrease in steering wheel corrections with a significant negative correlation between steering wheel corrections and position error. "This may be taken to indicate that either the subject perceptually samples the road position less frequently after driving a number of hours or he processes and reacts to his road position less frequently during long-duration driving" (Sussman et al., 1971, p. 30). Also, Sussman et al. reported that when a measure of position accuracy was taken during a simulated emergency the driver was less likely to control the vehicle accurately after 4 hours of driving. This effect was most pronounced when the driver was exposed to a high level of acoustic noise.

While low event driving has been shown to induce drowsiness while driving, research support for the parallel hypothesis that the arousal level of a driver increases in high event driving (with a large number of stimuli in the driving environment) even after driving for a long duration is evident in a simulator study conducted by Muto and Wierwille (1982).

Muto and Wierwille (1982) studied the effects of 30, 60, and 150 minutes of continuous driving on the response times of drivers to a simulated emergency using repeated response trials. The simulated emergency involved reacting to a sudden deceleration of a lead car in a car-following scenario.

The experiment took place on two consecutive days. On the first day, each subject drove a baseline run. The baseline run was a 15-minute driving period in which ten emergencies were presented at random time intervals. On the second day, the subject performed a second baseline run. Then, the subject was given a two-hour break. After the break, the subject was exposed to an extended duration run (EDR) of either 30, 60, or 150 minutes. No emergencies were presented during the EDR run. Following the EDR run was a post-EDR run which introduced the simulated emergency randomly. The post-EDR trial was the same as the baseline runs presented on Day 1 and Day 2 of the study. The transition between EDR and post-EDR was designed to minimize the change so as to not alert the subject.

The results of the study indicated that the mean response times to the initial post-EDR emergencies tended to be slower than those of the later post-EDR emergencies, and of the Day 1 and Day 2 baseline response times. (There were no significant differences among the response times of drivers who had driven 30, 60, or 150 minutes.) The longer response times associated with the post-EDR trials in the first two or three emergencies presented, were long enough to constitute the difference between accident avoidance and an accident. But after the presentation of repeated response trials the decrement normally associated with fatigue was eliminated or severely reversed.

These results suggest that the use of repeated response trials in driving studies may not yield valid indications of fatigue-induced performance decrements. Thus, they should not be generalized to on-the-road driving performance under normal driving conditions (Muto and Wierwille, 1982).

In a more extensive analysis of the data from the simulator study of Muto and Wierwille (1982), Wierwille and Muto (1981) used the 30, 60, and 150 minute extended duration runs in an effort to examine trends in driver-vehicle response measures, physiological measures, and subjective measures. The measures collected included: number of body movements per unit time, heart beat interval standard deviation, vehicle lateral standard deviation, steering standard deviation, large steering reversals and small steering reversals per unit time, steering reversal mean amplitude, yaw standard deviation, yaw reversals, and subjective ratings. All of these measures were recorded for consecutive 10-minute intervals.

In the study, three emergency classes were introduced to the subjects. They were 1) recovery from step side gusts, 2) evasive or braking maneuvers during car-following, and 3) lane changes required by light signals. Each subject was exposed to only one of these three emergencies and only one of the three driving duration times.

All the performance and physiological measures analyzed resulted in statistically-significant trends over all three of the extended time runs. The data showed a high level monotonic trend when averaged over the subjects for the 150 minute run. Eight of the nine measures had positive trends; while one, the small steering wheel reversals, had a negative trend. This indicated that the changes both in performance and physiological measures over driving time were pronounced and well behaved. Similar trends were evident in the 30 and 60 minute extended duration runs. No statistically-significant differences were indicated in driving performance for the type of emergency presented.

As for the opinion measures, the mean rating for "before" and "after" the EDRs indicated that the subjects judged themselves to be less alert after having driven for a prolonged period than beforehand. The subjects rated themselves as being significantly more fatigued as run length was increased from one-half hour to one hour, and there was a slight increase in the ratings from one hour to two and one-half hours (although it was not statistically-significant). The trend for the subjective ratings was a negative trend from "extremely alert" to "extremely tired".

These results indicated that in simulated driving asymptotic performance is not reached within a two and one-half hour driving period. Drivers cannot be assumed to have practiced "to asymptote" (Wierwille and Muto, 1981). Therefore, it is extremely important for researchers to use equal amounts of practice and time-on-task when collecting data for simulator driving. As a final note, Wierwille and Muto (1981) suggest that both subjective and performance-related measures be used to assess the effects of time-on-task driving to help account for result discrepancies.

Simulator Validity

Issues have been raised regarding the use of simulation for driving research. An argument which is often presented is that simulation of an event does not sufficiently represent the real world. However, the advantages of using simulation for driving research are attractive when given the alternative of conducting a field study. Simulation is a means of collecting a wide variety of driver-vehicle performance and response data safely and efficiently. In simulation, the experimenter can maintain control of the traffic, roadway, and meteorological variables which might otherwise reduce the precision of an on-road experiment. The subjects may be provided with a variety of stimuli consistently, without inducing greater stimulation to any one subject at any given time. Thus, the arousal level of the subjects may be controlled effectively.

In 1975, Leonard and Wierwille conducted a human performance validation of simulators both experimentally and theoretically through the comparison of a full-scale vehicle and a driving simulator. The results of the study indicated that for each performance measure at least one simulator condition produced a correspondingly valid result. Leonard and Wierwille concluded that if a simulator is properly adjusted performance validation with a full-scale vehicle system can be obtained.

The following simulator and experimental design criteria were presented by Leonard and Wierwille (1975, p. 451) as requirements for the validation of driving performance measures:

1. The simulator must possess good fidelity in those aspects corresponding to the measures taken.
2. The simulator must have the capability of parameter adjustment.
3. A sufficient number of properly selected independent variables and corresponding settings must be employed.
4. Performance data must be obtainable for the standard full-scale vehicle and for each adjustment of the simulator, and
5. Accepted methods of experimental design must be used to insure unbiased data and correct conclusions regarding validity.

As a final note regarding the use of simulation Sussman *et al*. (1971) state: "In short, each type of research problem requires a decision as to which kind of simulation technique is appropriate or, alternatively, whether full-scale testing, or some combination of simulation and full-scale testing, would be most efficacious" (Sussman *et al*. 1971, p. 31).

STUDIES IN VIGILANCE

Another area of research which has provided relevant information regarding automobile drivers and their driving tendencies and characteristics is vigilance. Vigilance was defined by N. H. Mackworth in 1957 as "a state of readiness to detect and respond to certain specified small changes occurring at random time intervals in the environment" (Davies and Parasuraman, 1981). By this definition, it is easy to see why vigilance studies have been used for comparison with the driving situation.

Many of the theories which explain vigilance stem from two questions: (1) what determines the decline in performance during a vigilance task? and (2) what determines the overall level of performance? (Davies and Parasuraman, 1981). However, more emphasis has been placed on explaining vigilance decrement. Of the seven theories of vigilance presented by Davies and Parasuraman (1981), the theory of arousal is often used in describing the driving situation (e.g. Boadle, 1976; Fagerstrom and Lisper, 1977; Mackie and O'Hanlon, 1977; Riemersma _et al_., 1977). The arousal theory emphasizes the general state of the drivers at the time the task is carried out as a determinant of performance changes. Three explanations of arousal decrement have been developed. They are arousal or activation theory, habituation theory, and motivation theory. Arousal theory provides an adequate explanation of the driving situation stating that

> a progressive reduction in the level of arousal of the central nervous system takes place during task performance, largely brought on by the monotonous nature of the vigilance situation. As a result, the brain becomes less responsive to and less efficient at dealing with external stimulation (Davies and Parasuraman, 1981, p. 16).

Vigilance studies have been conducted on a number of factors which influence vigilance including personality; psychophysiological states; subject population characteristics; general state variables -- time of the day (diurnal rhythms), sleep deprivation, and drugs; and environmental factors. Below is a summary discussion of findings from studies of vigilance which apply directly to drivers in driving tasks (for more information and references regarding the conclusions which are discussed see Davies and Parasuraman, 1981).

Personality

There are two main findings that emerge from the studies of temperament and vigilance: (1) Generally, when extreme groups of subjects are selected, extroverts show a greater decrement in vigilance than introverts when performing a 'speed' task with a high event rate (usually greater than 24 events per second); and (2) there is an overall difference in the sensitivity during vigilance between the temperament groups. This latter result may be interpreted as a difference in the arousal levels of the two groups. Extroverts are believed to become bored and distracted more easily by monotonous work situations.

Psychophysiology

Attempts have been made to find reliable physiological correlates of vigilance decrement. In general, the results appear to be discouraging as a result of the criticism surrounding the collection of physiological measures in previous vigilance studies. Three major criticisms are: 1) the situation or task specificity is not provided due to the lack of control data, 2) the vigilance task is often distorted to meet psychophysical requirements, and 3) the performance assessment is inadequate, in that, measures of sensitivity and bias are largely neglected (Davies and

Parasuraman, 1981). In conducting psychophysiological studies, Davies and Parasuraman (1981) have imposed two mandatory requirements on physiological measures for them to qualify as reliable measures. The two requirements are first, that the decrement of vigilance is accompanied by a reliable change in a physiological index and second, that performance is correlated with the index. Some physiological findings which were obtained under these guidelines are: (1) skin conductance decreases during a vigilance task, but shows little correlation with performance, (2) mean heart rate either declines or remains stable with time, but is uncorrelated with performance, (3) respiration rate and muscle tension are not statistically-significant, or correlates of performance, and (4) heart rate variability and adrenalin level are strongly associated with detection efficiency in sustained attention monitoring tasks. In general, though, it is difficult to derive firm conclusions about vigilance performance using physiological measures despite some promising results from well-conducted experiments.

Subject Populations

Age. In studies where reliable age differences in performance have been reported, older individuals consistently perform at a lower level than younger individuals. Also, older individuals develop a more cautious response criterion and have less confidence in their responses. The performance differences between older and younger populations are more likely to be found in visual tasks, as opposed to auditory, and in tasks which have high event rates.

Sex. Sex differences in vigilance performance are slight and of little theoretical or practical importance. However, it is wise to control for sex differences in multi-factor designs.

State Variables

It should be noted that the state variables described below have been shown to exert reliable effects on vigilance performance; however, the effects are not always consistent.

Time of day. The effects of time of day on vigilance performance are evident in the type of task presented and also in the diurnal level of arousal assumed. If a task imposes a load on memory, particularly short term memory, fewer items are correctly recalled as the day progresses.

Conversely, performance generally improves from early to late in the day in tasks not requiring short term memory in performance. There are substantial results which suggest that variations in task performance with the time of day are related to diurnal rhythm variations. The level of arousal is presumed to increase from the morning to the afternoon and evening reflecting the diurnal rhythm of the body.

Sleep deprivation. Sleep deprivation studies of vigilance are usually conducted under two conditions, either total sleep deprivation, which is normally about 100 hours or 4 nights without sleep, or partial sleep deprivation, which is sleeping some fraction of the normal sleeping time. In total sleep deprivation, the performance level of a subject undergoes periodic lapses of efficiency upon an otherwise unchanged level of performance. These lapses of efficiency generally coincide with a slowing of the EEG frequency and/or a brief period of apparent sleep.

The effects of partial sleep deprivation are less severe than those of total sleep deprivation. The amount of performance decrement is due to partial sleep deprivation related to the amount of sleep lost (Wilkinson, 1968). Also, the reliability of time-of-day effects on performance are not apparent under conditions of partial sleep deprivation.

Drugs. Amphetamines and caffeine reduce the amount of performance decrement in vigilance tasks, while depressants such as Benadryl or alcohol have either impaired or shown no effect upon the overall level of vigilance performance. As for smoking, it appears to maintain the level of behavioral arousal during task performance while preventing a decrement in performance from occurring in vigilance and other monotonous tasks.

Environmental Factors

Noise tends to raise the arousal level of the subject, while heat, in the long run, lowers the sensitivity. However, increased arousal and improved performance are noted upon initial exposure to heat.

Development of Physiological Alertness Detectors

Vigilance investigators have recognized that the loss of alertness in many monitoring tasks may jeopardize the safety of an operation. As a result, alerting devices have been developed introducing "synthetic" targets or "secondary" tasks into the job. By providing the monitor with a stimulus, the event rate of a monotonous job may be increased and the monitor's response reaction time may be measured, thereby checking the vigilance level of the monitor. An example of such a device is a reaction time device of a train engineer, which requires the operator to constantly, or in regular intervals, depress a button, pedal, or horizontal bar. Whenever the monitoring equipment is not satisfied within a predetermined time, an alarm sounds. If the appropriate response is then neglected for another time period, the train brakes are automatically applied. Criticisms of this type of device primarily lie in the fact that the train operator can respond properly to the alerting device and yet not be vigilant or attentive to the task of driving the train (Wilde and Stinton, 1983). The operation of the device also suffers from habituation.

To overcome some of the deficiencies related to the alerting devices presently used in train locomotives, Wilde and Stinton (1983) have proposed the use of an alerting device DAME (Device for Attention Monitoring and Excitation) which directly involves stimuli which are important to the control of the train. By doing so, the alerting device verifies if attention is directed toward the control elements of the driving task.

Another type of "alerting" system which has been attempted is the monitoring of physiological signs for detecting lowered states of alertness. The advantage of a system using physiological measures is that the alerting method can be transferred from one type of environment to another. The earliest such attempt included neck EMG activity (Travis and Kennedy, 1947), which proved to be impractical. Other investigations are being conducted using heart rate variability and EEG measures. Two measures which have provided meaningful results are event-related potentials (ERP) and pupilometry (Beatty, 1978; Davies and Parasuraman, 1981; Isreal, Wickens, Chesney, and Donchin, 1980). Both parietal ERPs (P300s) and pupillary movements have been shown to be sensitive to variations in cognitive load or information processing and brain activation. For detailed discussions regarding these measures, see Davies and Parasuraman (1981).

In general, physiological monitoring devices appear to show merit for use in alerting devices. However, the question remains open as to how acceptable physiological alerting devices would be to the public.

SUMMARY

In reviewing the driving drowsiness, fatigue, and vigilance literature, several important considerations in conducting drowsy driver research may be emphasized. These points should be observed where applicable to design optimal experimental methodology. The design considerations below are listed under their appropriate measurement area.

<u>Physiological Measures</u>	<u>Reference</u>
(1) The electroencephalogram (EEG) is the most universally-accepted measure of the sleep-wake continuum, but it offers little variation in readings between drowsiness and Stage I sleep. It is impractical for normal driving.	Lemke (1982) Erwin (1976)
(2) Eyelid position data offers little intersubject variation in eyelid aperture opening and no intrasubject variation over time. Since eyelid closure causes a hazardous driving condition, there is no ambiguity as to its significance. Also, eyelid closure has been highly correlated with defective performance.	Erwin (1976)
<u>Performance Measures</u>	
(1) Mechanical signals of the vehicle may be used to predict decreased driver performance and decreased vigilance.	Lemke (1982)

Performance Measures (cont.)	Reference
(2) Discriminant functions based on driver performance measures may be developed to predict 'awake' versus 'drowsy' driving.	Atwood and Scott (1981)
(3) Subsidiary tasks must be sensitive to the possible changes in the reserve capacity of drivers to avoid automatization of control skills in prolonged driving.	Brown (1967)
(4) Reaction time measures show great promise in the detection of driver fatigue.	Lisper (1966) Lisper *et al.* (1968, 1971)
(5) High stimulation or repeated response trials reverse the effects of fatigue-induced performance.	Brown (1967) Lisper *et al.* (1971) Muto and Wierwille (1982) Wierwille and Muto (1981)
(6) Sleep deprivation affects performance via the arousal system. Thus, the effect that sleep deprivation has on performance is related only to the level of arousal, which in turn is related mainly to sensory and cortical inputs to the arousal system.	Lisper *et al.* (1971) Wilkinson (1965)
(7) There are large individual variations in the performance impairment due to sleep loss.	Wilkinson (1965)
(8) Alcohol and drugs may reverse the performance effects due to sleep loss.	Huntley and Centeybear (1974) Safford and Rockwell (1967)

(9) Diurnal variations as a single factor have minor effects on subsidiary task reaction times. Diurnal variation is usually confounded with more than one factor (e.g. sleep loss, time-on-task) whenever a decrease in physiological arousal is recorded in highway driving.	Harris and Mackie (1972) Hoffman *et al.* (1971, 1972)
General Design Considerations	**Reference**
(1) Do not specify the driving duration to the subjects in prolonged driving. The subjects tend to goal set which reduces the rate at which performance decrements occur.	Safford and Rockwell (1967)
(2) Monotony of the road has been subjectively noted to be the cause of driving drowsiness.	Riemersma, Sanders, Wildervanck, and Gaillard (1977)
(3) In simulator driving research, equal amounts of practice and time-on-task should be carefully exercised for each subject.	Wierwille and Muto (1981)
(4) Extroverts as opposed to introverts generally become bored and distracted in vigilance tasks causing greater performance decrements.	Davies and Parasuraman (1981)
(5) Older subjects tend to adopt more cautious criteria in vigilance research.	Davies and Parasuraman (1981)
(6) In diurnal variations, the arousal level is presumed to increase from the morning to the afternoon and evening reflecting the diurnal rhythms of the body.	Davies and Parasuraman (1981)

General Design Considerations (cont.)	Reference
(7) Sleep deprivation results in lapses of inefficiency coinciding with a slowing of the EEG frequency.	Davies and Parasuraman (1981)
(8) Partial sleep deprivation effects are less severe than those associated with total sleep deprivation.	Davies and Parasuraman (1981)
(9) Time of day effects are not apparent under conditions of partial sleep deprivation.	Davies and Parasuraman (1981)
(10) Smoking during vigilance research often prevents performance decrements by maintaining the level of behavioral arousal.	Davies and Parasuraman (1981)
(11) Noise increases the arousal level in vigilance and other monotonous tasks.	Davies and Parasuraman (1981)

RESEARCH OBJECTIVES

Due to the absence of a drowsiness countermeasure device that is reliable and/or practical, the primary goal of this research was to learn more about the phenomenon of driver drowsiness. By acquiring information regarding the performance characteristics and responses of drowsy drivers, progress towards developing a reliable countermeasure could be achieved.

A central problem with many of the past attempts in designing countermeasures was that the driving parameters used as the basis of the designs were not appropriate or they were "late" drowsiness characteristics. If devices to detect drowsiness are to be developed, parameters directly or indirectly associated with the <u>onset</u> of drowsiness must be identified.

The most accurate method of identifying the various stages of the sleep continuum being used today is the electroencephalogram (EEG) (Erwin, 1976). But for obvious reasons, the electroencephalogram may not be incorporated into the normal driving situation. Therefore, an alternative measure for detecting drowsiness was utilized in this study. The alternative measure which was chosen was eyelid droop and slow closure. Eyelid droop and closure were found to be highly correlated with drowsiness and associated performance decrements in the Duke University studies (Erwin, 1976). In fact, Erwin (1976) recommended the use of eyelid droop as a valid indicator of drowsiness and fatigue. He suggested using that 'moment when persistent eyelid closure occurs' as the standard for measuring intrusive sleep or drowsiness. Persistent eyelid closure refers to a duration of closure which suggests inattention to the task at hand. This approach seemed extremely appropriate for driving research, since a driver cannot monitor the driving environment with his/her eyes closed. Also, a potential research advantage which was obtained in eyelid closure data was that they offered measures with little intersubject variation and no intrasubject variation over time (Erwin, 1976).

In this research, that 'moment when persistent eyelid closure occurs' was used as a measurement standard of drowsiness. Persistent closure was defined as the slow ramp closures which occur with drowsiness onset. The slow ramp closures were used since slow ramp closures could not be consciously produced by the drivers (Erwin, 1976). By using eyelid closure, a parameter known to be associated with drowsiness, two primary research goals were attained.

(1) A better understanding of driver performance characteristics and their association with driver drowsiness were obtained.

(2) A predictive model of drowsy drivers was developed for use in the design of new drowsiness countermeasures.

Specific issues which were addressed in this research include:

1. Were there significant performance and response decrements associated with drowsiness while driving (eyelid droop and closure)?
2. Which responses to low-level stimuli were most relevant in the detection of drowsy driver performance? And, which stimuli were the most appropriate for testing the response characteristics of rested, sleep-deprived, and drowsy drivers?
3. What response and performance differences occurred between driving under normal rested conditions and driving after partial sleep deprivation? What influence did driving experience have on these conditions?
4. Could one or more of the performance and response variables be combined in a linear model to obtain a predictive model of drowsiness?

5. Did drowsy drivers produce waveform signatures which were identifiable as typical drowsy driver performance characteristics?

A secondary purpose of this research was to obtain information concerning the effects of sleep deprivation and time-on-task on driving performance characteristics and responses. This phase of the research provided feedback concerning how effectively fatigue or drowsiness was induced in the drivers and what type of arousal level was maintained by the drivers. Also, the response-stimuli which were designed and introduced into the vehicle system were reviewed for their potential advantages and disadvantages in detecting fatigue or deteriorating driver performance.

Experimental Design

The experimental design which was used for this research was a 2 x 3 complete-factorial, within-subject design. The two factors in the design were driving condition and segment (time-on-task). The first factor, driving condition, had two levels -- rested and sleep-deprived. The second factor, segment, had three levels -- low, medium, and high. Each of the subjects received all of the factor levels in the design. To control for differential transfer effects due to one driving condition always being presented first, driving condition was counterbalanced across the design. That is, ten of the subjects drove in the rested condition first, and ten drove in the sleep-deprived condition first. The experimental design layout used is shown in Figure 1.

For each of the design cells shown in the experimental block diagram in Figure 1, 17 dependent variables were recorded for each of ten subjects. Per subject, fifteen repeated measures were collected for each dependent variable for two types of stimulus inputs (torque and displacement). Figure 2 shows a single cell from Figure 1 with the corresponding data which was recorded. All six of the design cells in Figure 1 contained the data represented in Figure 2.

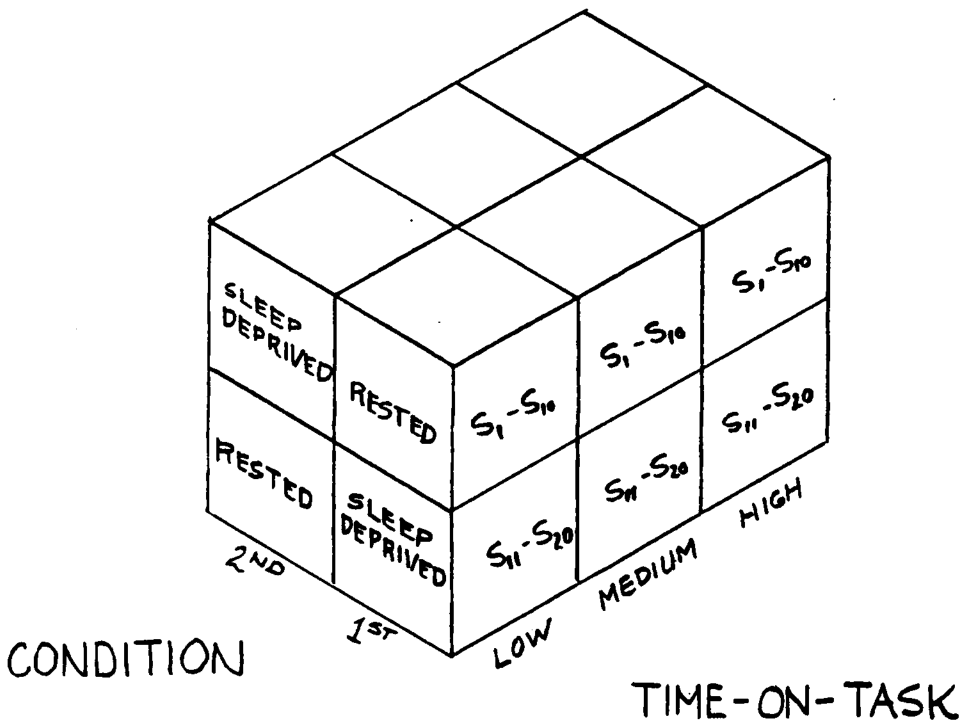

Figure 1. Experimental design

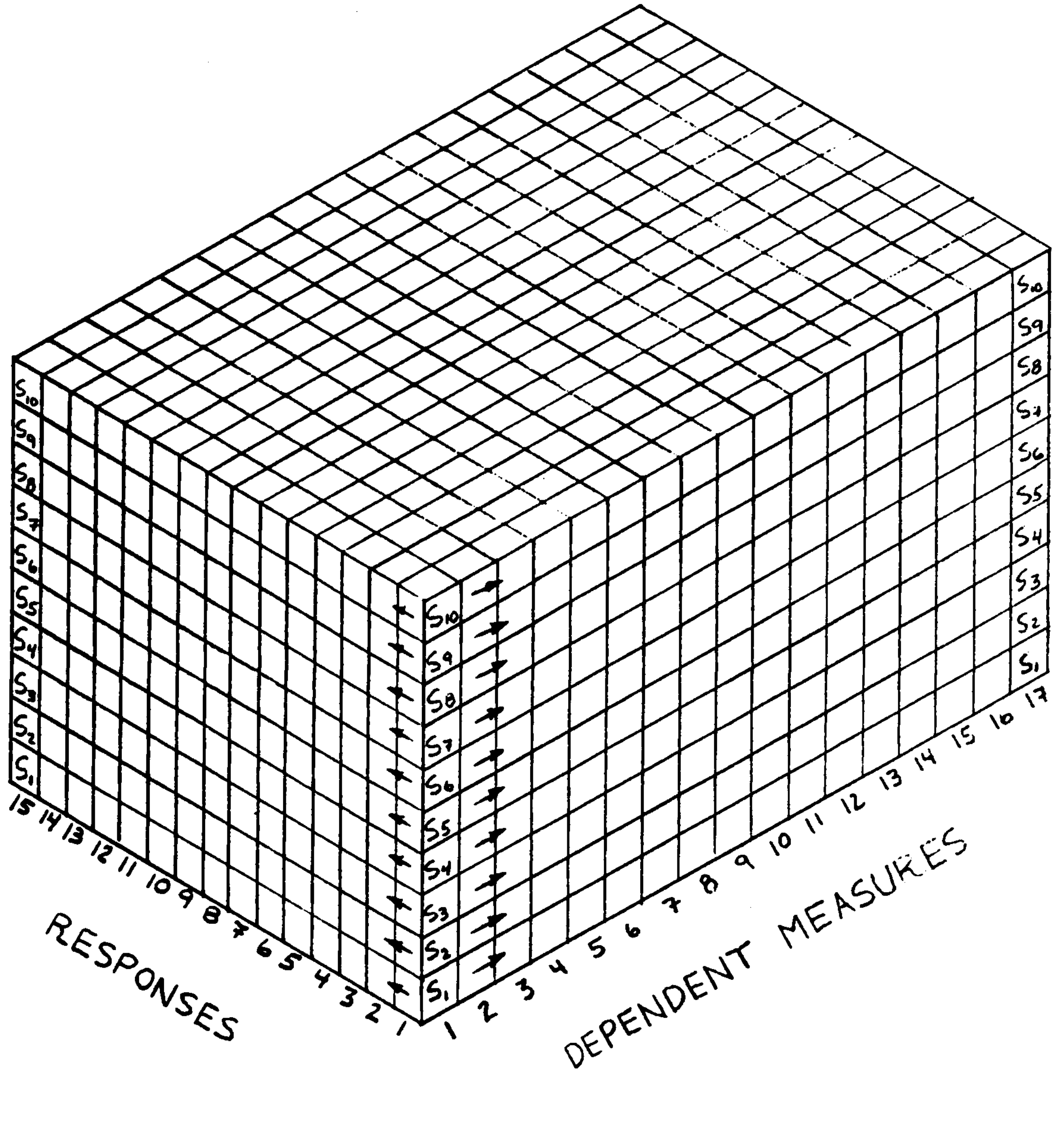

Figure 2. Experimental cell design

Subjects

In this study, ten male and ten female volunteer subject/drivers drove an automobile simulator both in a rested state and after partial sleep deprivation. The subjects were screened initially using a questionnaire (Appendix A) to eliminate drivers who were not prone to drowsiness and those who exhibited pathological sleep disorders. Each subject also provided biographical data and information regarding his/her driving and sleeping habits in the questionnaire.

Each driver was required to have 20/30 far visual acuity or better, corrected or uncorrected; and, each held a current driver's license. The subjects received $4.00 per hour or $60.00 maximum for their time involved in the study. In addition, small bonuses of approximately $10.00 were given to each of the subjects for completing both experimental runs.

The mean ages of the male and female drivers were 30.7 years and 31.6 years, respectively. The age ranges of the drivers were males 18 to 50 and females 19 to 47. Both the male and female driver samples included drivers whose yearly milage totals ranged from approximatly 3,000 to over 20,000 miles per year. The distributions for both age and experience were relatively uniform for the males and females.

Apparatus

Automobile simulator. The automobile simulator which was used in this research was a computer-controlled driving simulator. The simulator was programmed to produce a realistic highway driving scenario and to handle like a midsized, rearwheel-drive American sedan. As previously noted, Leonard and Wierwille (1975) experimentally validated this simulator with an on-the-road, full-scale vehicle. Through the proper adjustment of the simulator dynamics using parallel measures in full-scale and simulation, validation was demonstrated. The results showed that for each of five driver performance measures used at least one simulator condition produced corresponding valid results (Leonard and Wierwille, 1975).

The simulator, through the incorporation of four major systems, produces four degrees of platform motion, six degrees of image/display motion, and four audio cues. The four major systems are 1) a roadway imaging/display system, 2) a motion platform, 3) an audio system, and 4) an analog/hybrid computational system. Each of the systems are briefly discussed below. (For more information regarding the design and operation of the simulator see Wierwille, 1975).

1) The roadway imaging/display system produced the image of a concrete two-lane roadway. A specially designed computer system combined digital, hybrid, and high-speed analog techniques to generate the image with a series of parallel lines in the horizontal plane. The roadway image included a dashed centerline, field markings at the left and right sides of the road, and additional horizontal lines to give the road the appearance of being embedded in the horizontal plane. The final image of the system was produced on a 58 cm (23 in) monochrome monitor, which was viewed through a fresnel lens. The fresnel lens was located immediately in front of the driver through the simulator windscreen. The roadway image as viewed through the fresnel lens appeared to be at a distance of approximately 10 meters (33 feet). Control of the image was varied through six degrees of display motion -- forward velocity, lateral position, yaw, roll, pitch, and inverse radius of curvature.

2) The motion platform system provided the motion and vibration cues for the vehicular motion of the simulator. The platform was equipped with a vehicle cockpit mockup consisting of a driver's seat, steering wheel, speedometer, brake and accelerator pedals, and the image/display system. Platform motion was acheived using closed-loop

servo-controlled hydraulic actuators. Four degrees of motion were provided for -- roll, yaw, lateral translation, and longitudinal translation. Engine-drivetrain vibration was also simulated on the platform by means of a motor with an eccentric mass. The velocity of the motor was controlled by the simulated engine speed. This motor was also used to generate automobile engine sound.

3) The audio system simulated the sounds of rolling resistance, engine/drivetrain noise, tire screech on severe braking, and tire squeal on severe cornering. All of these sounds were modulated and controlled by the simulator dynamics.

4) An analog/hybrid computational system was used to simulate the vehicle dynamics of the simulator. The simulator dynamics were produced using steering, braking, accelerator signals, as well as gust and curvature signals as inputs. The outputs of the computer then updated the position of the motion platform through control of the electrohydraulic servos. The outputs were vehicle velocity, lateral position, yaw, roll, and pitch. Conditioned signals were also provided to the motion servos, the speedometer, the image generator, the audio system, and the FM recording

system used for data processing. Thus, all of the simulator systems were interconnected and controlled by the analog/hybrid computer.

Additional simulator features. In conducting this research, several modifications were made to the existing simulator system. First, the simulator was equipped with a low-light level RCA Model TC1004-U01 closed-circuit television camera (CCTV). The camera continuously monitored the eyes of the subjects so that accurate measures of eyelid droop and closure were video recorded and stored. The camera was largely unobtrusive and did not block the driver's roadway viewing.

Second, a control unit was added to the simulator steering system to provide the simulator with an active steering system. Through the control unit, the steering torque, viscous friction, restoring force, disturbance level, and steering limits were made adjustable. This additional control over the simulator's steering system allowed torque stimulus inputs to be introduced into the steering wheel.

The final feature which was added to the simulator system was a D/A - A/D, unipolar - bipolar, eight channel interface. The interface offered flexibility in the control of the simulator system by linking a TRS-80 microcomputer with the simulator dynamics. Through the interface, specific qualities of the simulator dynamics were monitored and read by digital logic. Provided that the appropriate conditions were met, a program stored by the TRS-80 was initiated. The TRS-80 was programmed to introduce a realistic highway driving scenario and low-level stimuli into the simulator dynamics. Curved and straight highway segments, as well as two types of driving stimuli were pre-programmed into the TRS-80 for use in the driving scenarios.

Driving Scenario

The complete driving scenario was designed to last 90 minutes. In designing the 90-minute scenario, one 30-minute driving segment was programmed and initiated three consecutive times. So, each of the 30-minute segments was identical and was controlled by the TRS-80 microcomputer. By providing three identical 30-minute segments, data could be collected during driving for low, medium, and high time-on-task. Subjects were not aware that the 30-minute scenario was repeated.

To provide realistic highway driving scenarios, the 30-minute segments were further divided into six five minute divisions. These six divisions consisted of either curved highway driving or straight highway driving. The roadway pattern which was introduced was curved, straight, curved, straight, curved, straight. The three curved divisions were programmed to provide different curvature frequencies with varying degrees of curvature.

Stimuli

Whenever the steering wheel was not in motion (defined as steering wheel velocity within $\pm$ 8 degrees per second for 0.4 second) as detected by special circuitry in the steering system, a low-level stimulus of known amplitude and shape was introduced into the driver-vehicle system. The driver responded to the low amplitude test signal while simultaneously performing the instructed highway driving task. The stimulus was presented at a low enough level that it did not interfere with the normal driving process to any significant degree. However, the driver's eventual response was required after the stimulus introduction to maintain the vehicle on the roadway. (It should be pointed out that the driver needed to produce steering inputs under any circumstances to remain on the highway due to a low-level random noise waveform impressed on the torque input to the steering system. The random noise was similar to the steering noise encountered in highway driving.)

So that the subjects were not alerted or aroused during the driving scenarios, the stimuli presentation rate was constrained. No two stimuli were introduced during the same 55 second interval. Also, the stimuli were designed to simulate stimuli typically encountered in highway driving.

Each of the responses following the input-stimulus was assumed to be a result of the stimulus plus normal driving responses. An advantage which the stimulus approach offered was that the response variables could be analyzed and compared during the presence and absence of corresponding eyelid droop and closure. Variations in driving performance were then determined. The following stimulus inputs were used in the driving scenarios:

Torque stimulus. A torque input was applied to the steering shaft of the simulator steering system. The torque pulse created a movement in the steering wheel to which the driver eventually had to respond to maintain position on the highway. The torque stimulus width was approximately 5 seconds in duration and was Gaussian in shape. Since the torque stimulus was 5 seconds in duration, the drivers responded to the torque over its duration. The magnitude to the input was such that the drivers perceived turning in the steering system. The drivers subsequently provided a counteracting response.

Displacement stimulus. A displacement pulse was applied to the front wheels of the simulator dynamics. This stimulus provided both a visual cue and a motion cue through the image/display of the roadway and through the motion of the platform. The eventual response of the driver was required to maintain roadway position. The width of the displacement stimulus was approximately one second and the pulse was Gaussian shaped. Since the displacement pulse was abrupt, the driver typically responded to the consequences of the displacement. The perception of the driver to the displacement stimulus was similar to the vehicle hitting a bump or rock on the roadway surface.

These two stimuli were predesigned into a semi-random presentation pattern prior to the experimental runs. Thus, the introduction of the stimuli appeared random to the subjects, as opposed to being alternated or predictable.

The presentation scheme remained constant from subject to subject and from scenario to scenario. Thirty stimuli, 15 of each type, were induced during one 30-minute driving scenario. That is, 15 response measures were recorded for each stimulus in each 30-minute time-on-task scenario.

Procedures

Screening. Initially, all subjects in this study completed a driver questionnaire, Appendix A. This questionnaire was designed to incorporate some of the aspects of the Tilley et al. (1973) questionnaire used in the Duke University studies. Since the purpose of this study was to investigate the performance characteristics and responses of drowsy drivers, subjects were screened using the questionnaire to eliminate drivers who were not prone to drowsiness and those who exhibited pathological sleep disorders. The questionnaire provided biographical data on each of the subjects, as well as information regarding the subject's driving habits and sleeping habits. All data obtained in the questionnaire were confidential and was handled with anonymity by using a number as the only identifier.

Pretesting. After the subjects were screened and selected, they were notified for participation in the study. When the subjects reported to the simulation laboratory, a vision examination was given to each of the subjects. Each subject was required to have 20/30 far visual acuity or better, corrected or uncorrected. A Landolt C-Ring vision test was administered. This test was designed to measure the minimum separable acuity for a subtended arc of 1.50 minutes, which is the equivalent of 20/30 visual acuity (Riggs, 1965). This requirement insured that all roadway stimuli and vehicle instrumentation readings were properly interpreted by the subjects.

General driving task. Each subject who participated drove the automobile simulator under two separate conditions. The first condition was after a 'normal' night of rest, while the second was after a period of sleep deprivation. The scenario in each condition was 90 minutes of simulated low-event interstate driving at 55 miles per hour. The driving environment simulated night driving.

After each of the subjects completed the vision pretest, they were asked to read the general instructions of the experiment and the participant's consent form (Appendix A). If the subjects wished to participate after reading these documents, they were required to sign the consent form. The signature of the subjects indicated that they understood what was expected of them during the study and what their rights were as experimental volunteers. If at any time the subjects needed clarification of the task or had questions, the experimenters were available to answer questions.

Before any of the simulation runs began, the subjects were briefed on the operation and features of the simulator. After the subjects were briefed, they were given 15 minutes of practice driving to familiarize themselves with the driving scenarios and with the handling characteristics of the simulator. The simulator was equipped with a standard lap seat belt which was worn by the subjects at all times. Also, the simulator and the experimenter's control station were equipped with emergency stop buttons. If at any time during the scenarios the subjects or the experimenters felt that it was necessary to stop the motion of the simulator, the emergency stop button was activated. Since the subjects were apt to doze while driving, a trained experimenter monitored the performance of the subjects at all times.

Rested condition. In general, the rested driving was performed 2 to 8 hours after the regular wake-up time of the subjects. The subjects were encouraged to obtain a 'normal' night of rest the night before the scheduled run. The rested run duration was 90 minutes. During those 90 minutes, the subjects responded to inconspicuous low-level stimuli which were introduced, while performing a typical highway driving task. The subjects' pre-experimental instuctions for the driving task were to maintain a driving speed of 55 miles per hour, to drive in the right lane position, and to drive in a typical manner. When the experimental run was completed, the simulator motion was stopped. The subjects exited the simulator and were dismissed.

Sleep deprived condition. For the sleep-deprived condition, the subjects were asked to report to the Vehicle Simulation Laboratory in the early evening (6 PM) for sleep deprivation prior to the experimental run. The subjects were asked not to drive to the lab for the sleep-deprived run. If the subjects could not find transportation to the lab, an experimenter provided transportation from their homes to the laboratory.

Each driver upon reporting to the laboratory reported his/her wake-up time that morning. The reported wake-up time had to be near the subject's regular wake-up time reported in the questionnaire. Otherwise participation that evening was cancelled.

During the sleep deprivation period, the subjects were given the choice of reading magazines, watching television, studying, listening to music, or any combination. Meals were purchased for each of the subjects and the intake of caffeine , stimulants, and sugars were regulated. To insure that they remained awake, a research assistant monitored the subjects. The subjects were wakened from any lapses of drowsiness, when they occurred.

To define the state of sleep deprivation, a dual criterion was established. The first criterion was the occurrence of two lapses into drowsiness or sleep by the subjects, as detected through the direct observation by a research assistant. The second criterion was nineteen straight hours of wakefulness by the subjects. By using nineteen hours past the drivers' reported wake-up times, the subjects should have been near minimum metabolic rate due to circadian rhythm.

The second criterion was met by all twenty subjects. All the experimental runs were conducted after nineteen hours of sleep deprivation. For most of the subjects, these runs took place between 2 AM and 4 AM.

Shortly after the sleep deprivation criterion was met, fresh researchers joined the experimental team and the simulated driving scenario began. The scenario was the same highway driving task used in the rested condition. The subjects were encouraged to continue driving even if drowsy.

In the event that a driver fell asleep, the driver was in no danger. The simulator reached a limiting value of excursion from the highway and was then reset. No data were lost during the runs due to a subject falling asleep.

After the experimental run was completed, the simulator motion was stopped and the subjects were instructed to exit the simulator. The subjects were subsequently driven home and instructed to sleep.

<u>Debriefing</u>. Since the experimental conditions were counterbalanced across the subjects, each of the subjects were paid and debriefed after their second experimental run. The subjects received $4.00 per hour or $60.00 maximum for their actual time involved in the study after completing the experiment. Thus, the subjects were paid for the rested driving session, for the evening hours prior to sleep-deprived driving, and for the sleep-deprived driving. Then, if the subjects completed both of the driving tasks, they were given small bonuses of approximately $10.00. If the subjects did not complete the two sessions, they were paid a pro-rated amount based on their total hours of sleep deprivation after midnight and their total task time.

Two subjects did not complete the experiment. One subject was removed from the study after learning that she did not have regular sleeping patterns. The second subject was eliminated due to a simulator malfunction during the rested driving condition. If the subject had been rerun, she would have had additional driving hours with the simulator, thus she would have had more experience with the simulator. Both of these subjects were replaced in the data set.

<u>Data Collection and Processing</u>

All data were stored during the experiment and were later retrieved and processed off-line. By storing the data on FM tape, the data could be analyzed in a variety of analyses employing different data processing techniques.

In general, the data which included 17 dependent measures were sampled at two different time intervals over approximately one minute. The first interval was a 50 second time interval for which one weighted or averaged measure was obtained to describe the driving characteristics of the entire 50 seconds. The interval immediately <u>preceded</u> the introduction of a stimulus. This interval was considered to be a "normal" highway driving segment. That is, no stimulus inputs were introduced into the vehicle simulation during the 50-second interval. The second sampling interval was a 6-second period of data collection which was obtained when the stimulus pulse was introduced. Thus, the dependent measures from the 6-second interval were stimulus-response measures.

All data for these analyses were recorded using a Honeywell 5600E instrumentation tape recorder and a Panasonic NV-8310 videotape recorder. Three separate classes of dependent variables were obtained: (1) <u>Eye Closure Measures</u> - from both the 50 second and the 6 second intervals; (2) 50 Second Measures - from the 50 second time interval before a stimulus pulse was introduced; and (3) 6 Second Measures - from the 6 second time interval when a stimulus pulse was introduced. Each of these variables for each of the classes is described below. There were a total of 17 dependent variables. They included three eye closure measures, seven 50 second measures, and seven 6 second measures. Fifteen repeated measures were collected for each of the two pulses, torque and displacement, for each 30-minute driving segment.

During data collection the following dependent variables were obtained:

Eye closure measures. Two methods were used to record eyelid droop and closure data from the 90-minute driving scenarios. They were videotape recording and manually tracked analog signal recording of the eyelid position. The videotaped data were collected using a low-light level monochrome RCA Model TC1004-U01 CCTV camera with zoom lens focused on the eyes of the subjects, and a Panasonic Omnivision VHS videotape recorder Model NV-8310. For the analog signal recording, an experimenter manually tracked the eyes of the subjects using a manual tracking control. By following the eyelids with the tracking control, an analog signal of the eyelid movement was produced and the signal was recorded on the Honeywell FM tape recorder along with other performance data. By manually tracking the eyes, the time, rate, and percent of eyelid closure were recorded. Since "that moment when persistent eyelid closure occurs" was used as the standard for drowsiness, a continuous recording of eyelid closure at all degrees of closure was obtained for both the 50 second and the 6 second sampling intervals. (The processing of these measures is discussed under their appropriate classifications).

In addition to the video and analog recordings of the eyelid closure, a voice track was also recorded on both the videotapes and the FM tapes. The voice track described the actions of the subject/drivers during the driving scenarios.

The three eye closure measures collected and used for analysis were:

EYEMEAS: An eye closure measure which weighted the distribution of eyelid closures heavily near closure. The weighting function used for the sampled frequency distribution of percent closures was: (0-20% closure x 1) + (21-40% closure x 2) + (41-50% closure x 3) + (51-60% closure x 5) + (61-80% closure x 7) + (81-100% closure x 10) = EYEMEAS. Thus, the range for EYEMEAS was from 100 to 1000.

PERCLOS: The percent of time that 80 to 100% closures were exhibited during the 50 second interval.

EYELID: The average percent closure over the 6 second interval during a pulse introduction.

50 second interval measures. Seven 50-second measures were obtained from the Honeywell 5600E tape recordings for each of the 90-minute driving scenarios for each subject. Each of these measures was collected during the 50 second time interval preceeding the introduction of a stimulus. Fifteen observations were obtained for each 30-minute driving segment for both the torque and displacement pulses.

To simplify the 50 second interval measures and to produce a single value for the 50 second interval, the FM tape recordings were played back through an A/D converter interfaced with a preprogrammed TRS-80 micro-computer. The TRS-80 program sampled the FM tape at a rate of 4 samples per second. The sampling rate was moderately slow but was sufficient for detecting changes in steering, because steering changes occur rather gradually in "typical" highway driving.

For each of the analog driving signals, a frequency sampling distribution was created. The distributions were formed by defining meaningful distribution intervals for various levels of each of the taped variables. In obtaining a single 50-second value for the interval, both distribution weightings and descriptive statistics were utilized. Descriptions of the 50 second measures follow:

<u>LOGHIGH</u>: Total time that the steering logic was high, no steering velocity (less than ±8 degrees steering angle per second) encountered for at least 0.4 sec.

<u>MTHIGH</u>: Mean length of time that steering logic was high.

<u>STDHIGH</u>: Standard deviation of the time lengths of steering high.

<u>TRANS</u>: Number of logic transitions from steering high to low and low to high.

<u>LANESTD</u>: Lateral lane deviation standard deviation.

<u>LANDEVM</u>: Lateral lane deviation distribution for the 50 second interval weighted heavily for lane exceedences. The weighting function used was: [(3

feet in lane right/left) x 0.5] + [(right/left wheel out of lane) x 1.0] + [(right/left 1st degree out of lane) x 2.0] + [(right/left 2nd degree out of lane) x 4.0] + [(right/left 3rd degree out of lane) x 7.0] + [(right/left beyond out of lane) x 10] = LANDEVM The range for this measure was 0 to 1000.

<ins>STVELM</ins>: Steering velocity measure weighted the distribution of steering manuevers heavily for fast manuevers. The weighting function used was: [(right/left small steering inputs) x 0.5] + [(right/left large steering inputs) x 5.0] + [(right/left saturated inputs) x 10.0] = STVELM. The range for this measure was from 50 to 1000.

<ins>6 second interval measures</ins>. The seven 6 second interval measures were also obtained from the Honeywell FM tape recordings, but the measures were collected manually. First, the FM tape was played back through a Sanborn chart-recorder. Hard copy chart recordings were produced for each of the intervals in which a stimulus pulse was introduced. Approximately every minute, a chart recording was obtained from the point where the pulse was initiated until ten seconds had passed. Then, a six second blocked

interval was used to determine maximum response in lane and yaw deviation, maximum steering response, time to maximum steering response, total steering time at logic high (zero velocity for at least 0.4 sec.), number of steering logic reversals, and time to steering input which counteracted the stimulus. Each of these measures is defined below. Again, for both the torque and displacement pulses, fifteen observations were obtained for each 30-minute driving segment.

LOGSUM: Total time that the steering logic was high.

LOGTR: Number of steering logic transitions.

LANDEV: Global maximum lane deviation. The absolute value of the measured lane position from the introduction of the stimulus to the maximum lateral deviation.

YAWDEV: Global maximum yaw deviation. The absolute value of the measured yaw position from the introduction of the stimulus to the maximum yaw deviation.

<u>MAXPK</u>: The global maximum steering position resulting from the stimulus pulse introduction. The response was positive if it was in the direction of the stimulus and negative if it opposed the direction of the stimulus.

<u>TMTOPK</u>: The time which elapsed from the introduction of the stimulus to the time where the MAXPK occurred.

<u>RESPTM</u>: The time which elapsed from the introduction of the stimulus to the point in time where the first response counteracting the stimulus was detected.

RESULTS

In conducting this research, two primary objectives were (1) to gain an understanding of how sleep deprivation and time-on-task driving influenced driver performance and driver response characteristics and (2) to identify driving characteristics (e.g., individual or multiple linear combinations of dependent variables) which were significantly correlated with eyelid droop and closure or predictive of eyelid droop and closure. Three separate data analysis approaches were used to pursue the research objectives.

The three analyses--classical, predictive, and post hoc--were labeled as to the information they generated. The first analysis, the classical analysis, included several standard multivariate statistical analyses. These statistical tests were relevant in determining the effects of sleep deprivation and time-on-task driving. More importantly they established whether the designed driving scenario successfully provided a driving environment in which there were occurrences of drowsiness. The statistical analyses performed in this analysis are outlined in Figure

3. The second analysis, the predictive analysis, focused on identifying the relationships of the obtained dependent variables with eyelid closure. Attempts were made to predict eyelid closure with the dependent variables which were highly correlated with eyelid closure. Analyses included in the predictive analysis are shown in Figure 4.

The final analyses performed on the data were a series of post hoc analyses. Several driver blocking factors were analyzed in one-way MANOVAs. The blocking factors were established arbitrarily and included: presentation order, sex, personality type, driving experience, and age. The blocking factors which provided statistically-significant group mean differences were then used as blocking factors to perform additional predictive analyses in an attempt to improve the dependent variable prediction of eyelid closure (Figure 5).

In all three of the data analyses, the torque pulse and the displacement pulse data were treated separately. The responses of the subjects to these pulses were entirely independent of each other, and the pulses had no physical similarities by which their responses could have been compared. Thus, two separate data analyses, a torque and a displacement, were performed for each of the result phases. Unless stated otherwise, both the torque and the

Condition X Time-On-Task MANOVAs
(Subsequent Analyses)

↓

Principal Components Analysis

↓

Eyelid Closure MANOVAs
(Eyelid Closure as an Independent Variable)

Figure 3. Statistical analyses of the classical analysis

Correlation Analyses
Using One, Three, Five, and Fifteen Observations
in Calculating the Mean Score Values

Linear Optimization Analysis
Using Fifteen Observation Means

Discriminant Analysis

Mannerisms Analyses
(Wierwille and Christensen(1984)--Appendix C)

Lane Exceedence Analyses
(Hardee and Wierwille (1984)--Appendix D)

Figure 4. Statistical analyses of the predictive analysis.

Blocking Factor MANOVAs

↓

Predictive Analyses
Re-Conducted Utilizing the Blocking Factor

↓

Correlation Analysis

↓

Optimization Analysis

↓

Discriminant Analysis

Figure 5. Statistical analyses of the posthoc analyses

displacement data sets contained 1800 observations (20 subjects X 15 pulse observations X 2 conditions X 3 time-on-task segments). The torque and the displacement analyses are presented in the results simultaneously so that the relative effectiveness of the stimuli may be evaluated. It should be noted that torque and displacement are not levels of an independent variable called stimulus, but are data sets which were analyzed independently of one another.

In the predictive analysis, to provide as much information as possible about the driving characteristics and their relationships to eyelid closure, two additional analyses were performed independently of the first three predictive analyses outlined in Figure 4. The two analyses were a driver mannerisms analysis and a lane exceedence analysis. These two analyses and their results are described in Appendices C and D. They appear in appendices because they are not analyses performed by the dissertation author. The driver mannerisms analysis was contributed by Wierwille and Christensen (1984) and the lane exceedence analysis was contributed by Hardee and Wierwille (1984). The two analyses help provide a broader understanding of both drowsy driver mannerisms and drowsy driver lane and steering performance characteristics.

The results of the classical, the predictive, and the post hoc analyses follow. To perform a majority of these statistical analyses, the Statistical Analysis System (SAS) computer software was used (SAS Institute, 1982). To simplify the presentation of the multivariate analyses, all the results are presented using the F-approximation F-values and degrees of freedom from Wilks' criterion tests. Wilks' criterion was used due to its robustness in analyzing both concentrated and diffuse data.

Classical Analysis Results

Two major groups of MANOVA analyses were performed in the classical analysis. These two groups of MANOVAs handled the eyelid closure data differently. In one set of MANOVA analyses, the eyelid closure measures were treated as dependent variables along with the other dependent variables. Two-way, condition by segment, MANOVAs derived directly from the experimental design were analyzed. The data from all twenty subject/drivers were included in these analyses. An outline of the statistical steps performed for the MANOVA analyses appear in Figure 6.

The second set of MANOVA analyses was aimed at detecting which dependent variables were sensitive to degree of eyelid closure. These analyses were one-way MANOVAs.

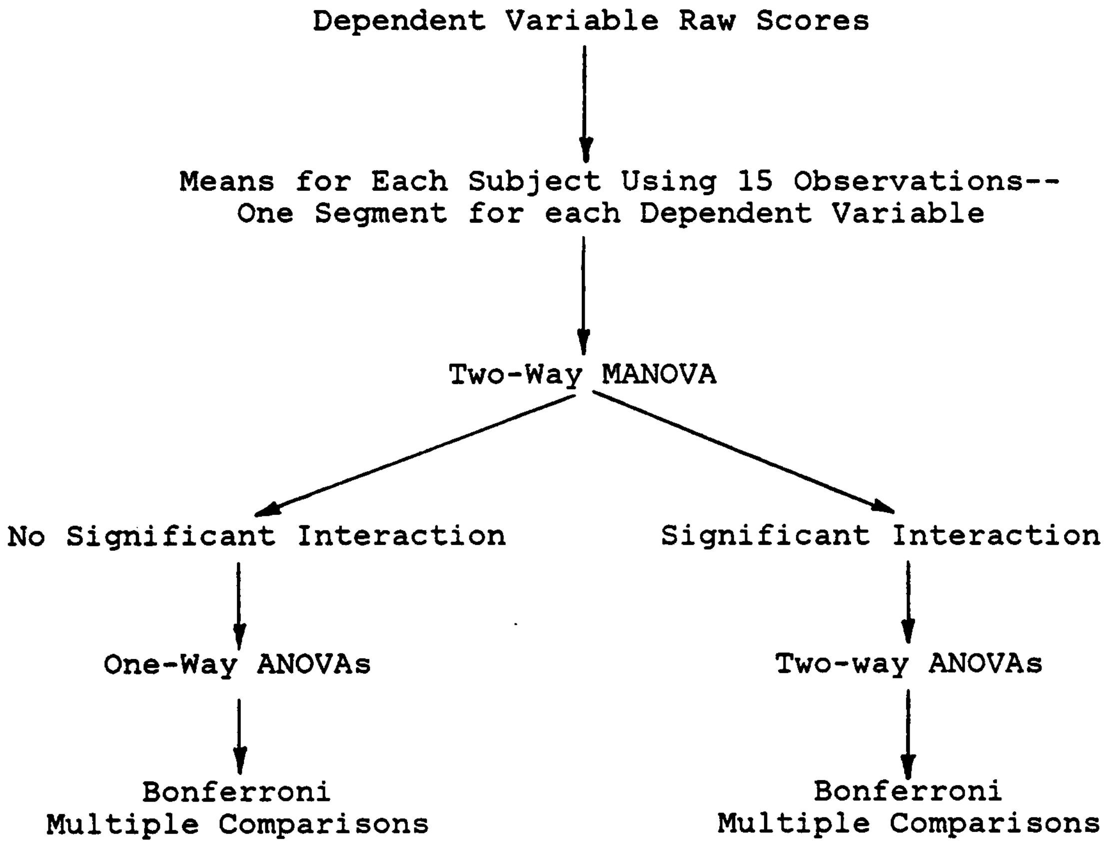

Figure 6. Statistical analysis steps for the classical analysis two-way MANOVAs

They treated eyelid closure, specifically EYEMEAS, as an independent variable. Three degrees of eyelid closure were established using EYEMEAS, the weighted 50 second measure, as a criterion variable for sorting the levels of eyelid closure. Through careful examination of the data, three levels of eyelid closure (low, medium, and high) were defined. The respective low, medium, and high closure level ranges for EYEMEAS were: 100 to 224, 225 to 449, and 450 to 820. These values were computed using the eyelid closure weighting distribution described earlier. Since, all twenty subjects did not record closures from all three of the EYEMEAS levels established, data from some of the subjects were excluded from these analyses.

The final analyses which were performed in the classical analysis were principal components analyses. The principal components analyses aided the interpretation of the variation in the data.

<u>Dependent variable raw scores</u>. For each 30-minute driving condition segment, fifteen observations were recorded. Each observation consisted of 17 dependent variables. The variables were obtained from either the 50-second interval or the 6-second interval.

<u>Dependent variable means</u>. The fifteen observations for each dependent variable were averaged to obtain a single

score for each of the 30-minute segments (3 rested and 3 sleep deprived). These means of fifteen observations were used in all the classical analyses with the exception of the eye closure MANOVAs. For the eye closure MANOVAs, the raw data were sorted into three groups of eye closure for each subject. Of the 90 observations obtained for each of the subjects, at least one observation was required in each of the three eyelid closure levels to be maintained in the analysis. Averages were then computed for each of the three closure levels by subject. Thus, in computing the closure means one to 88 observations could have been used in averaging.

Condition X segment two-way MANOVAs. The independent variables in each of these analyses were condition (rested or sleep-deprived) and segment (low, medium, and high time-on-task). The three groups of dependent variable means which were analyzed in separate MANOVAs were eye closure measures, 50 second measures, and 6 second measures. The results of these analyses may be seen in Tables 1 and 2. To simplify the presentation of these results, abbreviated MANOVA summary tables are provided. A full model summary table of the torque 50 second MANOVA is presented in Appendix B for the interested reader. All the MANOVA analyses included here use this model.

TABLE 1

Two-way Condition X Segment Torque MANOVAs

Eye Measures

Source	df	F	p
Cond	(3,17)	4.22	0.0210*
Segment	(6,72)	9.83	0.0001****
Cond X Segment	(6,72)	4.25	0.0010***

50 Second Measures

Source	df	F	p
Cond	(7,13)	4.54	0.0092**
Segment	(14,64)	4.60	0.0001****
Cond X Segment	(14,64)	2.34	0.0111*

6 Second Measures

Source	df	F	p
Cond	(7,13)	3.23	0.0325*
Segment	(14,64)	2.44	0.0081**
Cond X Segment	(14,64)	1.34	0.2083

* $p<0.05$, ** $p<0.01$, *** $p<0.005$, and **** $p<0.001$.

TABLE 2

Two-way Condition X Segment Displacement MANOVAs

Eye Measures

Source	df	F	*p*
Cond	(3,17)	4.04	0.0245*
Segment	(6,72)	8.48	0.0001****
Cond X Segment	(6,72)	3.38	0.0055***

50 Second Measures

Source	df	F	*p*
Cond	(7,13)	4.83	0.0071**
Segment	(14,64)	4.52	0.0001****
Cond X Segment	(14,64)	1.97	0.0345*

6 Second Measures

Source	df	F	*p*
Cond	(7,13)	1.89	0.1522
Segment	(14,64)	3.40	0.0004****
Cond X Segment	(14,64)	1.86	0.0478*

* $p<0.05$, ** $p<0.01$, *** $p<0.005$, and **** $p<0.001$.

By dividing the dependent variables into three independent groups, the power of each MANOVA analysis was increased. If all 17 dependent variables were analyzed in the same analysis, the degrees of freedom for the analysis would have been reduced because there would have been only 20 subjects (repeated measures) and 17 dependent variables in the analysis. A large number of dependent variables in relation to the number of repeated observations (subjects) reduces the statistical power of the test. Thus, by forming three MANOVA classes, the largest number of dependent variables in any one MANOVA analysis was seven. In these analyses, statistical significance was defined at $\alpha = 0.05$.

Both the torque and displacement two-way MANOVAs indicated significant condition X segment interactions (Tables 1 and 2) for all three of the measurement classes, except for the 6 second torque measures. Thus, univariate two-way ANOVAs for each dependent variable were analyzed for each of the statistically-significant measurement classes. Univariate ANOVAs were analyzed to determine which of the dependent variables contributed to the statistically-significant interaction.

Univariate ANOVAs. Abbreviated summary tables for the two-way ANOVAs for each of the condition X segment interaction measurement classes of torque and displacement are presented in Tables 3, 4, 5, 6, and 9. Since, the 6 second torque MANOVA did not have a statistically-significant interaction but did have statistically-significant main effects of condition (p=0.0325) and segment (p=0.0081), univariate one-way ANOVAs for each of the seven 6 second dependent variables were performed for the main effects of condition and segment (Tables 7 and 8).

A full model summary table for the two-way torque 50 second ANOVA appears in Appendix B. The hypothesis and error terms for this analysis are the same hypothesis and error terms used in all the reported ANOVA analyses included in this section.

In the eye closure measures analysis, all three of the dependent variables, EYEMEAS, PERCLOS, and EYELID, contributed to the multivariate condition X segment interaction for both torque and displacement. The p-values for the univariate condition X segment interactions were all less than $p = 0.002$. Thus, the eyelid closure measures obtained were sensitive to both driving condition and driving segment (time-on-task). In addition, all the segment main effects of torque and displacement had p-values of less than $p = 0.001$, and condition main effects had p-values of less than $p = 0.0158$ for all three eyelid closure measures.

As expected, the percent eyelid closure increased from segment one to segment three in both the rested and sleep-deprived driving. The driving scenario presented to the subjects successfully induced drowsiness in the subjects and no arousal factors were encountered. Of the twenty subject/drivers who participated, only two of the subjects, one male and one female, did not suffer from bouts of slow eyelid closure in either of the two driving conditions. The remaining eighteen subjects exhibited slow eyelid closures and eyelid droop in at least one of the two driving conditions.

The results of the 50 second measures for torque and displacement, Tables 5 and 6, indicate that three dependent variables LANDEV (p=0.0268 and p=0.0409), LANESTD (p=0.0023 and p=0.0002), and STVELM (p=0.0151 and p=0.0479) for torque and displacement respectively, contributed to the multivariate condition X segment interaction. For torque, all three of these variables also had statistically-significant segment main effects along with STDHIGH. The segment main effect significance levels of the torque variables--LANDEVM (p=0.0006), LANESTD (p=0.0001), STVELM (p=0.0042), and STDHIGH (p=0.0459)--and the displacement variables-- LANDEVM (p=0.0001), LANESTD (p=0.0001), and STVELM (p=0.0002)--indicated that each of

TABLE 3

Eye Measures Two-way Cond X Segment Torque ANOVAs

EYEMEAS

Source	df	F	p
Cond	(1,19)	13.75	0.0015***
Segment	(2,38)	32.23	0.0001****
Cond X Segment	(2,38)	12.46	0.0001****

PERCLOS

Source	df	F	p
Cond	(1,19)	7.40	0.0136*
Segment	(2,38)	13.82	0.0001****
Cond X Segment	(2,38)	10.61	0.0002****

EYELID

Source	df	F	p
Cond	(1,19)	13.41	0.0017***
Segment	(2,38)	33.47	0.0001****
Cond X Segment	(2,38)	8.23	0.0011***

* $p<0.05$, ** $p<0.01$, *** $p<0.005$, and **** $p<0.001$.

TABLE 4

Eye Measures Two-Way Condition X Segment Displacement ANOVAs

EYEMEAS

Source	df	F	p
Cond	(1,19)	13.36	0.0017***
Segment	(2,38)	30.84	0.0001****
Cond X Segment	(2,38)	9.35	0.0005****

PERCLOS

Source	df	F	p
Cond	(1,19)	7.03	0.0158*
Segment	(2,38)	15.37	0.0001****
Cond X Segment	(2,38)	7.35	0.0020***

EYELID

Source	df	F	p
Cond	(1,19)	12.73	0.0021***
Segment	(2,38)	31.95	0.0001****
Cond X Segment	(2,38)	11.12	0.0002****

* $p<0.05$, ** $p<0.01$, *** $p<0.005$, and **** $p<0.001$.

TABLE 5

50 Second Two-Way Cond X Segment Torque ANOVAs

LOGHIGH

Source	df	F	p
Cond	(1,19)	1.02	0.3259
Segment	(2,38)	1.02	0.3696
Cond X Segment	(2,38)	1.10	0.3432

MTHIGH

Source	df	F	p
Cond	(1,19)	3.37	0.0822
Segment	(2,38)	1.21	0.3094
Cond X Segment	(2,38)	0.20	0.8205

STDHIGH

Source	df	F	p
Cond	(1,19)	9.21	0.0068**
Segment	(2,38)	3.34	0.0459*
Cond X Segment	(2,38)	0.37	0.6912

TRANS

Source	df	F	p
Cond	(1,19)	0.02	0.8808
Segment	(2,38)	1.30	0.2851
Cond X Segment	(2,38)	2.60	0.0873

* $p<0.05$, ** $p<0.01$, *** $p<0.005$, and **** $p<0.001$.

TABLE 5

50 Second Two-way Cond X Segment Torque ANOVAs (Cont.)

LANESTD

Source	df	F	p
Cond	(1,19)	9.04	0.0072**
Segment	(2,38)	19.75	0.0001****
Cond X Segment	(2,38)	7.14	0.0023***

LANDEVM

Source	df	F	p
Cond	(1,19)	8.38	0.0093**
Segment	(2,38)	9.20	0.0006****
Cond X Segment	(2,38)	3.99	0.0268*

STVELM

Source	df	F	p
Cond	(1,19)	9.53	0.0061**
Segment	(2,38)	6.34	0.0042***
Cond X Segment	(2,38)	4.69	0.0151*

* $p<0.05$, ** $p<0.01$, *** $p<0.005$, and **** $p<0.001$.

TABLE 6

50 Second Two-way Cond X Segment Displacement ANOVAs

LOGHIGH

Source	df	F	p
Cond	(1,19)	3.93	0.0619
Segment	(2,38)	0.10	0.9041
Cond X Segment	(2,38)	0.30	0.7437

MTHIGH

Source	df	F	p
Cond	(1,19)	6.12	0.0230*
Segment	(2,38)	1.58	0.2197
Cond X Segment	(2,38)	0.33	0.7225

STDHIGH

Source	df	F	p
Cond	(1,19)	10.57	0.0042**
Segment	(2,38)	2.75	0.0765
Cond X Segment	(2,38)	1.07	0.3521

TRANS

Source	df	F	p
Cond	(1,19)	0.01	0.9146
Segment	(2,38)	2.01	0.1475
Cond X Segment	(2,38)	0.58	0.5640

* $p<0.05$, ** $p<0.01$, *** $p<0.005$, and **** $p<0.001$.

TABLE 6

50 Second Two-way Cond X Segment Displacement ANOVAs (Cont.)

LANESTD

Source	df	F	p
Cond	(1,19)	14.75	0.0011***
Segment	(2,38)	34.27	0.0001****
Cond X Segment	(2,38)	11.06	0.0002****

LANDEVM

Source	df	F	p
Cond	(1,19)	10.20	0.0048***
Segment	(2,38)	18.44	0.0001****
Cond X Segment	(2,38)	3.48	0.0409*

STVELM

Source	df	F	p
Cond	(1,19)	4.01	0.0596
Segment	(2,38)	10.69	0.0002****
Cond X Segment	(2,38)	3.30	0.0479*

* $p<0.05$, ** $p<0.01$, *** $p<0.005$, and **** $p<0.001$.

the dependent variables resulted in high driving segment sensitivity. The influences due to driving segment may have been a result of time-on-task and fatigue factors, as well as a lowered state of arousal. The loci of the driving segment mean differences are shown in the Bonferroni multiple comparison tests which are presented later.

Dependent variables which resulted in significant mean differences due to driving condition for torque were STDHIGH ($p=0.0068$), LANESTD ($p=0.0072$), LANDEVM ($p=0.0093$), and STVELM ($p=0.0061$), while for displacement they were LANDEVM ($p=0.0048$), LANESTD ($p=0.0011$), MTHIGH ($p=0.023$), and STDHIGH ($p=0.0042$). Each of these dependent variables was influenced by the driving condition. All of these dependent variable mean values increased from the rested to the sleep-deprived driving conditions. Thus, lane keeping as indicated by LANESTD and LANDEVM was typically poorer and the steering velocity characteristics tended to have longer zero velocity durations. A behavioral response particular to the torque analysis was that the steering velocity measure, STVELM, increased. Thus, a larger degree of high velocity steering inputs was indicative of the sleep-deprived driving condition. This result was near significance ($p=0.0596$) for the displacement analysis. The two steering measures, MTHIGH and STDHIGH, which were particular to the displacement analysis indicated that there were steering characteristic changes associated with the displacement data. These results suggest that there were longer steering holds (zero steering velocity as defined earlier) and greater variations in the steering holds for the sleep deprived condition when compared with the rested condition.

Since, the 50 second interval measures were indicative of "normal" highway driving (there were no stimulus inputs), there should have been slight, if any, systematic differences between the torque and displacement analyses. The results of these two analyses, in general, tracked closely. That is, the dependent variables indicated the same main effects at comparable significance levels. Thus, no major systematic differences in the respective torque and displacement 50 second intervals resulted. The fact that the same dependent variables exhibited statistical significance supported the strength of these variables in reflecting the driving characteristic changes from condition to condition and from segment to segment.

In reviewing the results of the 6 second measures, a similarity among the dependent variables' sensitivity to condition and segment was present, but was not as prevalent as the 50 second dependent variables. A likely explanation

TABLE 7

6 Second One-way Condition Torque ANOVAs

LOGSUM

Source	df	F	p
Cond	(1,19)	2.11	0.1629

LOGTR

Source	df	F	p
Cond	(1,19)	0.06	0.8035

LANDEV

Source	df	F	p
Cond	(1,19)	13.39	0.0017***

YAWDEV

Source	df	F	p
Cond	(1,19)	4.64	0.0442*

* $p<0.05$, ** $p<0.01$, *** $p<0.005$, and **** $p<0.001$.

TABLE 7

6 Second One-way Condition Torque ANOVAs (Cont.)

MAXPK

Source	df	F	p
Cond	(1,19)	2.10	0.1634

TMTOPK

Source	df	F	p
Cond	(1,19)	0.06	0.8094

RESPTM

Source	df	F	p
Cond	(1,19)	5.70	0.0275*

* $p<0.05$, ** $p<0.01$, *** $p<0.005$, and **** $p<0.001$.

TABLE 8

6 Second One-Way Segment Torque ANOVAs

LOGSUM

Source	df	F	p
Segment	(2,38)	1.43	0.2512

LOGTR

Source	df	F	p
Segment	(2,38)	1.17	0.3204

LANDEV

Source	df	F	p
Segment	(2,38)	15.03	0.0001****

YAWDEV

Source	df	F	p
Segment	(2,38)	9.02	0.0006***

* $p<0.05$, ** $p<0.01$, *** $p<0.005$, and **** $p<0.001$.

TABLE 8

6 Second One-Way Segment Torque ANOVAs (Cont.)

MAXPK

Source	df	F	p
Segment	(2,38)	1.68	0.1994

TMTOPK

Source	df	F	p
Segment	(2,38)	0.70	0.5045

RESPTM

Source	df	F	p
Segment	(2,38)	0.80	0.4558

* $p<0.05$, ** $p<0.01$, *** $p<0.005$, and **** $p<0.001$.

TABLE 9

6 Second Two-Way Cond X Segment Displacement ANOVAs

LOGSUM

Source	df	F	p
Cond	(1,19)	4.67	0.0437*
Segment	(2,38)	11.09	0.0002****
Cond X Segment	(2,38)	0.99	0.3805

LOGTR

Source	df	F	p
Cond	(1,19)	3.11	0.0937
Segment	(2,38)	16.29	0.0001****
Cond X Segment	(2,38)	0.92	0.4073

LANDEV

Source	df	F	p
Cond	(1,19)	14.67	0.0011***
Segment	(2,38)	8.09	0.0012***
Cond X Segment	(2,38)	4.13	0.0240*

YAWDEV

Source	df	F	p
Cond	(1,19)	6.03	0.0239*
Segment	(2,38)	6.51	0.0037***
Cond X Segment	(2,38)	6.55	0.0036***

* $p<0.05$, ** $p<0.01$, *** $p<0.005$, and **** $p<0.001$.

TABLE 9

6 Second Two-Way Cond X Segment Displacement ANOVAs (Cont.)

MAXPK

Source	df	F	p
Cond	(1,19)	2.11	0.1622
Segment	(2,38)	0.51	0.6044
Cond X Segment	(2,38)	2.46	0.0985

TMTOPK

Source	df	F	p
Cond	(1,19)	4.81	0.0409*
Segment	(2,38)	0.08	0.9253
Cond X Segment	(2,38)	1.83	0.1736

RESPTM

Source	df	F	p
Cond	(1,19)	2.15	0.1592
Segment	(2,38)	0.70	0.5007
Cond X Segment	(2,38)	0.42	0.6598

* $p<0.05$, ** $p<0.01$, *** $p<0.005$, and **** $p<0.001$.

for the lack of similarity among the 6 second torque and displacement dependent variables is that the physical design of the two stimuli was unrelated. As a result, the responses required of the driver to maintain vehicle lane position during a torque or displacement input were different. The results of the 6 second measure MANOVAs appear below. In presenting these results simultaneously, an attempt was made to identify which of the stimulus inputs, torque or displacement, was the most sensitive in reflecting driver performance changes associated with driver drowsiness. This enables the reader to evaluate which of the stimuli might provide the most information about drowsiness if a stimulus were to be selected for a countermeasure device. Since, the 6 second torque MANOVA did not have a statistically-significant interaction, the one-way condition and segment ANOVA results are compared to the two-way condition X segment ANOVA results for displacement.

The two variables which were factors in the displacement condition x segment interaction were LANDEV (p=0.024) and YAWDEV (p=0.0036). These two variables also had main effect mean differences of condition and segment for both torque and displacement. The mean values for both condition and segment increased from the rested to the sleep-deprived conditions and with time-on-task. This suggests that the lane keeping characteristics of the drivers changed and perhaps became more erratic with sleep deprivation and time-on-task, especially when a stimulus is introduced into the driving environment.

The main effect of condition was indicated for torque in LANDEV (p=0.0017), YAWDEV (p=0.0442), and RESPTM (p=0.0275), and for displacement in LANDEV (p=0.0011), YAWDEV (p=0.0239), LOGSUM (p=0.0437), and TMTOPK (p=0.0409). In all cases, the rested condition resulted in the smaller mean values. LANDEV for both analyses was the most sensitive of the variables in discriminating between the rested and sleep-deprived driving means.

LANDEV was also the variable most sensitive to the influences of driving segment. The only other variable which had a significance level comparable to LANDEV's was YAWDEV. For the torque main effect of segment, LANDEV was p=0.0001 and YAWDEV was p=0.0006. They were the only two variables which varied significantly due to time-on-task for torque. In the displacement analysis, four variables--LANDEV (p=0.0012), YAWDEV (p=0.0037), LOGSUM (p=0.0002), and LOGTR (p=0.0001) were all influenced by the driving segment. In general, two lane position variables and two steering variables were affected by the amount of driving time and/or the arousal level of the driver. Again, each of these variables' mean values for segment increased with time-on-task. The fact that two steering measures are important in the displacement analysis may be due to the nature of the displacement stimulus. The stimulus simulated a front wheel displacement which had a duration of one second. Typically, the stimulus was introduced and then the driver reacted to its effects. The torque pulse, on the other hand, was introduced for a five second duration and the driver responded to the presence of the stimulus over its duration.

Bonferroni multiple comparison tests. To investigate the sensitivity of the various dependent variables with relation to their significant main effects, Bonferroni multiple comparison tests were performed. The Bonferroni procedure was selected for the multiple comparisons analyses because it utilized a correction factor for alpha which was similar to performing simultaneous comparisons in multivariate analyses.

The mean values for each of the independent variable levels and the results of the comparisons analyses at α = 0.05 are presented in Tables 10, 11, 12, and 13. For significant condition main effects, the respective means are reported even though the significant main effect of the two level independent variable implies a statistical mean difference between the rested and sleep-deprived conditions.

Of the three eyelid closure variables, only EYEMEAS, a 50 second measure, resulted in significant mean differences among the three time-on-task driving segments--1-low, 2-medium, and 3-high--for torque and displacement. The two remaining eyelid variables also provided sensitive measures, but they did not have significantly different mean values among low, medium, and high for both torque and displacement. PERCLOS for torque and displacement resulted in statistically-significant differences between the comparison of two and three levels respectively, while EYELID resulted in two levels of discrimination for both analyses.

Again, a high degree of similarity in the 50 second variable results was evident. The mean values for EYEMEAS and PERCLOS of torque and displacement were nearly equal.

In the torque 50 second comparisons, LANDEVM and STVELM had significant mean differences between the first and third driving segments, while LANESTD had differences between the first and second segments, as well as between the first and third segments. Even though STDHIGH was statistically-significant ($p=0.046$) in the ANOVAs, STDHIGH failed to discriminate among any of the three driving

TABLE 10

Torque Bonferroni Multiple Comparisons for Condition*

EYEMEAS

Condition	
R	SD
174.7	246.0
A	B

PERCLOS

Condition	
R	SD
0.52	2.15
A	B

EYELID

Condition	
R	SD
20.41	28.15
A	B

STDHIGH

Condition	
R	SD
0.420	0.531
A	B

LANESTD

Condition	
R	SD
12.14	14.29
A	B

LANDEVM

Condition	
R	SD
33.36	47.26
A	B

* Mean values designated by different letters are <u>significantly</u> different ($p < 0.05$).

TABLE 10

Torque Bonferroni Multiple Comparisons for Condition (Cont.)*

STVELM

Condition	
R	SD
52.30	55.09
A	B

LANDEV

Condition	
R	SD
17.75	21.41
A	B

YAWDEV

Condition	
R	SD
0.059	0.067
A	B

RESPTM

Condition	
R	SD
0.397	0.446
A	B

* Mean values designated by different letters are significantly different ($p < 0.05$).

TABLE 11

Displacement Bonferroni Multiple Comparisons for Condition*

Measure	Condition R	Condition SD
EYEMEAS	177.04	250.69
	A	B
PERCLOS	0.69	2.39
	A	B
EYELID	20.12	27.90
	A	B
MTHIGH	0.582	0.657
	A	B
STDHIGH	0.452	0.562
	A	B
LANESTD	10.85	13.42
	A	B

* Mean values designated by different letters are significantly different ($p < 0.05$).

TABLE 11

Displacement Bonferroni Multiple Comparisons for Condition (Cont.)*

LANDEVM

Condition	R	SD
Mean	25.41	38.51
Group	A	B

STVELM

Condition	R	SD
Mean	51.99	53.70
Group	A	B

LOGSUM

Condition	R	SD
Mean	0.620	0.707
Group	A	B

LANDEV

Condition	R	SD
Mean	23.65	27.05
Group	A	B

YAWDEV

Condition	R	SD
Mean	0.104	0.110
Group	A	B

TMTOPK

Condition	R	SD
Mean	1.45	1.63
Group	A	B

* Mean values designated by different letters are significantly different ($p < 0.05$).

TABLE 12

Torque Bonferroni Multiple Comparisons for Segment*

EYEMEAS

Segment 1	Segment 2	Segment 3
150.3	222.7	258.2
A	B	C

PERCLOS

Segment 1	Segment 2	Segment 3
0.36	1.17	2.47
A	A	B

EYELID

Segment 1	Segment 2	Segment 3
16.81	26.20	29.85
A	B	B

STDHIGH

Segment 1	Segment 2	Segment 3
0.445	0.484	0.498
A	A	A

LANESTD

Segment 1	Segment 2	Segment 3
11.56	13.60	14.47
A	B	B

* Mean values designated by different letters are significantly different ($p < 0.05$).

TABLE 12

Torque Bonferroni Multiple Comparisons for Segment (Cont.)*

LANDEVM

Segment 1	Segment 2	Segment 3
32.70	40.88	47.36
A	A	
	B	B

STVELM

Segment 1	Segment 2	Segment 3
52.13	53.33	55.63
A	A	
	B	B

LANDEV

Segment 1	Segment 2	Segment 3
16.90	19.82	22.03
A	B	B

YAWDEV

Segment 1	Segment 2	Segment 3
0.055	0.066	0.068
A	B	B

* Mean values designated by different letters are <u>significantly</u> different (p < 0.05).

TABLE 13

Displacement Bonferroni Multiple Comparisons for Segment*

EYEMEAS

Segment 1	Segment 2	Segment 3
153.0	225.3	263.4
A	B	C

PERCLOS

Segment 1	Segment 2	Segment 3
0.38	1.57	2.67
A	B	C

EYELID

Segment 1	Segment 2	Segment 3
16.94	25.71	29.37
A	B	B

STDHIGH

Segment 1	Segment 2	Segment 3
0.474	0.517	0.530
A	A	A

LANESTD

Segment 1	Segment 2	Segment 3
10.21	12.67	13.53
A	B	B

LANDEVM

Segment 1	Segment 2	Segment 3
25.05	32.64	38.19
A	B	C

* Mean values designated by different letters are significantly different ($p < 0.05$).

TABLE 13

Displacement Bonferroni Multiple Comparisons for Segment (Cont.)*

STVELM

Segment 1	Segment 2	Segment 3
51.32	52.74	54.47
A	A	B

LOGSUM

Segment 1	Segment 2	Segment 3
0.589	0.673	0.729
A	B	B

LOGTR

Segment 1	Segment 2	Segment 3
3.12	3.65	3.72
A	B	B

LANDEV

Segment 1	Segment 2	Segment 3
23.76	25.41	26.87
A	A	
	B	B

YAWDEV

Segment 1	Segment 2	Segment 3
0.104	0.107	0.109
A	A	
	B	B

* Mean values designated by different letters are significantly different ($p < 0.05$).

segments in the Bonferroni analyses. LANESTD for the 50 second torque variables was the most sensitive in discriminating driving segment differences; however, this was not the case in the displacement analyses. LANDEVM was the only 50 second displacement variable to provide differences among all three of the driving segment means. Of the remaining statistically-significant segment effect variables (LANESTD, STVELM, and STDHIGH), LANESTD and STVELM resulted in differences between two time-on-task segments and STDHIGH did not result in any segment mean differences.

The Bonferroni results for the 6 second variables indicated statistically-significant differences between the first and second segments and the first and third segments for the torque analyses. These same two variables in the displacement analysis resulted in significant differences between only the first and third driving segments. On the other hand, LOGSUM and LOGTR for the displacement analysis discriminated between two pairs of mean value comparisons, that is, between the first and second segments and between the first and third segments.

Eyelid Closure Analysis

The eyelid closure analysis was performed to identify the dependent variables which were sensitive to three levels of eyelid closure. The analysis complemented the condition X segment analysis in that it provided additional information about the dependent variables and their respective sensitivities. Those variables which were statistically-significant in the condition X segment analyses along with the other dependent variables were further analyzed in the eyelid closure analyses along an eyelid closure dimension. By conducting these eyelid closure analyses, a deeper understanding of the factors influencing the dependent variables was obtained.

The results of the torque and displacement analyses for eyelid closure were not directly comparable, as they were in the condition X segment MANOVAs. The number of subjects' data utilized in the torque and displacement analyses were different. Of the twenty subjects' data, not all contained observations for the three eyelid closure levels. Data from eleven subjects were used in the torque analyses, while data from thirteen subjects were used in the displacement analyses. Thus, the power for the displacement analyses was slightly greater.

In performing one-way MANOVAs on the 50 second and 6 second measures using eyelid closure as a fixed-effect independent variable, all four of the MANOVAs resulted in statistically-significant ($p<0.05$) main effects of eyelid closure (Tables 14 and 15). The torque closure main effect p-values for the 50 second and 6-second measures were $p=0.0274$ and $p=0.0019$, and the displacement p-values were $p=0.0133$ and $p=0.0372$. These significance levels were rather moderate, with the exception of the torque 6-second MANOVA. (The full model for the torque 50 second MANOVA appears in Appendix B.)

To identify which dependent variables were contributing to the closure main effect, one-way univariate ANOVAs were obtained for the 50 second (Tables 16 and 17) and 6 second (Tables 18 and 19) measures (the torque 50 second ANOVA full model appears in Appendix B). The 50 second variables for torque which resulted in differences among the closure mean values were LANESTD ($p=0.0007$) and STDHIGH ($p=0.0021$). These same dependent variables were statistically-significant for displacement, LANESTD ($p=0.0001$) and STDHIGH ($p=0.0126$), along with LANDEVM ($p=0.0001$) and MTHIGH ($p=0.0200$). As in the condition X segment MANOVA analyses presented earlier, the measures which indicated statistically-significant mean differences

TABLE 14

Torque One-Way Eyelid Closure MANOVAs

50 SECOND MEASURES

Source	df	F	p
Closure	(14,28)	2.33	0.0274*

6 SECOND MEASURES

Source	df	F	p
Closure	(14,28)	3.60	0.0019***

* $p<0.05$, ** $p<0.01$, *** $p<0.005$, and **** $p<0.001$.

TABLE 15

Displacement One-Way Eyelid Closure MANOVAs

50 SECOND MEASURES

Source	df	F	p
Closure	(14,36)	2.51	0.0133*

6 SECOND MEASURES

Source	df	F	p
Closure	(14,36)	2.10	0.0372*

* $p<0.05$, ** $p<0.01$, *** $p<0.005$, and **** $p<0.001$.

TABLE 16

Torque One-Way 50 Second Eyelid Closure ANOVAs

LOGHIGH

Source	df	F	p
Closure	(2,20)	2.66	0.0945

MTHIGH

Source	df	F	p
Closure	(2,20)	1.91	0.1737

STDHIGH

Source	df	F	p
Closure	(2,20)	8.49	0.0021***

TRANS

Source	df	F	p
Closure	(2,20)	0.81	0.4596

* $p<0.05$, ** $p<0.01$, *** $p<0.005$, and **** $p<0.001$.

TABLE 16

Torque One-Way 50 Second Eyelid Closure ANOVAs (Cont.)

LANESTD

Source	df	F	p
Closure	(2,20)	10.71	0.0007****

LANDEVM

Source	df	F	p
Closure	(2,20)	2.71	0.0912

STVELM

Source	df	F	p
Closure	(2,20)	2.14	0.1440

* $p<0.05$, ** $p<0.01$, *** $p<0.005$, and **** $p<0.001$.

TABLE 17

Displacement One-Way 50 Second Eyelid Closure ANOVAs

LOGHIGH

Source	df	F	p
Closure	(2,24)	2.98	0.0700

MTHIGH

Source	df	F	p
Closure	(2,24)	4.62	0.0200*

STDHIGH

Source	df	F	p
Closure	(2,24)	5.27	0.0126*

TRANS

Source	df	F	p
Closure	(2,24)	0.04	0.9628

* $p<0.05$, ** $p<0.01$, *** $p<0.005$, and **** $p<0.001$.

TABLE 17

Displacement One-Way 50 Second Eyelid Closure ANOVAs (Cont.)

LANESTD

Source	df	F	p
Closure	(2,24)	13.37	0.0001****

LANDEVM

Source	df	F	p
Closure	(2,24)	18.63	0.0001****

STVELM

Source	df	F	p
Closure	(2,24)	1.93	0.1668

* $p<0.05$, ** $p<0.01$, *** $p<0.005$, and **** $p<0.001$.

TABLE 18

Torque One-Way 6 Second Eyelid Closure ANOVAs

LOGSUM

Source	df	F	*p*
Closure	(2,20)	0.31	0.7387

LOGTR

Source	df	F	*p*
Closure	(2,20)	4.55	0.0234*

LANDEV

Source	df	F	*p*
Closure	(2,20)	15.49	0.0001****

YAWDEV

Source	df	F	*p*
Closure	(2,20)	14.57	0.0001****

* $p<0.05$, ** $p<0.01$, *** $p<0.005$, and **** $p<0.001$.

TABLE 18

Torque One-Way 6 Second Eyelid Closure ANOVAs (Cont.)

MAXPK

Source	df	F	p
Closure	(2,20)	0.51	0.6109

TMTOPK

Source	df	F	p
Closure	(2,20)	0.61	0.5544

RESPTM

Source	df	F	p
Closure	(2,20)	9.18	0.0015***

* $p<0.05$, ** $p<0.01$, *** $p<0.005$, and **** $p<0.001$.

TABLE 19

Displacement One-Way 6 Second Eyelid Closure ANOVAs

LOGSUM

Source	df	F	p
Closure	(2,24)	5.15	0.0138*

LOGTR

Source	df	F	p
Closure	(2,24)	2.99	0.0692

LANDEV

Source	df	F	p
Closure	(2,24)	3.35	0.0522

YAWDEV

Source	df	F	p
Closure	(2,24)	3.50	0.0464*

* $p<0.05$, ** $p<0.01$, *** $p<0.005$, and **** $p<0.001$.

TABLE 19

Displacement One-Way 6 Second Eyelid Closure ANOVAs (Cont.)

MAXPK

Source	df	F	p
Closure	(2,24)	3.88	0.0346*

TMTOPK

Source	df	F	p
Closure	(2,24)	5.31	0.0123*

RESPTM

Source	df	F	p
Closure	(2,24)	1.77	0.1926

* $p<0.05$, ** $p<0.01$, *** $p<0.005$, and **** $p<0.001$.

were two lane deviation variables and two steering variables associated with the variation and the means of steering hold. Each of these measures increased monotonically with increasing levels of eyelid closure. All of these variables were further analyzed for their differences between means using the Bonferroni multiple comparison tests presented later in Tables 20 and 21.

As was the case with the condition X segment MANOVAs, YAWDEV was an important 6 second variable in discriminating closure levels, while the additional closure main effect variables for torque and displacement were quite different. For torque (Table 18), LOGTR (p=0.0234), LANDEV (p=0.0001), YAWDEV (p=0.0001), and RESPTM (p=0.0015) resulted in significant mean differences of closure while, LOGSUM (p=0.0.138), YAWDEV (p=0.0464), TMTOPK (p=0.0123), and MAXPK (p=0.0346) were the sensitive variables for displacement (Table 19).

Again, an explanation for why these variables differed can be attributed to the physical differences of the two pulses and the driver responses required. For the torque analysis, the number of logic transitions from steering hold to active steering decreased with increased eyelid closure. This supports the previous 50 second STDHIGH mean value increase in the standard deviation of steering hold with

TABLE 20

Torque Bonferroni Multiple Comparisons for Closure*

STDHIGH

Closure 1	Closure 2	Closure 3
0.420	0.550	0.748
A	A	
	B	B

LANESTD

Closure 1	Closure 2	Closure 3
11.81	14.86	19.58
A	A	B

LOGTR

Closure 1	Closure 2	Closure 3
4.66	4.90	4.02
A	A	
	B	B

LANDEV

Closure 1	Closure 2	Closure 3
17.25	20.52	31.48
A	A	B

YAWDEV

Closure 1	Closure 2	Closure 3
0.059	0.071	0.097
A	A	B

RESPTM

Closure 1	Closure 2	Closure 3
0.422	0.413	0.629
A	A	B

* Mean values designated by different letters are significantly different ($p < 0.05$).

TABLE 21

Displacement Bonferroni Comparisons for Closure*

MTHIGH

Closure 1	Closure 2	Closure 3
0.583	0.711	0.747
A	A	
	B	B

STDHIGH

Closure 1	Closure 2	Closure 3
0.458	0.628	0.658
A	A	
	B	B

LANESTD

Closure 1	Closure 2	Closure 3
10.79	14.71	17.43
A	B	B

LANDEVM

Closure 1	Closure 2	Closure 3
25.76	42.11	61.54
A	B	C

LOGSUM

Closure 1	Closure 2	Closure 3
0.586	0.826	0.886
A	A	
	B	B

* Mean values designated by different letters are significantly different ($p < 0.05$).

TABLE 21

Displacement Bonferroni Multiple Comparisons for Closure (Cont.)*

YAWDEV

	Closure	
1	2	3
0.105	0.114	0.117
A	A	
	B	B

MAXPK

	Closure	
1	2	3
-5.44	-5.02	-3.25
A	A	
	B	B

TMTOPK

	Closure	
1	2	3
1.52	1.60	2.14
A	A	B

* Mean values designated by different letters are significantly different ($p < 0.05$).

high eyelid closure. The other three torque variables, LANDEV, YAWDEV, and RESPTM, increased with an increase in eyelid closure. Thus, there were larger lateral and yaw deviations associated with an increased response time to the torque stimuli. The fact that low-level, random torque was added to the steering system may have contributed to the increased response time with increased eyelid closures since the driver may not have easily identified the torque stimuli from the random torque disturbances.

The variables which were prominent in the displacement analysis suggest that the time which elapsed from the introduction of the stimuli to the point in time where the maximum steering response occurred increased with eyelid closure but, that the maximum steering response to oppose the presentation of the pulse was less extreme. These two conclusions tend to contradict one another. This is especially true when the LANDEV and the YAWDEV mean values for each closure level are examined. They indicated larger lateral and yaw deviations than were experienced during the torque stimuli from the first closure level to the third closure level. Since there were larger deviations, it would have been reasonable to have had larger MAXPK steering corrections to oppose the large deviations. Perhaps the decrease in the MAXPK with increased eyelid closure was a result of a combination of responses which were confounded; or perhaps the drivers never completely recovered from the lateral and yaw deviations due to drowsiness onset.

The results of the Bonferroni comparisons for the torque analyses indicated that none of the dependent variables (50 second or 6 second) was able to show significant differences among all three of the mean comparisons, see Table 20. The 50 second variable LANESTD indicated significant mean differences between the mean pairs of first and third closure levels and second and third closure levels. STDHIGH, on the other hand, only showed differences between the first and third closure levels. An important point which may be emphasized here is that both LANESTD and STDHIGH had significant main effects of segment in the previous MANOVA analyses. These two variables appear to vary as a result of time-on-task and the resulting influences of fatigue.

Similar results were obtained in the displacement analyses (Table 21). LANDEVM and LANESTD were both important variables in the condition X segment analyses, and they appear again in the eyelid closure analysis in the detection of mean value differences for degrees of closure. LANDEVM (p=0.0001) in the Bonferroni test resulted in significant mean differences among all three levels of eyelid closure, while LANESTD had differences between the first and second closure levels and the first and third closure levels. These two variables discriminated well in both analyses. Other 50 second variables which indicated significant differences among the displacement closure levels were MTHIGH and STDHIGH, but they resulted in differences between the first and third closure levels only.

Of the 6 second variables reported as having significant main effects of closure (Table 18 and 19), none of the dependent variables was sensitive enough to discriminate among all three of the closure levels. This might have been due to the magnitude of the designed stimuli. The Bonferroni results for these measures are reported in Tables 20 and 21. YAWDEV had statistically different mean values for torque between the first and third levels and between the second and third levels, and for displacement only between the first and third levels. For the torque variables LANDEV and RESPTM, significant mean differences were indicated between the first and third mean values and between the second and third mean values for closure. The final torque variable LOGTR had differences only between the first and third closure level means.

In the 6 second displacement comparisons, all of the variables with the exception of TMTOPK resulted in differences between the first and third closure levels. TMTOPK resulted in mean differences between the first and third closure levels and between the second and third closure levels.

Principal Components Analysis

Principal components analyses were performed on both the torque and the displacement 50 second, 6 second, and eyelid measures. Thus, seventeen dependent variables were utilized--three eyelid closure, seven 50 second, and seven 6 second variables. In examining the principal components which resulted (Table 22 and 23), the first two principal components in each of the analyses were interpretable as steering components and eyelid closure components. The first two principal components were the only components which offered interpretation.

For the torque analysis, the first principal component accounted for 33.3% of the variance. The component was weighted relatively evenly with variables which have already been shown to be associated with eyelid closure, see Table 22. The important variables were EYELID, EYEMEAS, LANDEV, YAWDEV, and LANESTD. The correlations of these variables with the first principal component were the five highest correlations in the analysis. The correlations ranged from $\underline{r}=0.90$ for LANESTD to $\underline{r}=0.76$ for YAWDEV. Thus, these variables contributed significantly to the structure of the first principal component.

The second principal component in the torque analysis which accounted for 20.1% of the variance included only

TABLE 22

Torque Principal Components with their Respective Correlations

	Principal Components			
	First		Second	
EYEMEAS	0.329	(0.80)	-0.089	(0.72)
PERCLOS	0.295	(0.72)	-0.176	(0.80)
EYELID	0.334	(0.81)	-0.082	(0.81)
LOGHIGH	0.195	(0.47)	0.357	(0.67)
MTHIGH	0.214	(0.52)	0.230	(0.43)
STDHIGH	0.271	(0.66)	0.307	(0.58)
TRANS	0.051	(0.12)	0.472	(0.89)
LANESTD	0.370	(0.90)	0.005	(0.01)
LANDEVM	0.286	(0.70)	-0.024	(-0.05)
STVELM	0.163	(0.40)	-0.219	(-0.41)
LOGSUM	-0.009	(-0.02)	0.449	(0.85)
LOGTR	-0.046	(-0.11)	0.414	(0.78)
LANDEV	0.355	(0.86)	-0.054	(-0.10)
YAWDEV	0.311	(0.76)	-0.164	(-0.31)
MAXPK	-0.042	(-0.10)	-0.032	(-0.06)
TMTOPK	0.063	(0.15)	0.020	(0.04)
RESPTM	0.240	(0.58)	0.060	(0.11)

*The values in parentheses are the correlation values of the variable to the principal component, while the other values are the principal component weightings.

TABLE 23

Displacement Principal Components with their Respective Correlations

	Principal Components			
	First		Second	
EYEMEAS	0.232	(0.64)	0.261	(0.54)
PERCLOS	0.202	(0.55)	0.307	(0.58)
EYELID	0.242	(0.66)	0.261	(0.50)
LOGHIGH	0.250	(0.68)	-0.360	(-0.68)
MTHIGH	0.283	(0.77)	-0.267	(-0.51)
STDHIGH	0.291	(0.80)	-0.248	(-0.47)
TRANS	0.143	(0.39)	-0.419	(-0.80)
LANESTD	0.326	(0.89)	0.134	(0.26)
LANDEVM	0.265	(0.73)	0.126	(0.24)
STVELM	0.037	(0.10)	0.367	(0.70)
LOGSUM	0.301	(0.82)	-0.210	(-0.40)
LOGTR	0.259	(0.71)	-0.178	(-0.34)
LANDEV	0.320	(0.88)	0.059	(0.11)
YAWDEV	0.249	(0.68)	0.171	(0.33)
MAXPK	0.158	(0.43)	0.074	(0.14)
TMTOPK	0.215	(0.59)	0.166	(0.32)
RESPTM	0.166	(0.46)	0.099	(0.19)

*The values in parentheses are the correlation values of the variable to the principal component, while the other values are the principal component weightings.

variables which were related to steering. The variables were LOGSUM and LOGTR which were 6-second steering measures and LOGHIGH and TRANS which were 50-second steering measures. Both these sets of variables reflected the same type of steering measurement. LOGSUM and LOGHIGH represented the total time that the steering logic was high, while LOGTR and TRANS were counts of the number of logic transitions from zero steering velocity to steering velocity greater than $\pm$ 8 degrees of steering angle per second.

The correlations of these variables with the second principal component were again the four highest correlations. The coefficients of determination ranged from $r=0.89$ for TRANS to $r=0.67$ for LOGHIGH. Thus, the second principal component was described as a steering component related to the number of logic transitions while driving. The combination of the first and second principal components for the torque analysis accounted for 54.2% of the total variance in the dependent variables.

In the displacement analysis (Table 23), similar results were reported. The first principal component accounting for most of the variance was a combined lateral and yaw deviation steering component. The variables included in the first principal component varied significantly with eyelid closure in the MANOVA analyses, suggesting that the component was related to eyelid closure. The second component was also an eyelid closure component, but the eyelid closure variables correlated negatively with many of the steering velocity variables. The components in this analysis were not as easily interpreted as in the torque analysis. Each of the components had a large number of dependent variables contributing to the component structures.

The first principal component in this analysis was moderately weighted with a number of dependent variables. Those variables which had the greatest weightings were LOGSUM, LOGTR, and LANDEV of the 6 second variables and MTHIGH, STDHIGH, LANDEVM, and LANESTD of the 50 second variables. The correlations of these variables to the first principal component were from $\underline{r}=0.89$ for LANESTD to $\underline{r}=0.71$ for LOGTR. The first principal component accounted for 44.1% of the total variance and was interpreted as a component of drowsy driving which included steering hold (zero velocity) variables and lane position variables. These variables typically increased during drowsy driving and its associated eyelid closure.

The second principal component accounted for an additional 21.3% of the variance. The variable weightings indicated a contrast between the eyelid closure variables--EYELID, EYEMEAS, and PERCLOS-- and the 50-second steering hold (zero velocity) measures--LOGHIGH, MTHIGH, STDHIGH, and TRANS. The correlation of these variables with the second principal component ranged from *r*=0.70 (STVELM) and *r*=0.50 (EYELID) to *r*=-0.80 (TRANS) and *r*=-0.47 (STDHIGH). The results of this principal component indicated a strong negative association between the eyelid closure variables and the 50-second steering velocity measures. The first and second components combined accounted for 65.4% of the total variance in the dependent variables.

Predictive Analysis

In an attempt to develop a predictive model of driver drowsiness, correlation analyses, linear optimization analyses, and discriminant analyses were performed on the dependent variables. The emphasis in these analyses was to provide driving parameters which were closely associated with EYEMEAS, a 50 second measure. EYEMEAS was selected based on its relative sensitivity in both the torque and the displacement classical analyses.

All 17 dependent variables were included in the correlation analyses, and those variables which were highly correlated with EYEMEAS were utilized in the linear optimization procedure. The optimization analyses were performed for three sets of standardized variables -- 50 second measures only, 6 second measures only, and combinations of 50 and 6 second measures. Variable weightings were obtained for each of the dependent variables in the analyses which minimized the model error in predicting EYEMEAS. The predicted EYEMEAS was then correlated with EYEMEAS to determine the usefulness of the optimization procedure for providing a model which increased the prediction of EYEMEAS by combining the correlative components of the dependent variables. In the discriminant analyses, separate analyses were performed for the 50 second and 6 second dependent measures.

Correlation analysis. The correlation analysis results include four separate correlation analyses (Tables 24 through 31). The purpose in performing the four correlation analyses was to show how the correlations between the driving parameters and EYEMEAS changed from using individual observations (1800 observations) in a correlation analysis to correlating the averages of three, five, and fifteen observations, respectively. The complete matrix for each correlation analysis was a 17 X 17 matrix (see Appendix B for a complete correlation matrix for the average of 15 observations for both torque Table 56 and displacement Table

57). Thus, to simplify the presentation and interpretation of the results, only those dependent variables which were highly correlated with the eye closure measures are included in the results. The correlation matrix tables (Tables 24 through 31) on the following pages are abbreviated correlation matrices.

The use of individual observations (1800 data points) in the correlation analyses resulted in modest correlations between the driving variables and EYEMEAS. The best correlations for the torque analysis ranged from r=0.41 for LANESTD to r=0.31 for LANDEV and LANDEVM (Table 24), while the displacement correlations ranged from r=0.46 for LANESTD to r=0.27 for LANDEV (Table 25). However, when averages were computed for three consecutive observations these same correlations increased for torque to r=0.56 for LANESTD and r=0.47 for LANDEV (Table 26), and for displacement r=0.60 for LANESTD and r=0.38 for LANDEV (Table 27). The increase in the correlations due to averaging is modest, but the increase could have practical significance in the design of predictive drowsy driver models.

Similarly, correlation increases resulted from the averaging of five, Table 28 and 29, and fifteen, Table 30 and 31, simultaneous observations. The most encouraging results obtained from the correlation analyses supporting

TABLE 24

Correlation Matrix using Individual Torque Pulses

	LANDEV*	YAWDEV*	EYEMEAS	PERCLOS	LANDEVM	LANESTD	STVELM
EYELID*	0.34	0.26	0.85	0.50	0.29	0.40	0.09
EYEMEAS	0.31	0.22	--	0.63	0.31	0.31	0.14
PERCLOS	0.29	0.21	0.63	--	0.32	0.34	0.13
LANDEVM	0.26	0.19	0.31	0.32	--	0.63	0.10
LANESTD	0.44	0.29	0.41	0.34	0.03	--	0.13

* These measures are 6-second measures. All others are 50-second measures.

TABLE 25

Correlation Matrix using Individual Displacement Pulses

	LANDEV*	YAWDEV*	EYEMEAS	PERCLOS	LANDEVM	LANESTD	STVELM
EYELID*	0.30	0.20	0.87	0.53	0.41	0.46	0.13
EYEMEAS	0.27	0.19	--	0.67	0.41	0.46	0.13
PERCLOS	0.27	0.19	0.67	--	0.29	0.36	0.08
LANDEVM	0.31	0.26	0.41	0.29	--	0.55	0.10
LANESTD	0.43	0.29	0.45	0.36	0.55	--	0.17

* These measures are 6-second measures. All others are 50-second measures.

TABLE 26

Correlation Matrix using the Average of Three Consecutive Torque Pulses

	LANDEV*	YAWDEV*	EYEMEAS	PERCLOS	LANDEVM	LANESTD	STVELM
EYELID*	0.44	0.37	0.91	0.61	0.39	0.51	0.18
EYEMEAS	0.42	0.34	--	0.71	0.42	0.49	0.22
PERCLOS	0.41	0.34	0.71	--	0.44	0.47	0.24
LANDEVM	0.43	0.31	0.42	0.44	--	0.69	0.15
LANESTD	0.68	0.46	0.49	0.47	0.69	--	0.18

* These measures are 6-second measures. All others are 50-second measures.

TABLE 27

Correlation Matrix using the Average of Three Consecutive Displacement Pulses

	LANDEV*	YAWDEV*	EYEMEAS	PERCLOS	LANDEVM	LANESTD	STVELM
EYELID*	0.40	0.32	0.93	0.61	0.56	0.62	0.24
EYEMEAS	0.38	0.31	--	0.72	0.55	0.60	0.25
PERCLOS	0.37	0.32	0.72	--	0.43	0.52	0.23
LANDEVM	0.46	0.36	0.55	0.43	--	0.64	0.10
LANESTD	0.66	0.46	0.60	0.52	0.64	--	0.21

* These measures are 6-second measures. All others are 50-second measures.

TABLE 28

Correlation Matrix using the Average of Five Consecutive Torque Pulses

	LANDEV*	YAWDEV*	EYEMEAS	PERCLOS	LANDEVM	LANESTD	STVELM
EYELID*	0.50	0.43	0.93	0.64	0.46	0.61	0.23
EYEMEAS	0.47	0.41	--	0.72	0.46	0.56	0.23
PERCLOS	0.49	0.41	0.72	--	0.48	0.54	0.28
LANDEVM	0.51	0.37	0.46	0.48	--	0.66	0.15
LANESTD	0.78	0.60	0.56	0.54	0.66	--	0.21

* These measures are 6-second measures. All others are 50-second measures.

TABLE 29

Correlation Matrix using the Average of Five Consecutive Displacement Pulses

	LANDEV*	YAWDEV*	EYEMEAS	PERCLOS	LANDEVM	LANESTD	STVELM
EYELID*	0.44	0.38	0.94	0.66	0.60	0.65	0.29
EYEMEAS	0.41	0.38	--	0.74	0.60	0.63	0.31
PERCLOS	0.44	0.39	0.74	--	0.50	0.59	0.29
LANDEVM	0.55	0.44	0.60	0.50	--	0.68	0.12
LANESTD	0.68	0.55	0.63	0.59	0.68	--	0.24

* These measures are 6-second measures. All others are 50-second measures.

TABLE 30

Correlation Matrix using the Average of Fifteen Consecutive Torque Pulses

	LANDEV*	YAWDEV*	EYEMEAS	PERCLOS	LANDEVM	LANESTD	STVELM
EYELID*	0.56	0.53	0.95	0.67	0.51	0.64	0.39
EYEMEAS	0.53	0.50	--	0.75	0.51	0.60	0.36
PERCLOS	0.59	0.54	0.75	--	0.52	0.59	0.40
LANDEVM	0.54	0.46	0.51	0.52	--	0.69	0.20
LANESTD	0.90	0.75	0.60	0.59	0.69	--	0.29

* These measures are 6-second measures. All others are 50-second measures.

TABLE 31

Correlation Matrix using the Average of Fifteen Consecutive Displacement Pulses

	LANDEV*	YAWDEV*	EYEMEAS	PERCLOS	LANDEVM	LANESTD	STVELM
EYELID*	0.49	0.43	0.96	0.69	0.64	0.69	0.36
EYEMEAS	0.46	0.42	--	0.77	0.62	0.66	0.35
PERCLOS	0.49	0.44	0.77	--	0.53	0.62	0.37
LANDEVM	0.63	0.53	0.62	0.53	--	0.72	0.11
LANESTD	0.87	0.65	0.66	0.62	0.72	--	0.25

* These measures are 6-second measures. All others are 50-second measures.

the development of an algorithm for the prediction of drowsiness were the averages of fifteen observations. The correlation between EYEMEAS and LANESTD for torque was r=0.60, and between EYEMEAS and LANDEV was r=0.53. The equivalent correlations for displacement were r=0.66 and r=0.46, respectively.

The major disadvantage in obtaining the correlations for the averages of 15 consecutive observations, is that, 15 minutes would be required for the average to be computed. Since the averages of three and five observations are practical and the resulting correlations are moderate, they may be incorporated into a predictive model in place of the averages of the 15 observations.

An important aspect of the variables in the correlation analyses which should be noted is that the same driving variables in both the torque and displacement analyses resulted in high correlations with EYEMEAS. These variables also have strong correlations with the two other eye closure measures, EYELID and PERCLOS. The variables which were consistently important are LANESTD, LANDEVM, and STVELM from the 50-second intervals and LANDEV and YAWDEV from the 6-second intervals. These variables have more promise in the development of a drowsy driver model than any of the other variables.

Optimization analysis. The purpose of the optimization analysis was to combine several variables known to be highly correlated with EYEMEAS in a linear model to attain additional model correlation with EYEMEAS through the integration of the driving variables. That is, if the driving variables had different attributes which strongly correlated with EYEMEAS, these attributes when combined could contribute in their own dimensions to the prediction of EYEMEAS. The optimization procedure selected for these analyses produced variable weights for the driving variables which minimized the model error in predicting EYEMEAS. The optimization model used for these analyses is shown in Figure 7.

In performing the optimization analyses, each of the dependent variable means of fifteen consecutive observations was standardized to N(0,1). By standardizing each of the variables, a more meaningful interpretation of the resulting variable weightings was provided. The variable weightings of the standardized variables reflected the relative contributions of the variables to the prediction of EYEMEAS. High weightings indicated a significant variable contribution, while low variable weightings indicated a lack of variable contribution. The optimization analysis was performed for 50 second measures only, 6 second measures

$$
\begin{bmatrix} \phi_1 \\ \cdot \\ \cdot \\ \cdot \\ \cdot \\ \cdot \\ \cdot \\ \phi_n \end{bmatrix}
=
\begin{bmatrix} \theta_{11} & \cdots & \theta_{1i} \\ \vdots & \ddots & \vdots \\ \theta_{n1} & \cdots & \theta_{ni} \end{bmatrix}
\begin{bmatrix} a_1 \\ \cdot \\ \cdot \\ \cdot \\ \cdot \\ \cdot \\ \cdot \\ a_n \end{bmatrix}
$$

$$\widehat{eyemeas} = a_1X_1 + a_2X_2 + a_3X_3 + \ldots + a_nX_n$$

a_n = The optimal values of the a_n's which produce the minimum model error.

n = dependent variables; i = dependent variables; and

N = number of observations

$$\phi_n = \frac{1}{N} \sum (X_{eyemeas} \cdot X_n)$$

$$\phi_n = \begin{matrix} \phi_1 = \overline{X_{eyemeas} \cdot X_{landev}} \\ \phi_2 = \overline{X_{eyemeas} \cdot X_{yawdev}} \end{matrix}$$

etc. . . .

$$\theta_{in} = \frac{1}{N} \sum (X_i \cdot X_n)$$

$$\theta_{in} = \begin{matrix} \theta_{11} = \overline{X_{landev} \cdot X_{landev}} \\ \theta_{12} = \overline{X_{landev} \cdot X_{yawdev}} \end{matrix}$$

etc. . . .

Figure 5. Optimization analysis model summary

only, and two combinations of 50 and 6 second measures (two of each and four of each) for both torque and displacement. Four analyses were performed. The linear models for the predicted EYEMEAS and their correlations with the observed EYEMEAS for each of the optimization analyses are presented in Tables 32 and 33.

Comparison of the variable weightings for the 50 second torque and displacement optimizations shows that STDHIGH contributed negatively and only slightly to the models. The torque model, showed a contribution of LANESTD, STVELM, and LANDEVM to the model, but LANESTD had twice the weighting value of the other two variables. The correlation of this model with EYEMEAS was r=0.65. For the displacement model, LANESTD, LANDEVM, and STVELM contributed proportionally to the model with variable weightings that were nearly equal. The correlation of the 50 second displacement model with EYEMEAS was r=0.73.

For the 6 second models both LANDEV and YAWDEV were the contributing variables for torque and displacement. The respective correlations of these models with EYEMEAS were 0.55 for torque and 0.49 for displacement. Thus, the 50 second variables predicted EYEMEAS more effectively than the 6 second variables.

TABLE 32

Torque and Displacement, 50 and 6 Second, Optimization Models and Correlations

50 SECOND MEASURES

	Torque	Displacement
Weighting:		
STDHIGH	-0.010	-0.044
LANESTD	0.427	0.339
LANDEVM	0.177	0.339
STVELM	0.205	0.210
Model Correlation with EYEMEAS:	0.65	0.73

6 SECOND MEASURES

	Torque	Displacement
Weighting:		
LOGSUM	-0.024	0.029
LANDEV	0.395	0.285
YAWDEV	0.165	0.233
MAXPK	-0.027	-0.038
Model Correlation with EYEMEAS:	0.55	0.49

TABLE 33

Torque and Displacement Combined Optimization Models and Correlations

50 SECOND & 6 SECOND MEASURES

	Torque	Displacement
Weighting:		
LANESTD	0.424	0.841
LANDEVM	0.183	0.307
LANDEV	-0.067	-0.539
YAWDEV	0.149	0.096
Model Correlation with EYEMEAS:	0.62	0.74

50 SECOND & 6 SECOND MEASURES

	Torque	Displacement
Weighting:		
STDHIGH	0.046	0.034
LANESTD	0.489	0.740
LANDEVM	0.161	0.339
STVELM	0.181	0.174
LOGSUM	-0.094	-0.065
LANDEV	-0.123	-0.413
YAWDEV	0.041	0.005
MAXPK	-0.051	0.027
Model Correlation with EYEMEAS:	0.65	0.76

TABLE 34

Optimization Analysis Model Summary

	Correlation Values	
	Torque	Displacement
50 Second Measures	0.65	0.73
6 Second Measures	0.55	0.49
4 Variable Combination	0.62	0.74
8 Variable Combination	0.65	0.76

TABLE 35

Highest Dependent Variable Correlations with EYEMEAS

	Correlation Values	
	Torque	Displacement
50 Second LANESTD	0.60	0.66
6 Second LANDEV	0.53	0.46

When the 50 second and 6 second variables were combined in the optimization procedure, both of the variable types influenced the model, and the 50 second variables were associated with the heavier weightings (Table 33). The variables which contributed in the 4-variable combined model were LANESTD and LANDEVM (50 sec.) and LANDEV (6 sec.) for displacement. As the combined model was increased to eight variables, four 50 second and four 6 second variables, the 50 second variables accounted for the heavier weightings. In the torque model, the important 50 second variables were LANESTD, STVELM, and LANDEVM, while the important displacement variables were LANESTD, STVELM, AND LANDEVM and in addition LANDEV a 6 second variable. The correlation values for predicted EYEMEAS and observed EYEMEAS for the eight variable models were higher than the correlations for the four variable models. This is expected since there are more variables to minimize the model errors.

To compare the relative effectiveness of the optimization analyses, Table 34 presents a summary of the correlations between the model EYEMEAS and the observed EYEMEAS. Also included in Table 35 are the highest correlations with EYEMEAS obtained in the correlation analysis. By comparing these two tables, the 50 second variables indicate that they have the higher capacity for predicting EYEMEAS, for both the torque and displacement analyses, and the optimization procedure only slightly improves the strength of the LANESTD correlation by the inclusion of additional highly correlated variables.

The optimization analysis provided only modest improvement in the prediction of EYEMEAS. Thus, the dependent variables may be similar in their attributes which correlate with EYEMEAS. However, the correlation values obtained indicate that eyelid droop and closure can be predicted with moderate accuracy from driver performance measures.

Discriminant analysis. All of the predictive analyses which have been presented so far have related the 50 second and 6 second dependent variables to the measurement of eyelid closure through correlations. Thus, no information has been provided regarding the false alarm rates or the miss rates associated with using an algorithm to predict eyelid closure. If the intention of deriving algorithms is to detect driver drowsiness, then the error rates associated with drowsy driver detection need to be identified. Through the discriminant analyses which follow, information regarding the effectiveness of a linear discriminant function for classifying observations was obtained.

The data used to perform the discriminant analyses were the eyelid closure data obtained from the 50 second EYEMEAS variable. Eleven of the twenty subject's data were used, and there were 990 total observations for both the torque and displacement analyses. From the three levels of eyelid closure established earlier in the data analyses, two new categories of eyelid closure were formed by combining the first and second levels of eyelid closure into one category and maintaining the third level as a second category. By using the data in this manner, the data was separated along the alert-drowsy continuum. The first category, 'alert', contained all data observations in which the driver on the average had 0% to 54% eyelid closure for 100% of the time, while the second category, 'drowsy', on the average had percent eyelid closures greater than 54%. For the purpose of promoting driving safety, the second category of eyelid closure was the most important to detect. A driver who exhibited the second category of eyelid closure should have been warned of drowsiness onset. The results of the discriminant analyses which follow are discussed in terms of detecting the 'drowsy' observations. A false alarm was encountered anytime an 'alert' observation was classified as a 'drowsy', and a miss was encountered whenever a 'drowsy' observation was not classified as being 'drowsy'.

It should be noted that there is statistical bias in the reported apparent error rates in this analysis due to the proportion of 'alert' observations as compared to the proportion of 'drowsy' observations. The individual false alarm and miss rates are provided to eliminate the statistical bias which occurs from reporting only the apparent error rates.

In discriminant analysis, rules are derived for optimal assignment or classification of new observations to a specific population. For this analysis, the two populations from which observations were classified were (1) 'alert' and (2) 'drowsy'. To classify the observations, the discriminant analysis built a linear discriminant function (LDF) which maximally separated the means of the populations relative to the population variance by considering linear combinations of the multivariate observations. The classification procedure which resulted was good if the probability of misclassifying observations was small. How 'small' the number of misclassifications should have been is dependent on the cost of misclassifying observations. Costs of misclassifying were not established for these analyses. However, to detect even a small percentage of the drowsy observations would make the implementation of a detection device worthwhile. By using the two eyelid closure categories, 'alert' and 'drowsy', the number of false alarms and misses which may be anticipated are presented in classification matrices in Tables 36 and 37.

To interpret the classification matrices properly, a short discussion of the confusion matrix layout follows. In each of the matrices, the actual and predicted observations are reported for both 'alert' and 'drowsy' observations. The number at the end of each row or column of cells is the total number of observations which fall into each of the respective categories. For instance, in the 50 second torque matrix in Table 36, the total number of actual 'alert' observations was 882, while the predicted number of

TABLE 36

Torque Discriminant Analysis

50 SECOND

		Predicted: Alert	Predicted: Drowsy	
Actual	Alert	756	126 (14.29%)	882
	Drowsy	37 (34.26%)	71	108
		793	197	

AER

$\frac{163}{990} = 16.46\%$

6 SECOND

		Predicted: Alert	Predicted: Drowsy	
Actual	Alert	734	148 (16.78%)	882
	Drowsy	52 (48.15%)	56	108
		786	204	

AER

$\frac{200}{990} = 20.20\%$

TABLE 37

Displacement Discriminant Analysis

50 SECOND

		Predicted: Alert	Predicted: Drowsy	
Actual	Alert	739	143 (16.21%)	882
	Drowsy	30 (27.78%)	78	108
		769	221	

AER

$\frac{173}{990} = 17.47\%$

6 SECOND

		Predicted: Alert	Predicted: Drowsy	
Actual	Alert	677	205 (23.24%)	882
	Drowsy	48 (44.44%)	60	108
		725	265	

AER

$\frac{253}{990} = 25.56\%$

'alert' observations was 793. The numbers which appear in each of the cells of the matrices are the number of observations which were classified to each of the two populations. In Table 36, 756 of the 882 'alert' observations were classified as 'alert', while 126 were classified as 'drowsy' (false alarms). This rationale holds true for the remaining cells. The percentage of false alarms and misses are enclosed in parentheses. For the 50 second torque discriminant analysis, a 14.29% false alarm rate was reported. The final information which appears in Table 36 is the AER--Apparent Error Rate. The AER is the total number of observations, 'alert' and 'drowsy', which were misclassified out of the 990 classified observations. This error rate is not as practical as the false alarm and miss rates when considering the use of a linear discriminant function for use in a drowsy driver detection device.

In Table 36, the 50 second torque confusion matrix, the apparent error rate (AER) for classifying alert and drowsy observations is 16.46%. The AER is composed of a 34.26% error rate for classifying drowsy observations as alert (misses), and 14.29% error rate for classifying alert observations as drowsy (false alarms). The drowsy detection error rate even at 34.26% can be interpreted as identifying approximately 66% of the drowsy observations with a false alarm rate of 14.29%.

Similar findings resulted in the 50 second displacement analysis. The overall AER was 17.47% with 16.21% false alarms and 27.78% misses associated with the detection of drowsy observations. The reduction of the number of drowsy detection misses between the torque and displacement 50 second analyses was nearly 7%, however, the false alarm rate increased by approximately 2%.

For the 6 second measures for both the torque and displacement analyses, the number of drowsy observation misses was particularly high. The torque miss rate was 48.15%, while the displacement miss rate was 44.44%. The respective AERs for each of these analyses were 20.20% and 25.56%. The false alarm rates for the 6 second discriminant analyses were slightly higher than the 50 second analyses false alarm rates. If the choice of using the 50 second or 6 second measures for detecting drowsy drivers using discriminant analysis needed to be made, the choice with regard to the data collected in this research would be the 50 second measures. The 50 second measure discriminant analyses error rates were consistently lower than the 6 second error rates.

The overall perspective of using a linear discriminant function for the detection and classification of drowsy drivers, especially using the 50 second measures, appears promising. In general, the false alarm rate was around 15%, while the percentage of misses varied between 34% and 28% for the 50 second torque and displacement analyses. If additional dependent driving measures associated with EYEMEAS could be identified, the effectiveness of discriminant analysis for deriving linear algorithms to detect drowsy drivers could be improved. At present, however, even with the current error rates, the use of discriminant analysis for deriving drowsy driver models is practical. Discriminant analysis is especially appealing since EYEMEAS, which the linear discriminant function classifies, was a true on-line measure of eyelid closure. Thus, all the dependent variables which contribute to the multivariate discriminant analysis are directly meaningful to the level of driver alertness.

Posthoc Analyses

In conducting this research, several blocking factors served as experimental control variables. These factors included presentation order of the experimental runs (R-SD or SD-R), sex, personality type (introvert or extrovert), mileage driven per year, and age. Each of these blocking factors in the posthoc analyses were divided into two experimental groups, and ten subjects were assigned to each of the two groups.

Of the blocking factors considered, only the presentation order and sex of the driver were established in the original experimental design of the research. The other factors were divided into two experimental groups on a posthoc basis. To determine whether the subjects were assigned to the first or second experimental posthoc group, the data collected from the driver questionnaires and the Eysenck Personality Inventory (EPI), a personality test, were used. A description of each of the posthoc experimental groups is presented below:

<u>Presentation Order</u> - The presentation order of the two driving sessions--rested and sleep deprived--was counterbalanced. Ten subjects (5 male and 5 female) received the rested - sleep deprived presentation order, while the remaining ten subjects (5 male and 5 female) received the sleep deprived - rested presentation order.

<u>Sex</u> - Ten male and ten female subjects were selected for participation. Five males and five females were assigned to each of the presentation order groups. Also, an attempt was made to distribute the ages and driving experience of the subjects across the presentation orders.

<u>Personality Type</u> - To determine the personality type of the subjects on the introversion-extroversion continuum, the introversion-extroversion portion of the Eysenck Personality Inventory (EPI) was administered to each of the subjects. After each of the inventories was scored, a criterion cutoff value for introversion versus extroversion was set at 12 on the EPI scale. This criterion value represented the 52nd percentile for an American college student population and the 68th percentile for the adult industrial population (Eysenck and Eysenck, 1968). By using an EPI cutoff score of 12, the two personality type experimental groups each had ten subjects and the two groups were divided close to the desired 50th percentile of the population.

<u>Mileage Driven Yearly</u> (<u>Driving Experience</u>) - The subjects were divided into two groups of ten subjects based on the amount of mileage the subjects reported to drive yearly. A low mileage group drove less than 10,000 miles per year, while a high mileage group drove 10,000 or more miles per year. The low mileage group had 3 males and 7 females and the high mileage group 7 males and 3 females. Mileage driven yearly was treated as a driving experience variable using the assumption

that those who drive fewer miles per year are less experienced drivers.

<u>Age</u> - The two subject groups for age included 10 subjects under 32 years of age and 10 subjects 32 years and older. Each group contained 5 males and 5 females.

<u>MANOVA analyses</u>. Since each of the blocking factors was a two-level, between-subject variable, the MANOVA sources of variation for each blocking factor analysis are the same. In determining whether the blocking factor was influential in driving performance and the onset of drowsiness, a one-way MANOVA was performed for each of the sets of dependent variables. Only the main effect of the blocking factor was statistically analyzed. The interaction of the blocking factor with driving condition and driving segment was not of primary concern in the posthoc analyses. The results of each MANOVA with respect to the eye measures, the 50 second measures, and the 6 second measures are presented for torque and displacement in Tables 38 and Table 39. (The full models for the torque 50 second MANOVA and ANOVA analyses appear in Appendix B.)

Of the five blocking factors examined, only two of the factors, sex and driving experience resulted in

TABLE 38

Blocking Factor MANOVA Posthoc Analyses for Torque

PRESENTATION ORDER

MANOVA	Source	df	F	p
Eyelid	Order	(3,16)	1.30	0.3096
50 Sec.	Order	(7,12)	0.57	0.7670
6 Sec.	Order	(7,12)	0.20	0.9790

SEX

MANOVA	Source	df	F	p
Eyelid	Sex	(3,16)	0.65	0.5952
50 Sec.	Sex	(7,12)	3.94	0.0183*
6 Sec.	Sex	(7,12)	1.12	0.4128

INTROVERSION-EXTROVERSION

MANOVA	Source	df	F	p
Eyelid	Person	(3,16)	0.58	0.6371
50 Sec.	Person	(7,12)	1.17	0.3881
6 Sec.	Person	(7,12)	0.52	0.8013

* $p<0.05$, ** $p<0.01$, *** $p<0.005$, and **** $p<0.001$.

TABLE 38

Blocking Factor MANOVA Posthoc Analyses for Torque (Cont.)

DRIVING EXPERIENCE

MANOVA	Source	df	F	p
Eyelid	Mileage	(3,16)	4.40	0.0194*
50 Sec.	Mileage	(7,12)	3.49	0.0279*
6 Sec.	Mileage	(7,12)	1.49	0.2586

AGE

MANOVA	Source	df	F	p
Eyelid	Age	(3,16)	2.21	0.1265
50 Sec.	Age	(7,12)	1.46	0.2688
6 Sec.	Age	(7,12)	1.50	0.2556

* $p<0.05$, ** $p<0.01$, *** $p<0.005$, and **** $p<0.001$.

TABLE 39

Blocking Factor MANOVA Posthoc Analyses for Displacement

PRESENTATION ORDER

MANOVA	Source	df	F	p
Eyelid	Order	(3,16)	1.34	0.2980
50 Sec.	Order	(7,12)	0.41	0.8752
6 Sec.	Order	(7,12)	0.94	0.5134

SEX

MANOVA	Source	df	F	p
Eyelid	Sex	(3,16)	1.13	0.3683
50 Sec.	Sex	(7,12)	1.59	0.2299
6 Sec.	Sex	(7,12)	1.18	0.3830

INTROVERSION-EXTROVERSION

MANOVA	Source	df	F	p
Eyelid	Person	(3,16)	0.61	0.6174
50 Sec.	Person	(7,12)	1.43	0.2794
6 Sec.	Person	(7,12)	0.46	0.8443

* $p<0.05$, ** $p<0.01$, *** $p<0.005$, and **** $p<0.001$.

TABLE 39

Blocking Factor MANOVA Posthoc Analyses for Displacement (Cont.)

DRIVING EXPERIENCE

MANOVA	Source	df	F	*p*
Eyelid	Mileage	(3,16)	3.98	0.0270*
50 Sec.	Mileage	(7,12)	4.60	0.0103*
6 Sec.	Mileage	(7,12)	2.44	0.0837

AGE

MANOVA	Source	df	F	*p*
Eyelid	Age	(3,16)	2.21	0.1264
50 Sec.	Age	(7,12)	1.48	0.2619
6 Sec.	Age	(7,12)	1.67	0.2068

* $p<0.05$, ** $p<0.01$, *** $p<0.005$, and **** $p<0.001$.

statistically significant main effects. The sex analysis 50 second torque MANOVA was significant at $p<0.05$, but sex did not consistently contribute to driving performance or drowsiness for both torque and displacement. The contribution of driving experience, on the other hand, was consistent, see Tables 38 and 39. The amount of mileage driven yearly by each of the subjects, less than 10,000 miles (low) or 10,000 miles or more (high), influenced both the eyelid measures ($p=0.019$ and $p=0.027$) and the 50 second measures ($p=0.028$ and $p=0.010$) for torque and displacement respectively. None of the 6 second measure MANOVAs resulted in statistical significance.

ANOVAs and Bonferroni multiple comparisons. To identify the dependent variables which contributed to the statistically significant driving experience MANOVAs, ANOVAs and Bonferroni multiple comparison analyses were performed. The results are presented in Tables 40 through 43. In reviewing the mean values in Tables 42 and 43 for the three eyelid measures, the results indicate that the drivers with less driving experience were more drowsy than the more experienced drivers. That is, the drivers with the low experience had higher mean values for all three of the eyelid measures than did the drivers with high experience. But as the ANOVAs and the multiple comparisons indicate, only the PERCLOS measure, which measured the percentage of time that 80% to 100% eyelid closure occurred, resulted in statistically significant mean value differences between the low and high driving experiences. These results were consistent for both the torque and the displacement analyses.

Additional support for the presumption that the less experienced drivers were more drowsy while driving was provided in the ANOVAs for the 50 second lane deviation measures. LANESTD (p=0.0038) for the torque analysis (Table 40) and LANESTD (p=0.0049) and LANDEVM (p=0.0335) for the displacement analysis (Table 41) all had larger mean values for the low experience drivers. These mean value differences were all statistically significant in the Bonferroni analyses, Tables 42 and 43. In summary, all the driving experience posthoc analyses suggest that the drivers who drove 10,000 or more miles per year were better able to maintain their lane position and their level of alertness while driving.

Posthoc Predictive Analyses using Driving Experience as a Blocking Variable

Since driving experience was the dominant posthoc blocking factor, only driving experience was considered throughout the remaining analyses. In these analyses an

TABLE 40

Driving Experience ANOVAs for Eyelid and 50 Second Torque Measures

EYELID MEASURES

ANOVA	Source	df	F	p
EYEMEAS	Mileage	(1,18)	1.66	0.2133
PERCLOS	Mileage	(1,18)	7.58	0.0131*
EYELID	Mileage	(1,18)	2.71	0.1173

50 SECOND MEASURES

MANOVA	Source	df	F	p
LOGHIGH	Mileage	(1,18)	0.07	0.7880
MTHIGH	Mileage	(1,18)	0.00	0.9695
STDHIGH	Mileage	(1,18)	1.30	0.2685
TRANS	Mileage	(1,18)	0.47	0.5010
LANESTD	Mileage	(1,18)	11.04	0.0038***
LANDEVM	Mileage	(1,18)	3.73	0.0693
STVELM	Mileage	(1,18)	0.02	0.8943

* $p<0.05$, ** $p<0.01$, *** $p<0.005$, and **** $p<0.001$.

TABLE 41

Driving Experience ANOVAs for Eyelid and 50 Second Displacement Measures

EYELID MEASURES

ANOVA	Source	df	F	p
EYEMEAS	Mileage	(1,18)	1.83	0.1930
PERCLOS	Mileage	(1,18)	7.06	0.0161*
EYELID	Mileage	(1,18)	2.62	0.1228

50 SECOND MEASURES

MANOVA	Source	df	F	p
LOGHIGH	Mileage	(1,18)	0.65	0.4314
MTHIGH	Mileage	(1,18)	0.85	0.3697
STDHIGH	Mileage	(1,18)	0.63	0.4372
TRANS	Mileage	(1,18)	0.48	0.4969
LANESTD	Mileage	(1,18)	10.28	0.0049***
LANDEVM	Mileage	(1,18)	5.30	0.0335*
STVELM	Mileage	(1,18)	0.92	0.3511

* $p<0.05$, ** $p<0.01$, *** $p<0.005$, and **** $p<0.001$.

TABLE 42

Driving Experience Bonferroni Multiple Comparisons for Eyelid and 50 Second Torque Measures*

EYEMEAS

Mileage	
LOW	HIGH
227.6	193.2
A	A

PERCLOS

Mileage	
LOW	HIGH
2.04	0.62
A	B

EYELID

Mileage	
LOW	HIGH
27.01	21.56
A	A

LANESTD

Mileage	
LOW	HIGH
15.62	10.80
A	B

* Mean values designated by different letters are significantly different ($p < 0.05$).

TABLE 43

Driving Experience Bonferroni Multiple Comparisons for Eyelid and 50 Second Displacement Measures*

EYEMEAS

Mileage	
LOW	HIGH
232.2	195.6
A	A

PERCLOS

Mileage	
LOW	HIGH
2.36	0.73
A	B

EYELID

Mileage	
LOW	HIGH
26.51	21.51
A	A

LANESTD

Mileage	
LOW	HIGH
14.26	10.01
A	B

LANDEVM

Mileage	
LOW	HIGH
37.66	26.26
A	B

* Mean values designated by different letters are significantly different ($p < 0.05$).

attempt was made to determine whether driving experience could be utilized in an effort to improve the detection of drowsy drivers through their driving performance. Thus, driving experience was used as a grouping factor to perform additional predictive analyses.

The data used in the correlation analyses were the mean values of 15 observations. The data used in the optimization and discriminant analyses were the eyelid closure data described earlier. The three respective eyelid closure levels were determined from the variable EYEMEAS, one of the 50 second eyelid measures. Individual observations of eyelid closure were used in the data analyses. To compare the differences in the new predictive analyses with the original predictive analyses, the "before" grouping by driving experience results and the "after" grouping by driving experience results are discussed simultaneously.

Correlation analyses. By using the two levels of driver experience to divide the eyelid closure data into two distinct driving groups, low and high experience drivers, two correlation analyses one for low and one for high driving experience were required. The results of each of these analyses are presented in Tables 44 through 47.

To provide a method for relating the original correlation results with the new driving experience group correlations, plus signs (+) are placed next to any correlation values which increased as a result of grouping by driving experience. If the actual difference is desired, refer to the original correlation tables, Tables 30 for torque and Table 31 for displacement.

The correlation analyses for the drivers with low experience for both the torque and the displacement analyses resulted in increased r-values for a majority of the correlations shown in Tables 44 and 46. These results encourage the separation of the subject population into driving experience groups for determining the dependent variables associated with driver drowsiness. This is especially true since the variables which resulted in increased correlations were the variables which have been continually associated with driver drowsiness (LANESTD, LANDEVM, LANDEV, and YAWDEV). However, the opposite results occurred for the high experience drivers. A majority of the correlations decreased, while only a few increased. The variable which resulted in increased correlations consistently was STVELM. In general, the grouping of the subjects according to their driving experience definitely influenced the correlation results. To determine the importance of using driving experience as a blocking factor, additional research would need to be conducted.

Optimization analyses. For the optimization analyses, both the four variable 50 second model (Table 48) using STDHIGH, LANESTD, LANDEVM, and STVELM and the four variable combined 50 second and 6 second model (Table 49) using LANESTD, LANDEVM, LANDEV, and YAWDEV were re-analyzed using driving experience as a blocking variable. These two models which included 50 second variables were used due to the statistical significance of the 50 second measures in the driving experience MANOVAs in the posthoc analyses. The correlations of EYEMEAS with the original optimization model are presented along with the low and high driving experience model correlations.

The 50 second model results in Table 48 indicate that the new driving experience model for low experience drivers provided a better predictor of EYEMEAS than the original 50 second optimization model for torque and displacement. However, the model for high experience drivers provided poorer model prediction. These same results occurred for the combined 50 second and 6 second models in Table 49. As was indicated in the correlation analyses and is re-emphasized here in the optimization analyses, dividing the subjects according to their level of driving experience

TABLE 44

Correlation Matrix for Torque Low Experienced Drivers Average of 15 Pulses

	LANDEV*	YAWDEV*	EYEMEAS	PERCLOS	LANDEVM	LANESTD	STVELM
EYELID*	0.61+	0.53	0.94	0.69+	0.56+	0.70+	0.27
EYEMEAS	0.62+	0.53+	--	0.80+	0.56+	0.68+	0.27
PERCLOS	0.57	0.50	0.80+	--	0.66+	0.59	0.40
LANDEVM	0.55+	0.46	0.56+	0.66+	--	0.72+	0.28+
LANESTD	0.89	0.68	0.68+	0.59	0.72+	--	0.37+

* These measures are 6-second measures. All others are 50-second measures.

TABLE 45

Correlation Matrix for Torque High Experienced Drivers Average of 15 Pulses

	LANDEV*	YAWDEV*	EYEMEAS	PERCLOS	LANDEVM	LANESTD	STVELM
EYELID*	0.40	0.44	0.96+	0.65	0.38	0.55	0.52+
EYEMEAS	0.35	0.38	--	0.67	0.38	0.50	0.48+
PERCLOS	0.41	0.48	0.67	--	0.10	0.36	0.60+
LANDEVM	0.38	0.30	0.38	0.10	--	0.63	0.17
LANESTD	0.82	0.74	0.50	0.36	0.63	--	0.41+

* These measures are 6-second measures. All others are 50-second measures.

TABLE 46

Correlation Matrix for Displacement Low Experienced Drivers
Average of 15 Pulses

	LANDEV*	YAWDEV*	EYEMEAS	PERCLOS	LANDEVM	LANESTD	STVELM
EYELID*	0.54+	0.56+	0.96	0.73+	0.72+	0.77+	0.34
EYEMEAS	0.52+	0.56+	--	0.83+	0.72+	0.74+	0.34
PERCLOS	0.44	0.48+	0.83+	--	0.65+	0.60	0.53+
LANDEVM	0.61	0.62+	0.72+	0.65+	--	0.78+	0.28+
LANESTD	0.83	0.67+	0.74+	0.60	0.78+	--	0.39+

* These measures are 6-second measures. All others are 50-second measures.

TABLE 47

Correlation Matrix for Displacement High Experienced Drivers
Average of 15 Pulses

	LANDEV*	YAWDEV*	EYEMEAS	PERCLOS	LANDEVM	LANESTD	STVELM
EYELID*	0.31	0.22	0.97+	0.67	0.51	0.59	0.46+
EYEMEAS	0.28	0.21	--	0.71	0.48	0.54	0.47+
PERCLOS	0.34	0.34	0.71	--	0.24	0.46	0.56+
LANDEVM	0.59	0.32	0.48	0.24	--	0.61	0.11
LANESTD	0.84	0.66+	0.54	0.46	0.61	--	0.44+

* These measures are 6-second measures. All others are 50-second measures.

TABLE 48

Driving Experience Optimization Analyses Correlations for the 50 Second Measures

50 SECOND MODELS

TORQUE:	Mileage		
	Original	Low	High
Model Correlation with EYEMEAS	0.65	0.69	0.62

DISPLACEMENT:	Mileage		
	Original	Low	High
Model Correlation with EYEMEAS	0.76	0.78	0.66

TABLE 49

Driving Experience Optimization Analyses Correlations for the Combined 50 and 6 Second Measures

50 SECOND AND 6 SECOND MODELS

TORQUE:

	Mileage		
	Original	Low	High
Model Correlation with EYEMEAS	0.62	0.70	0.52

DISPLACEMENT:

	Mileage		
	Original	Low	High
Model Correlation with EYEMEAS	0.74	0.79	0.66

improved the prediction of EYEMEAS for the low experience drivers only. These improvements were not realized for the high experience drivers. These results were consistent for both the torque and the displacement analyses.

Discriminant analyses. In performing the new discriminant analyses for both low and high driving experience, the data from five low experience drivers and six high experience drivers were used. The data from these drivers included observations for the 'alert' and 'drowsy' data categories used in the analyses. The data of the nine remaining subjects did not include data for both categories. The results of these analyses for torque and displacement appear in Tables 50 and 51.

In general, the apparent error rates (AERs) for the low and high experience groups were slightly higher than the AERs in the original analyses. However, there was a major difference between the low and high experience error rates for the classification of drowsy observations. For the low experience torque analysis, 76.92% of the drowsy observations were correctly classified leaving a miss error rate of 23.08%. This miss error rate was over 11% lower than the original drowsy observation error rate of 34.25%. Thus, more of the low experience drowsy observations were detected by grouping the eyelid closure data by driving experience. The opposite was true for the high experience drivers. The miss error rate for the high experience drivers increased to 48.84%, an increase of nearly 15%. The high experience AER was 22.59%. As in the previous analyses using driving experience as a blocking factor, the low experience group benefited, while the high experience group did not benefit.

For the high and low experience displacement discriminant analyses, the same trends in classification of the alert and drowsy observations occurred, however, the effects were not as dramatic. The total AERs for low and high experience increased by no more than 0.5%, and the largest individual error rate increase was 5%. The 5% increase was in classifying high experience drowsy observations as alert (misses).

The only true gains established in the discriminant analysis of using driving experience to classify were evident in the low experience group for detecting drowsy observations. Again, with more research and the identification of additional driving performance variables which are associated with drowsy driving, the discriminant analysis may prove to be an invaluable tool for the detection of drowsy drivers.

TABLE 50

Driving Experience Discriminant Analyses for Torque

LOW EXPERIENCE

		Predicted: Alert	Predicted: Drowsy	
Actual	Alert	321	64 (16.62%)	385
	Drowsy	15 (23.08%)	50	65
		336	114	

AER

$\frac{79}{450} = 17.56\%$

HIGH EXPERIENCE

		Predicted: Alert	Predicted: Drowsy	
Actual	Alert	396	101 (20.32%)	497
	Drowsy	21 (48.84%)	22	43
		417	123	

AER

$\frac{122}{540} = 22.59\%$

TABLE 51

Driving Experience Discriminant Analyses for Displacement

LOW EXPERIENCE

		Predicted: Alert	Predicted: Drowsy	
Actual	Alert	320	65 (16.88%)	385
	Drowsy	16 (23.08%)	49	65
		336	114	

AER

$\frac{81}{450} = 18.00\%$

HIGH EXPERIENCE

		Predicted: Alert	Predicted: Drowsy	
Actual	Alert	414	83 (16.70%)	497
	Drowsy	14 (32.56%)	29	43
		428	112	

AER

$\frac{97}{540} = 17.96\%$

CONCLUSIONS

In summarizing the results of the data analyses, several important findings which support the development of a drowsy driver countermeasure device are emphasized. Conclusions for each of the analyses are presented. After the specific conclusions are presented, some general conclusions based on observations of the study are reported. Then, to finalize the conclusion section, recommendations and topics worthy of further research are introduced.

Of the seventeen dependent variables considered in the main data analysis, several were repeatedly sensitive, regardless of whether the main effect was condition, segment, or eyelid closure. The 50 second variables which resulted in statistical significance or neared statistical significance for torque and displacement were LANESTD and LANDEVM. These variables along with STVELM were also highly correlated with EYEMEAS, the 50 second eyelid closure measure. All three of the dependent variables, LANESTD, LANDEVM, and STVELM are feasible measures for the detection of a drowsy driver and are potentially instrumentable. In addition to the 50 second measures, there were two 6 second measures which were highly correlated with eyelid closure and were sensitive to condition, segment, and eyelid closure. The two 6 second measures were LANDEV and YAWDEV.

Again, both of these measures could be instrumented along with the stimulus input, torque or displacement, which drives these responses. In addition to the lane deviation variables, two steering variables could be used to detect drowsiness when using the displacement stimulus. STDHIGH was important for the 50 second analysis and LOGTR for the 6 second analysis. Since steering variables are also included in the displacement analyses, the displacement stimulus may have a slight advantage over the torque stimulus for implementation. However, according to the data analyses, either a torque or a diplacement stimulus could be used in a drowsy driver detection device; although, additional dependent variables would need to be isolated for measuring eyelid closure.

Since the correlations of a few of the dependent variables supported the use of the dependent variables in a detection device, linear optimization of these variables was attempted. The correlations of LANESTD and LANDEV with EYEMEAS were only slightly improved when these variables were linearly combined with the other variables which had high bivariate correlations with EYEMEAS. Thus, the investigation of alternative parameters to combine with LANESTD and LANDEV is necessary if a viable countermeasure device based on the driver's behaviors and performance characteristics is to be found.

In the discriminant analyses, promise of detecting 'alert' and 'drowsy' driver observations was indicated. Through the utilization of a linear discriminant function, the torque 50 second LDF detected approximately 64% of the 'drowsy' observations with a false alarm rate of 14.29% and a miss rate of 34.26%, and the displacement 50 second LDF detected 72% of the 'drowsy' observations with a false alarm rate of 16.21% and a miss rate of 27.78%. Both of the derived LDFs provided relatively successful 'drowsy' detection algorithms.

In the results of the posthoc analyses, additional information was provided regarding blocking factors which may be used in drowsy driver detection devices. The posthoc blocking factor MANOVAs indicated that driving experience was a potential factor in the development of drowsy driver algorithms. The less experienced drivers appeared to have difficulties staying alert during the simulated driving scenarios, while the more experienced drivers maintained a higher level of arousal. The performance differences between these two groups of drivers was evident in the degree of lane exceedences each experienced. The less experienced drivers had difficulty maintaining their lane position. However, when the subjects were grouped by driving experience in the predictive analyses, improvements in the prediction of drowsiness were only evident in the low experience drivers and not in the high experience drivers. Thus, the influence of driving experience in drowsy driving needs to be studied further.

General Conclusions

The results of the drowsy driver project are optimistic. A few performance measures and blocking factors with further investigation may prove to be successful parameters for monitoring a driver's arousal level. Of particular interest in the development of algorithms is the use of discriminant analysis as a multivariate statistical technique for classifying 'drowsy' observations. Before using an LDF, however, additional parameters which contribute to the LDF should be identified to reduce the number of false alarms and misses of 'drowsy' observations. Thus, the use of linear discriminant functions needs to be further validated through continued research.

Also indicated in the results is the presumption that the torque and displacement stimulus inputs may not be needed. The 50 second measures which reflected 'normal' highway driving were the more sensitive of the dependent variables. Since the 50 second variables are just as instrumentable as the 6 second stimulus-response measures, further investigation of 'normal' driving parameters needs to be undertaken.

The fact that the low-light level CCTV camera recorded observable drowsy driver traits suggests that through telemetry a driver may be monitored. In particular, if vehicle proving grounds would install low-light level cameras in their prototype vehicles and provide personnel to monitor the resultant telemetered picture in real-time, accidents as a result of falling asleep at the wheel during time-on-task driving might be reduced. Thus, through direct observation of the driver's driving behavior and mannerisms, the onset of drowsiness may be detected and the driver may be informed and alerted.

Recommendations and Research Topics

1. Proving grounds should be made aware of the results of this drowsy driver study. Serious consideration should be given to the implementation of a video telemetering system on a trial basis to test its merit in reducing accidents.
2. Additional research needs to be conducted on the 'normal' driving measures. A driving study which does not have the stimulus inputs should be conducted to determine whether the 50 second measures are still

highly correlated with eyelid closure when the torque and displacement pulses are removed.

3. 'Active' countermeasure devices and secondary tasks which are not intrusive to the driving task should be designed and tested for their ability to increase a drowsy driver's arousal level or maintain an alert driver's arousal level.
4. Due to the optimistic results obtained in this study, the development of a drowsy driver algorithm needs to be advanced. There are many additional driving parameters and blocking factors which may be tested for their inclusion in an algorithm.

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Appendix A

DRIVING QUESTIONNAIRE

The following questionnaire is designed to investigate your driving and sleeping habits for participation in the automobile simulator study. All answers will be confidential and will be treated anonymously.

Complete the following items:

1. A. Year of birth ______________________________

   B. Circle one: Married Single Divorced Separated Widowed

   C. Occupation _________________________________

   D. Do you smoke (circle one)? Yes No

   E. If you are a smoker, do you smoke

      Lightly Moderately or Heavily

   F. Do you take such legal drugs as Antihistamines, Tranquilizers, etc. which might affect your sleep?

      Yes No

   G. Do you have a valid drivers license?

      Yes No

   H. Do you ordinarily wear glasses while driving?

      Yes No

      If yes, do you wear contact lenses?

      Yes No

2. Check one: Male ______ Female _______

3. A. What are your normal sleeping hours?

Retire ___________ Awake ___________

B. On the average what is your depth of sleep: (Circle one)

Restless Light Moderate Deep Very Deep

Sleeping Habits	NEVER	ALMOST NEVER	OCCASIONALLY	MODERATELY OFTEN	VERY OFTEN
A. Do you normally fall asleep during the day?	____	____	____	____	____
B. How often do you fall asleep watching TV?	____	____	____	____	____
C. How often do you fall asleep reading?	____	____	____	____	____
D. Do you fall asleep after lunch?	____	____	____	____	____
E. Do you fall asleep after dinner?	____	____	____	____	____
F. How often do you take daily naps?	____	____	____	____	____

Driving Habits	NEVER	ALMOST NEVER	OCCASIONALLY	MODERATELY OFTEN	VERY OFTEN
A. How often have you experienced drowsiness while driving?	____	____	____	____	____
B. How often have you driven for more than three hours at a time?	____	____	____	____	____
C. How often have you had trouble staying awake in situations other than driving?	____	____	____	____	____

1. Estimated mileage driven yearly: (Check one)

_____ a. 0 - 5,000 miles.
_____ b. 5,000 - 10,000 miles.
_____ c. 10,000 - 20,000 miles.
_____ d. greater than 20,000 miles.

2. On long trips: (Check one)

_____ a. I do all of the driving.
_____ b. I do most of the driving.
_____ c. I share the driving equally.
_____ d. I do little of the driving.
_____ e. I never drive on long trips.

3. <u>If I drive while drowsy</u>, I find that I

_____ a. Can continue driving safely.
_____ b. Occasionally have a problem such as running onto the shoulder of the road.
_____ c. Moderately likely to have a problem such as running onto the shoulder of the road.
_____ d. Very likely to have a problem such as running off the road or having an accident.

INTRODUCTION TO THE AUTOMOBILE SIMULATOR STUDY

The purpose of this study is to investigate driving performance and characteristics under normal rested conditions and after a period of partial sleep deprivation. The study is being conducted at the Vehicle Simulation Laboratory, Department of Industrial Engineering and Operations Research (IEOR), Virginia Polytechnic Institute and State University, Blacksburg, VA, 24061, telephone number 961-7962. The research team consists of Julie H. Skipper, Lenora Dunker, and Thomas Dingus, who are graduate students in Industrial Engineering and Operations Research; and Dr. Walter W. Wierwille, (Principal Investigator), Professor of Industrial Engineering and Operations Research.

In the study you will be asked to drive an automobile simulator in a simulated highway driving scenario. The simulator is instrumented with a highway image screen and experimental cameras to aid in the research. At all times during the simulated scenario, you will be required to wear the lap seat belt provided.

The study consists of two experimental driving sessions. One session will be a "normal" session. The other will be a sleep deprived session. You will participate in a practice session prior to the experimental driving sessions. Depending on the experimental group to which you are assigned, you may perform the "normal" session first or the "sleep deprived" session first. The two driving sessions will be scheduled within a few days of each other. The experimenter will inform you as to which session you will complete first.

For the "normal" driving session, you must obtain a reasonable night of sleep the night preceding the driving. Your driving instructions for the session will ask you to drive for approximately two hours as if you were driving normally at a highway speed of 55 mph in the right lane of an interstate highway.

For the sleep deprived session we will begin in the early evening. We will make arrangements to pick you up at your residence. We will purchase your supper for you and we will then take you to the building in which the vehicle simulation laboratory is located.

During the sleep deprivation period, you will be given the choice of studying, reading, watching television, listening to music, or any combination. You will remain awake throughout the evening and into the early morning hours. Laboratory personnel will awaken you if you should doze off.

Between 2:AM and 3:AM we will begin the sleep deprived driving task. The driving task itself will be similar to the "normal" driving task. If you happen to doze off during the drive, one of the experimenters will wake you. The simulator does not pose a danger to you if you run off the road, but you should make an effort to remain awake during the driving task. This task will again last for approximately two hours.

After completing the experiment, you will be paid for participation at a rate of $4.00 per hour. You will be paid for the normal driving session, the evening hours prior to the "sleep-deprived" driving, and for the sleep-deprived driving session itself. If you do not complete all sessions, you will be paid for the time you actually spent.

After you have been paid, you will be driven home. It is expected that you will sleep on returning home, so that you can recover. For your safety, it is imperative that you allow a member of the experimental team to drive you home.

Data will be recorded during the driving tasks. These data will be treated with anonymity.

If during the driving task you feel that you must discontinue for any reason, you have the right to do so. For your safety, the motion platform must be stopped before you leave the simulator. The procedure could be as follows:

> Inform the experimenter of your wish to stop and then press the emergency stop button on the dash;

Or alternatively,

> Inform the experimenter of your wish to stop, and the experimenter will stop the motion from the control console.

The experimenter will aid you in leaving the simulator. Obviously, the research team would like for you to complete the experiment if you can.

It is possible at times during the driving task that you may feel overcome by drowsiness and feel as though you are not performing the instructed task. During such instances we request that you please continue driving. The experiment is not designed to test your driving skills, but to obtain data on sleep deprived drivers. All we ask is that you attempt to drive normally.

If you have any questions about the experiment or your rights as a participant after reading the attached participant's consent form, please do not hesitate to ask. We will answer your questions as openly and honestly as possible. Answers to some of your questions may be delayed until after completion of the experimental sessions, to avoid affecting the outcome of the experiment. Please do not discuss the experiment with anyone especially someone who may participate. Since it is expected that all data will be collected by June 15, 1984, you may discuss the study freely after that date.

Risks inherent in this experiment include interference in your activities on the day following sleep deprivation and risk of injury if you attempt to leave the driving simulator before its motion is stopped.

PARTICIPANT'S INFORMED CONSENT

The purpose of this document is to obtain your consent to participate in this experiment and to inform you of your rights as a participant.

(1) You have the right to stop participating in the experiment at any time. If you choose to terminate the experiment, you will receive pay only for the time you participated in the experiment plus partial pay for recovery as described earlier.

(2) You have the right to see your data and to withdraw them from the experiment. If you decide to withdraw your data, please notify the experimenter immediately. Otherwise, identification of your particular data will not be possible, because the data will be treated anonymously.

(3) You have the right to be informed of the overall results of the experiment. If, after participation, you wish to receive information regarding this study, please include your address (six months hence) with your signature below. If more detailed information is desired after receiving the results summary, please contact the Vehicle

Simulation Laboratory, and a full report will be made available to you.

The faculty and graduate students involved in this study greatly appreciate your help as a participant.

Your signature below indicates you have read the above stated rights and you consent to participate in the study described. If you include your printed name and address below, a summary of the experimental results will be sent to you.

____
Signature

____
Date

____
Witness Date

This is to verify that this experiment has been explained to the subject and he/she has had an opportunity to have all aspects of the research explained.

____

____

____
Printed name and address

Vehicle Simulation Laboratory
IEOR Department
Virginia Tech
Blacksburg, Virginia 24061
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Appendix B

STATISTICAL ANALYSIS TABLES

FULL MODEL TORQUE 50 SECOND MANOVAS AND ANOVAS

TABLE 52

Full Model Cond X Segment Torque 50 Second MANOVA

Source	dv	df_h	df_e	F	p
Within-Subject					
Cond	7	7	13	4.54	0.0092
Cond X S	(Error Term for Cond)				
Segment (Seg)	7	14	64	4.60	0.0001
Segment X S	(Error Term for Segment)				
Cond X Seg	7	14	64	2.34	0.0111
Cond X Seg X S	(Error Term for Cond X Seg)				

where: dv = number of dependent measures
df_h = F-approximation degrees of freedom for treatment effect
df_e = F-approximation degrees of freedom for error effect
F = F-approximation for Wilk's U likelihood ratio statistic

TABLE 53

Full Model Cond X Segment Torque 50 Second ANOVA

Source	df	MS	F	p
Between-Subjects				
Subjects (S)	19	96.352		
Within-Subject				
Cond	1	138.800	9.04	0.0072
Cond X S	19	15.351		
Segment (Seg)	2	89.567	19.75	0.0001
Segment X S	38	4.536		
Cond X Seg	2	28.721	7.14	0.0023
Cond X Seg X S	38	4.022		

TABLE 54

Full Model Eyelid Closure Torque 50 Second MANOVA

Source	dv	df_h	df_e	F	p
Within-Subject					
Closure	7	14	28	2.33	0.0274
Closure X S	(Error Term for Closure)				

where: dv = number of dependent measures
df_h = F-approximation degrees of freedom for treatment effect
df_e = F-approximation degrees of freedom for error effect
F = F-approximation for Wilk's U likelihood ratio statistic

TABLE 55

Full Model Eyelid Closure Torque 50 Second ANOVA

Source	df	MS	F	p
LANESTD				
Between-Subjects				
Subjects (S)	10	52.800		
Within-Subject				
Closure	2	168.626	10.71	0.0007
Cond X S	20	15.748		

COMPLETE 17 X 17 CORRELATION MATRICES FOR TORQUE AND DISPLACEMENT

TABLE 56

Complete Correlation Matrix using the Average of Fifteen Torque Pulses

	EYEMEAS	PERCLOS	LOGHIGH	MTHIGH	STDHIGH	TRANS	LANESTD	LANDEVM	STVELM	LOGSUM*	LOGTR*	LANDEV*	YAWDEV*	MAXPK*	TMTOPK*	RESPTM*
EYELID*	0.95	0.67	0.31	0.43	0.36	-0.07	0.64	0.51	0.39	-0.11	-0.13	0.56	0.53	-0.10	-0.03	0.31
EYEMEAS		0.75	0.29	0.44	0.34	-0.13	0.60	0.51	0.36	-0.11	-0.11	0.53	0.49	-0.08	-0.04	0.31
PERCLOS			0.06	0.18	0.19	-0.20	0.59	0.52	0.39	-0.17	-0.19	0.59	0.54	-0.02	0.06	0.29
LOGHIGH				0.92	0.63	0.59	0.33	0.23	-0.08	0.37	0.28	0.25	0.09	-0.06	0.02	0.28
MTHIGH					0.48	0.31	0.32	0.26	0.01	0.15	0.09	0.27	0.15	-0.02	-0.05	0.25
STDHIGH						0.62	0.64	0.41	0.04	0.45	0.29	0.57	0.35	-0.18	0.19	0.49
TRANS							0.14	0.03	-0.25	0.73	0.63	0.05	-0.13	-0.13	0.10	0.22
LANDSTD								0.69	0.29	0.02	-0.06	0.90	0.75	-0.03	0.15	0.50
LANDEVM									0.2	-0.02	-0.07	0.54	0.46	-0.02	0.05	0.33
STVELM										-0.23	-0.29	0.31	0.39	-0.12	0.12	0.13
LOGSUM*											0.85	-0.10	-0.26	-0.03	-0.03	0.03
LOGTR*												-0.19	-0.30	0.03	-0.02	-0.07
LANDEV*													0.82	-0.11	0.21	0.56
YAWDEV*														-0.06	0.18	0.44
MAXPK*															-0.22	0.10
TMTOPK*																0.17

* 6 SECOND MEASURES

TABLE 57

Complete Correlation Matrix using the Average of Fifteen Displacement Pulses

	EYEMEAS	PERCLOS	LOGHIGH	MTHIGH	STDHIGH	TRANS	LANESTD	LANDEVM	STVELM	LOGSUM*	LOGTR*	LANDEV*	YAWDEV*	MAXPK*	TMTOPK*	RESPTM*
EYELID*	0.96	0.69	0.31	0.31	0.34	-0.10	0.69	0.64	0.36	0.35	0.29	0.49	0.45	0.16	0.32	0.29
EYEMEAS		0.77	0.11	0.26	0.30	-0.12	0.66	0.62	0.35	0.30	0.25	0.46	0.44	0.16	0.32	0.27
PERCLOS			0.02	0.13	0.19	-0.17	0.62	0.53	0.37	0.18	0.18	0.49	0.47	0.24	0.39	0.22
LOGHIGH				0.92	0.92	0.84	0.41	0.34	-0.36	0.79	0.63	0.48	0.24	0.14	0.16	0.14
MTHIGH					0.97	0.64	0.57	0.42	-0.21	0.80	0.60	0.58	0.38	0.14	0.23	0.19
STDHIGH						0.63	0.60	0.44	-0.17	0.79	0.61	0.60	0.40	0.14	0.25	0.19
TRANS							0.09	0.10	-0.50	0.61	0.52	0.19	-0.01	0.09	-0.02	0.07
LANDSTD								0.72	0.25	0.64	0.53	0.87	0.69	0.34	0.54	0.43
LANDEVM									0.11	0.46	0.35	0.63	0.53	0.19	0.36	0.33
STVELM										-0.11	-0.11	0.12	0.32	0.08	0.27	0.15
LOGSUM*											0.83	0.67	0.39	0.30	0.33	0.31
LOGTR*												0.57	0.28	0.38	0.31	0.24
LANDEV*													0.73	0.44	0.65	0.41
YAWDEV*														0.29	0.58	0.35
MAXPK*															0.69	0.34
TMTOPK*																0.40

* 6 SECOND MEASURES

FULL MODEL TORQUE 50 SECOND MANOVAS AND ANOVAS

TABLE 58

Full Model Driving Mileage Torque 50 Second MANOVA

Source	dv	df_h	df_e	F	p
Between-Subjects					
Mileage (Mile)	7	14	28	2.33	0.0274
Subject(Mile)		(Error Term for Mile)			

where: dv = number of dependent measures
df_h = F-approximation degrees of freedom for treatment effect
df_e = F-approximation degrees of freedom for error effect
F = F-approximation for Wilk's U likelihood ratio statistic

TABLE 59

Full Model Driving Mileage Torque 50 Second ANOVA

Source	df	MS	F	p
LANESTD				
Between-Subjects				
Mileage (Mile)	1	695.968	11.04	0.0038
Subjects(Mile)	18	63.039		

Appendix C

DRIVER MANNERISMS ANALYSIS

by

Walter W. Wierwille and Christina Christensen (1984)

in Skipper, Wierwille, and Hardee (1984)

DRIVER MANNERISMS ANALYSIS

Since the videotape recordings obtained during the experimental runs were a source of information regarding the subjects' driving mannerisms, the videotapes were reviewed for mannerism changes related to driver drowsiness. The videotape recordings included the subjects' upper torso and head. The approximate field of view of the videotapes was two feet in width and one and a half feet in height at the subject's face plane.

It was observed in reviewing the tapes on a casual basis that the frequency and type of driver mannerisms varied with time and possibly with the apparent drowsiness of the subjects. Consequently, a detailed analysis was performed to determine whether or not mannerisms were in fact related to time-on-task and eyelid closure. Such information could potentially be of value in developing driver detection algorithms. Another use for the identification of a mannerism and drowsiness relationship would be in situations where visual observation of drivers is available and monitoring of the drivers' mannerisms could be used as an additional safety measure. The following data examination was conducted with these real world applications in mind.

In the mannerisms analysis 40 videotapes were analyzed. Two for each driver/subject (rested and sleep-deprived). Each tape was approximately 90 minutes in duration. The mannerism data were sampled for 18 consecutive five-minute intervals per driving condition. The eighteenth time interval was excluded from analysis, as some of the runs ended before completion of the eighteenth interval. Thus, seventeen time-on-task intervals were obtained for analysis.

The formulation of a data collection tool involved determining categories of mannerisms for the 20 subjects. Three subjects were randomly selected, and a list and count of all mannerisms during each of the rested and sleep-deprived conditions was obtained. Based on intra- and inter-subject occurrence of mannerisms, 16 mannerisms were selected and then grouped by body area into eight categories: hair, eyebrow, eyes, closure, face, mouth, neck, and body (Figure 8). An "other" category was also provided in the data collection to account for mannerisms which did not clearly fit into any of the 16 defined categories.

The criterion for a reduced level of subject arousal was eyelid closures. Eyelid closures were separated into three types. The first type was slow eyelid closure as differentiated from blinking. The second type was slow closure with an unfocusing or "crossing" of the eyes or a rolling of the eyes upwards as if the subject were closing his or her eyes to sleep. The third type of eyelid closure was one in which the duration of the closure was greater than two seconds.

After the mannerism categories were established, each videotape was reviewed and the mannerism events were manually recorded for each of the five minute time intervals. They were observed at twice the videotape recording speed. By using double time, the mannerisms became more distinct with time compression. Also, the likelihood of error during data collection was reduced through minimizing experimenter fatigue and vigilance decrement. Data collection was accomplished by counting the subject's movements and mannerisms. The counts corresponding to each row and each column of Figure 8 for each subject and condition (rested and sleep deprived) were obtained. Thus, 40 arrays of mannerism events were recorded.

Two-Way Condition X Time-On-Task Mannerism MANOVAs

The initial mannerisms statistical analysis was a two-way (condition X time-on-task), within subject MANOVA. This analysis was performed to determine the basic relationship between the independent and dependent mannerism

CATEGORY	RUN NO. 1	2	3	4	5	6	7
					SUBJECT ___		
HAIR							
SCRATCHING/STRAIGHTENING							
EYEBROW							
RAISE-EYES OPEN WIDE							
LOWER-SCOWL							
EYES							
PERIPHERAL LOOKS							
RUBBING/SCRATCHING							
EXCESSIVE BLINKING							
SLOW CLOSURE							
SLOWCLOSURE W/ UNFOCUS/ROLLING							
CLOSURE > 2 SEC.							
FACE							
RUBBING/SCRATCHING/HOLD							
MOUTH							
YAWN							
LIPS LICKING, BITING							
TONGUE MOTION							
OTHER ___							
NECK							
RUBBING/SCRATCHING/HOLD							
HEAD POSITIONCHANGE/NOD							
BODY							
POSITION CHANGE/SHRUG							
OTHER (SPECIFY)							
___							

Figure 8. Mannerisms data collection sheet

variables. One independent variable which had two levels, rested and sleep deprived, was condition. The other independent variable was time-on-task which had 17 levels. Each level represented one five-minute time interval. The dependent variables in the analysis were the eight major mannerism categories derived for the analysis: hair, eyebrow, eyes, closure, face, mouth, neck, and body. The mannerism categories of eyebrow, eyes, closure, mouth, and neck were the addition of behaviors which occurred in that specific body area. For example, 'eyes' category was the combined set of mannerisms for the lesser categories of 'peripheral looks', 'rubbing/scratching', and 'excessive blinking'.

The two-way MANOVA resulted in a significant, $p=0.0143$, condition X time-on-task interaction (Table 60). So, to identify which of the dependent variables contributed to interaction, univariate two-way ANOVAs were performed for each of the eight major mannerisms (dependent variables).

The results of these analyses are presented in Table 61. In the ANOVAs, all of the mannerisms demonstrated a statistically significant main effect of time-on-task, and eyes (eyelid closures) demonstrated a significant condition x time-on-task interaction. It should be noted, also that both mouth and body mannerisms had main effect interactions

TABLE 60

Two-way Condition X Time-on-Task Mannerism MANOVA

Mannerisms

Source	df	F	p
Condition	(8,12)	1.13	0.4107
Time-On-Task	(128,2154)	2.60	0.0001****
Cond X TOT	(128,2154)	1.30	0.0143*

* $p<0.05$, ** $p<0.01$, *** $p<0.005$, and **** $p<0.001$.

which approached significance. Figures 9, 10, and 11 graphically indicate the relationship between the interaction of condition X time-on-task for each of the dependent variables which demonstrated or approached significance.

Eye Closure and Time as Independent Variables

To draw a relationship between drowsiness (eyelid closure) and the drivers' mannerisms, an attempt was made to determine whether runs containing more than five eyelid closures per 90 minute run had more mannerisms than runs containing five or fewer closures per 90 minute run. Eyelid closures were summed across the three types (slow, unfocusing and rolling, and greater than two seconds) to obtain a total closure count. Then, all mannerisms other than eyelid closures were summed for each time interval and subject. Subsequently, an average across subjects for each time interval was computed. The results of this analysis are presented in Figure 12. The triangles represent an average of the subject runs in which five or more closures occurred per 90 minute run; and X's represent an average of the subject runs for which subjects had four or fewer closures occurred per 90 minute run. Coincidently, the 40 subject runs were divided into 20 runs and 20 runs, respectively, based on the criterion described above.

TABLE 61

Two-Way Condition X Time-on-Task Mannerism ANOVAs

Hair

Source	df	F	p
Condition	(1,19)	0.02	0.9026
Time-On-Task	(16,304)	3.60	0.0001****
Cond X TOT	(16,304)	1.18	0.2833

Eyebrow

Source	df	F	p
Condition	(1,19)	5.88	0.0255*
Time-On-Task	(16,304)	4.30	0.0001****
Cond X TOT	(16,304)	0.93	0.5317

Eyes

Source	df	F	p
Condition	(1,19)	2.74	0.1142
Time-On-Task	(16,304)	2.36	0.0026***
Cond X TOT	(16,304)	0.82	0.6571

Closure

Source	df	F	p
Condition	(1,19)	1.18	0.2902
Time-On-Task	(16,304)	6.33	0.0001****
Cond X TOT	(16,304)	1.90	0.0202*

Face

Source	df	F	p
Condition	(1,19)	0.22	0.6428
Time-On-Task	(16,304)	3.36	0.0001****
Cond X TOT	(16,304)	1.18	0.2813

* $p<0.05$, ** $p<0.01$, *** $p<0.005$, and **** $p<0.001$.

TABLE 61

Two-Way Condition X Time-on-Task Mannerism ANOVAs (Cont.)

Mouth

Source	df	F	p
Condition	(1,19)	4.09	0.0575
Time-On-Task	(16,304)	3.01	0.0001****
Cond X TOT	(16,304)	1.62	0.0621

Neck

Source	df	F	p
Condition	(1,19)	0.12	0.7357
Time-On-Task	(16,304)	4.60	0.0001****
Cond X TOT	(16,304)	0.74	0.7475

Body

Source	df	F	p
Condition	(1,19)	0.58	0.4561
Time-On-Task	(16,304)	5.41	0.0001****
Cond X TOT	(16,304)	1.66	0.0526

* $p<0.05$, ** $p<0.01$, *** $p<0.005$, and **** $p<0.001$.

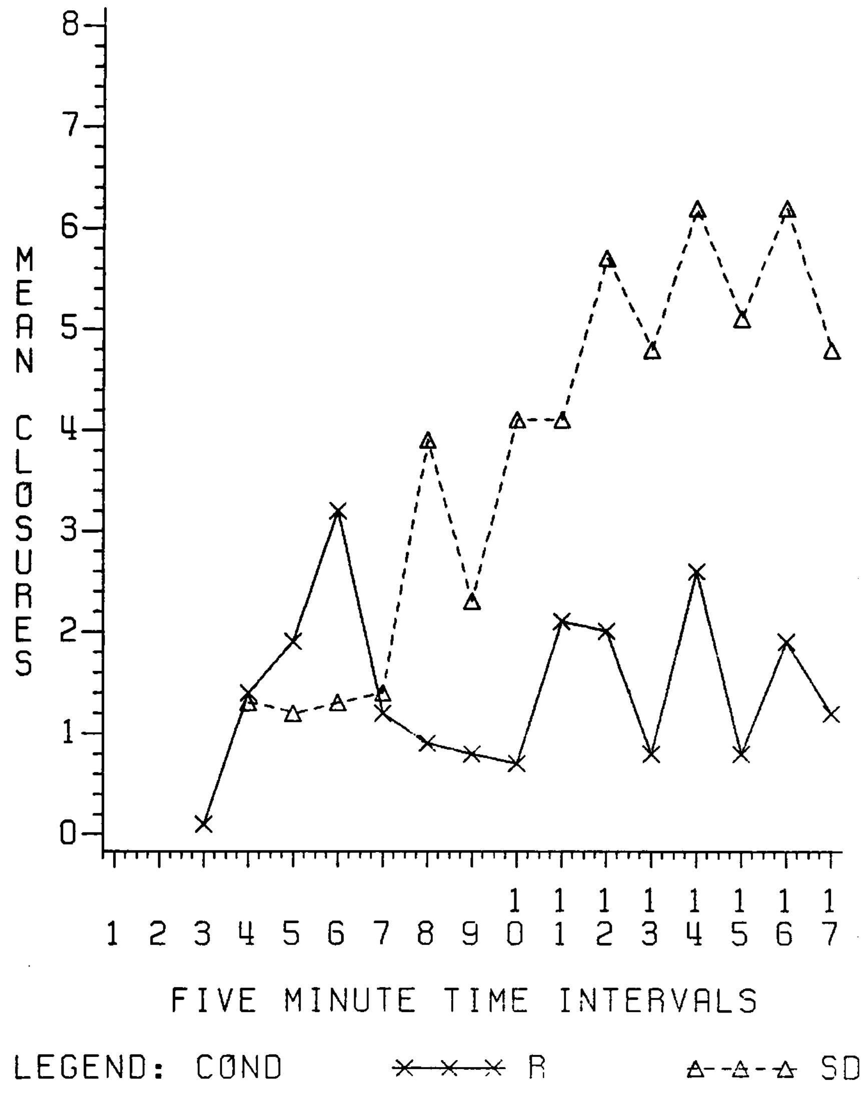

Figure 9. Closure mannerisms for condition over time-on-task

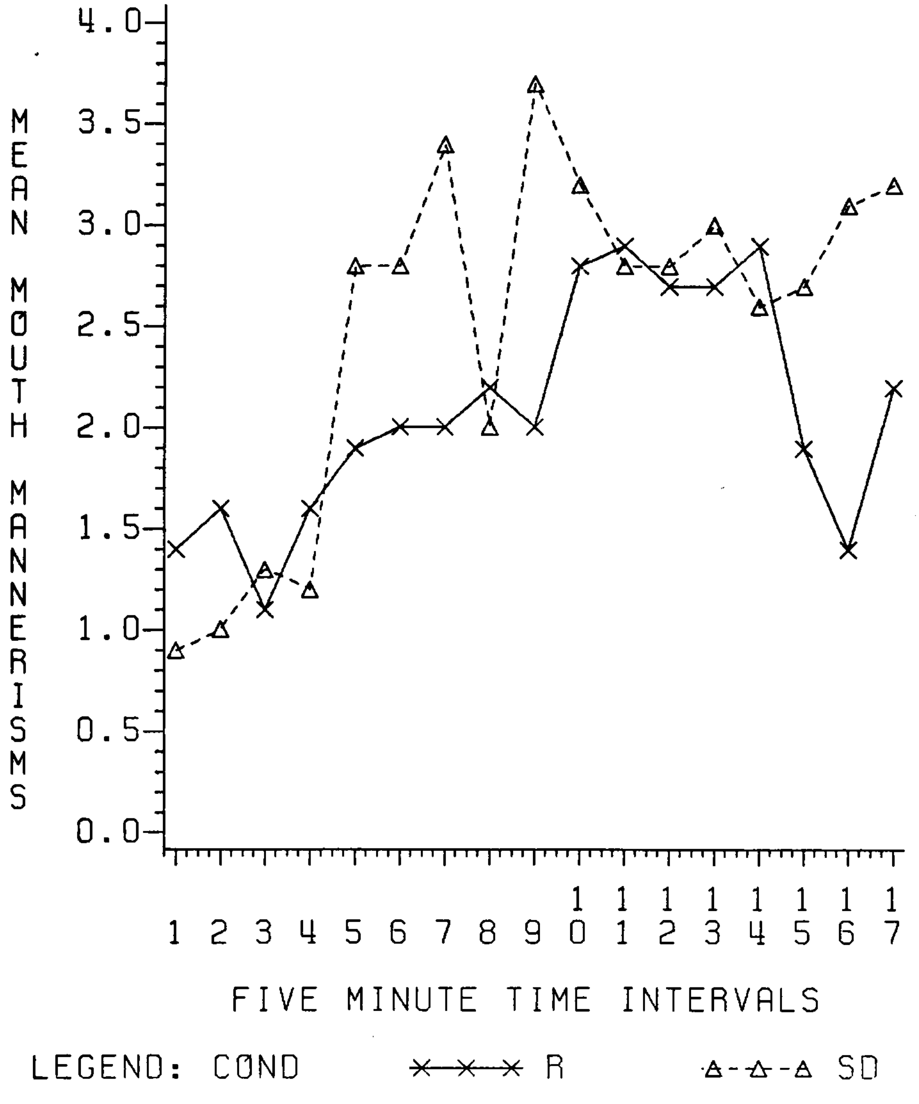

Figure 10. Mouth mannerisms for condition over time-on-task

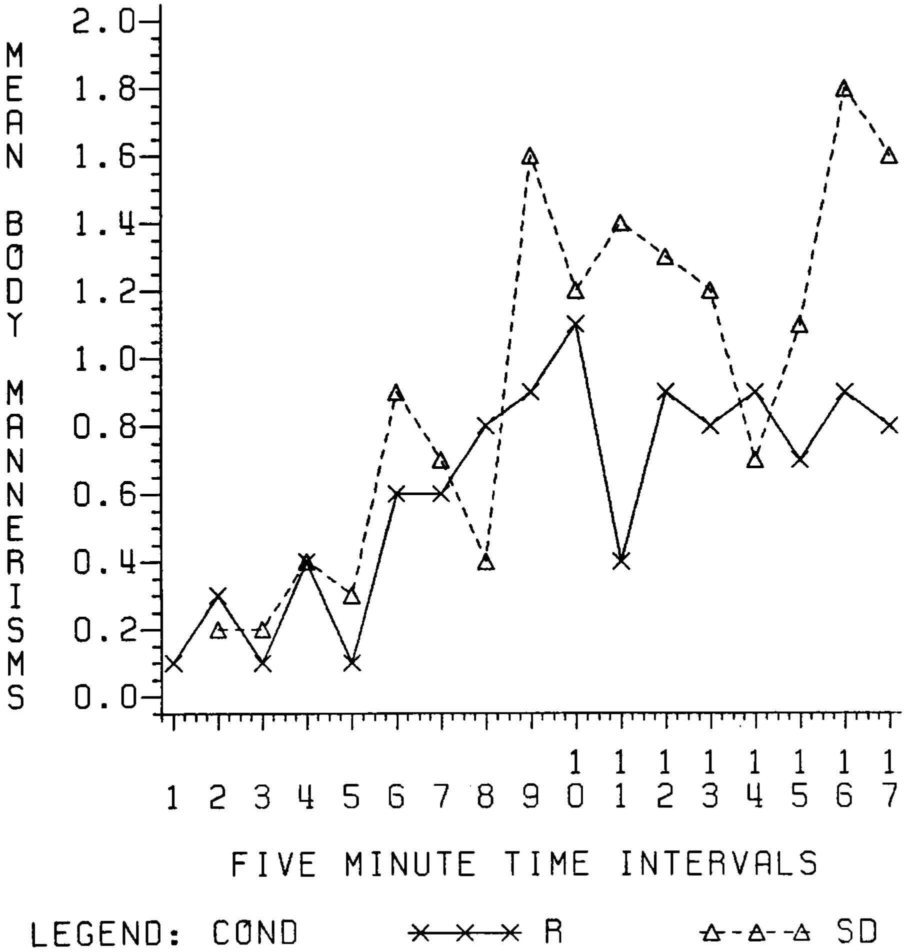

Figure 11. Body mannerisms for condition over time-on-task

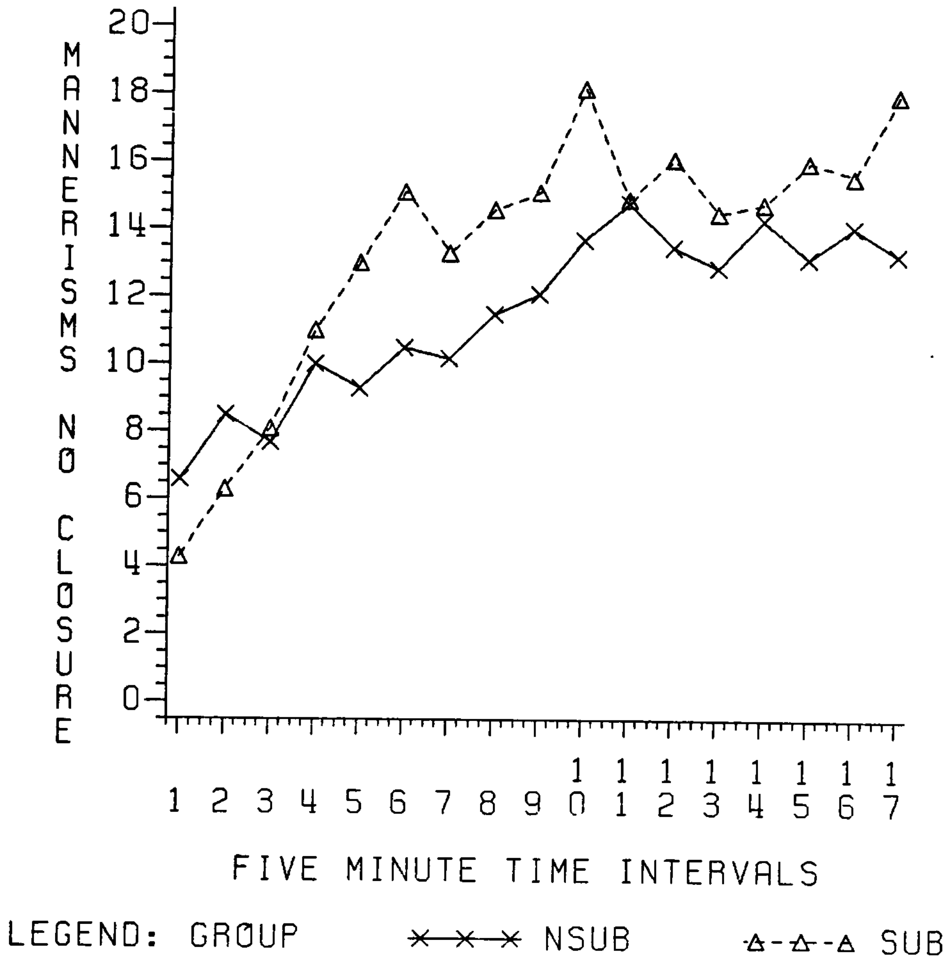

Figure 12. Average mannerisms for each of the two closure groups

The plot in Figure 12 showed a curvilinear relationship for each subject eyelid closure group which asymptoted approximately half-way through the 90 minute run. An ANOVA for these data revealed a significant difference between the two groups for the independent variable of time and the group x time interaction ($\underline{F} = 17.67$, $\underline{p} < 0.0001$, $\underline{F} = 2.22$, $\underline{p} < 0.0025$, respectively; Table 62).

To insure that the results shown in Figure 12 were representative of the data, an alternative plot of the data was made (also excluding the eyelid closure data). In this plot, eyelid closures per time interval per subject were categorized as follows: 1) no eyelid closures, 2) one to four closures, and 3) five or more closures in an interval. After the data were sorted by eyelid closure, mannerism averages across subjects and eyelid closure categories were computed for intervals which had three or more representative observations. Thus, average mannerism values were not obtained for all the time intervals. For each of the three eyelid closure categories separate curves of average mannerisms were plotted over time, see Figure 13.

Since, the plots in Figure 13 showed trends over time a linear regression analysis was performed on the data to analyze the trend differences for the three closure categories. A regression equation was obtained for each of

TABLE 62

Two-Way Group X Time-on-Task Mannerism ANOVAs

Source	df	MS	F	p
Between-Subjects				
Group (G)	1	662.12	1.07	0.3075
Subject/(S)	38	618.97		
Within-Subjects				
Time (T)	16	386.06	17.67	0.0001****
T X G	16	48.58	2.22	0.0040***
T X S/G	608	21.84		

* $p<0.05$, ** $p<0.01$, *** $p<0.005$, and **** $p<0.001$.

the three closure categories, and subsequently the slopes and intercepts for each of the respective equations were compared statistically. The statistic used for the slope and intercept comparisons had a t-distribution with n-2 degrees of freedom (Montgomery and Peck, 1982).

The results of these analyses showed a statistically significant difference between the slopes for the 'no closure' category when compared to the slopes of the other two categories 'one to four' and 'five or more' ($t = 2.73$, $p < 0.025$ and $t = 2.73$, $p < 0.025$). The comparison of the regression intercepts showed a significant difference between the 'no closure' category and the 'one to four' closure category ($t = 2.88$, $p < 0.025$) as well as a significant difference between the 'no closure' category and the 'five or more' closure category ($t = 5.44$, $p < 0.0025$). The 'no closure' category showed a significant relationship between the average number of total mannerisms (exclusive of closures) and time ($F = 30.91$, $p < 0.0001$). It is important to note that the averages shown in Figure 13 are based on different groupings of subjects at each time interval. This was due to the number of closures each subject exhibited in each time interval.

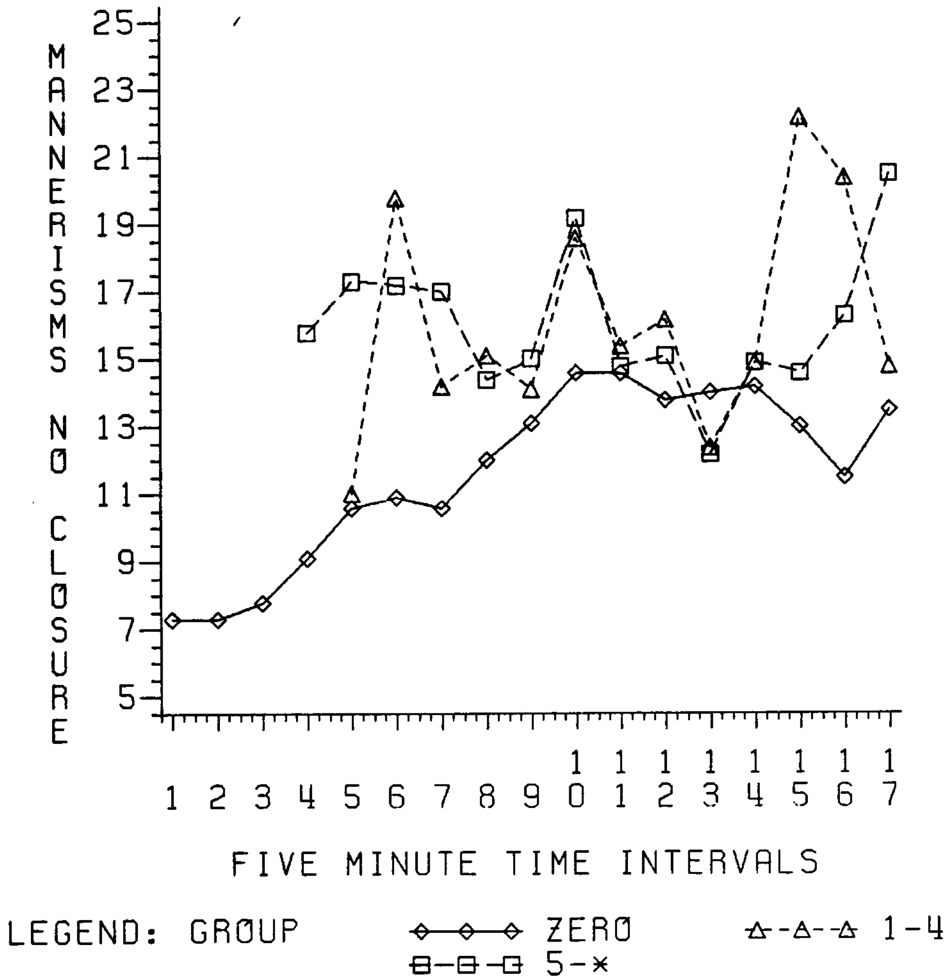

Figure 13. Mannerism comparisons for the three closure categories

<u>Eye Closure Means, Confidence Intervals, and ANOVAs</u>

The relationship of eye closures (the criterion for drowsiness) to the seven other mannerisms was the final analysis performed on the mannerism data. Subject runs were selected on the basis of the number of eyelid closures within one five minute time interval. Each of the ten subject runs selected for analysis had at least three time intervals for each of the three closure categories: no closures, one to four closures, and five or more closures. The total number of mannerisms, excluding eye closures, were averaged for each eye closure category and for each of the ten qualifying simulator runs. Means and 95% confidence intervals for averaged mannerisms and body position changes were computed for each closure category (Figures 14 and 15).

The plots of the means and confidence intervals showed differences in the number of mannerisms for each eye closure category. This hypothesis was tested in two one-way ANOVA's. One for the average total mannerisms (Table 63), excluding eye closures, and the second for body position changes (Table 64). Eyelid closure was the three level independent variable in both the ANOVA analyses. The total mannerisms and the body position ANOVAs both resulted in statistically significant main effects of eyelid closure ($\underline{F} = 19.04$, $\underline{p} < 0.0001$ and $\underline{F} = 6.21$, $\underline{p} < .0089$, Table 63 and 64).

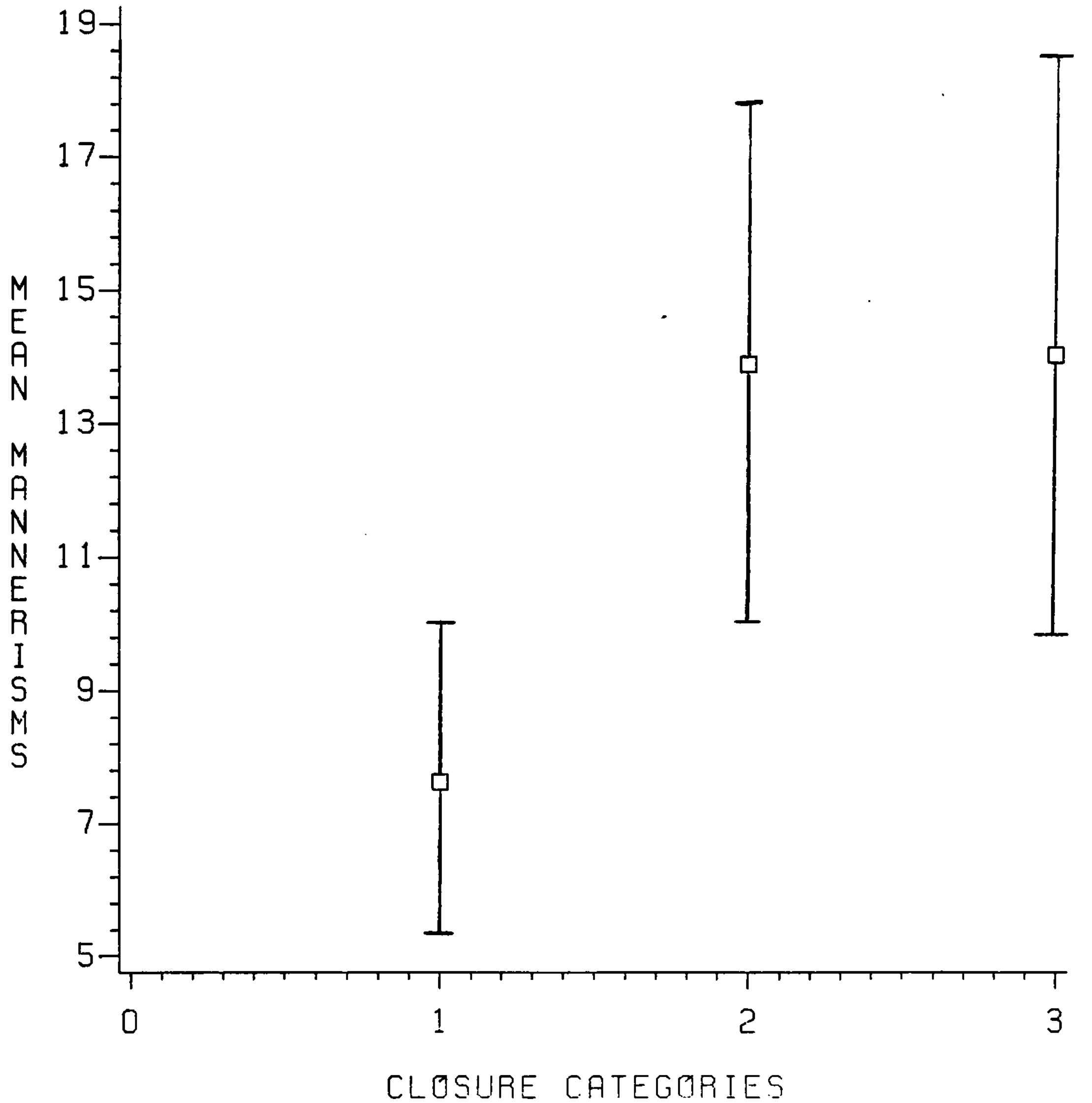

Figure 14. Total mannerisms (without eyelid closure) means and confidence intervals

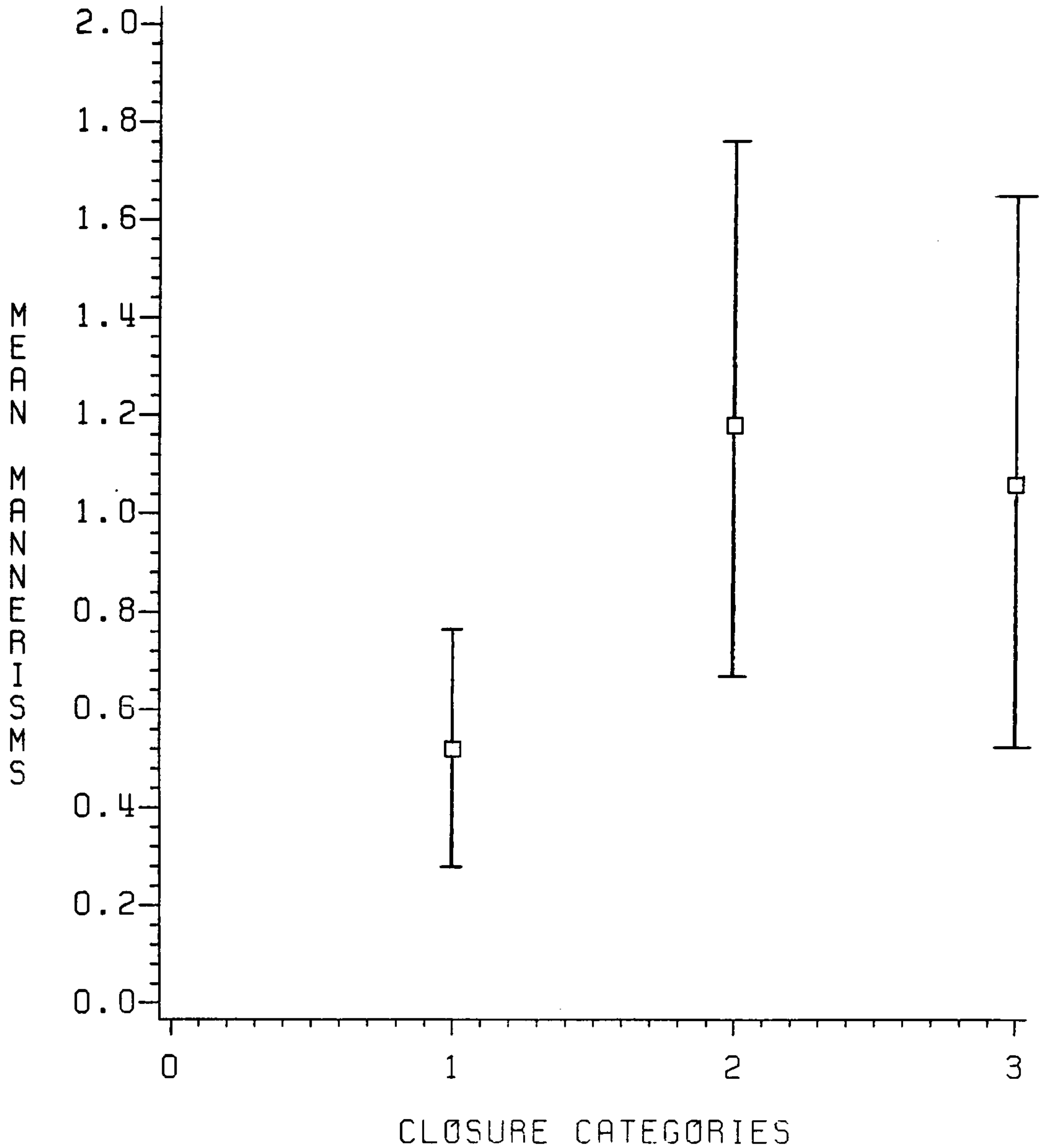

Figure 15. Body mannerisms means and confidence intervals

TABLE 63

Total Mannerisms, Eyelid Closure One-Way ANOVA

Source	df	MS	F	p
Between-Subjects				
Subject/(S)	9	68.950		
Within-Subjects				
Closure (Clos)	2	134.035	19.04	0.0001****
S X Clos	18	7.039		

* $p<0.05$, ** $p<0.01$, *** $p<0.005$, and **** $p<0.001$.

TABLE 64

Body Mannerisms, Eyelid Closure One-Way ANOVA

Source	df	MS	F	p
Between-Subjects				
Subject/(S)	9	0.971		
Within-Subjects				
Closure (Clos)	2	1.236	6.21	0.0089**
S X Clos	18	0.199		

* $p<0.05$, ** $p<0.01$, *** $p<0.005$, and **** $p<0.001$.

Based on these results a second comparison was performed. The mannerisms were re-grouped to provide more observable and a more instrumentable process. In this comparison, mannerisms were grouped to reflect all behaviors which involved removing a hand or hands from the steering wheel. The mannerisms were labeled 'hand to head' mannerisms. Examples of these mannerisms were: straightening hair and rubbing eyes, face or neck. The average number of 'hand to head' events was obtained for each of the three closure categories.

For each of the eye closure categories, 'hand to head' means and confidence intervals were computed and plotted in Figure 16. Again, the mean mannerism differences for closure levels, as indicated in Figure 16, were tested for statistical significance. A one-way eyelid closure ANOVA using 'hand to head' as a dependent variable was performed. This analysis resulted in a significant difference in 'hand to head' means among the three levels of eye closure ($\underline{F}$ = 9.14, $\underline{p} < 0.0018$, Table 65).

The 'hand to head' mannerism grouping and the body position change mannerism were selected for analysis as they appear to provide the most readily instrumentable approach to the detection of body changes in automobile driving. For example, a pressure sensitive steering wheel could be

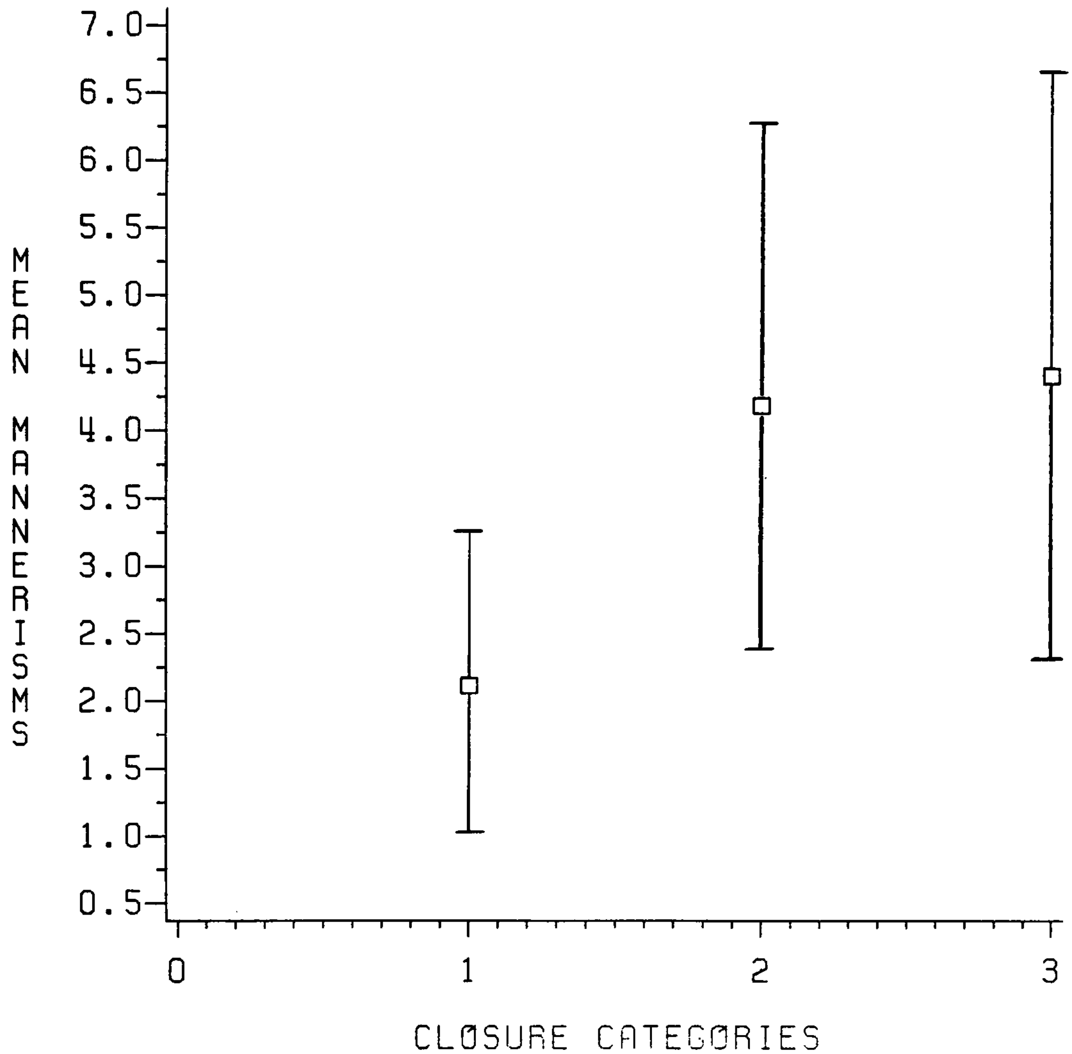

Figure 16. 'Hand to head' mannerisms for eyelid closure levels

TABLE 65

Hand to Head, Eyelid Closure One-Way ANOVA

Source	df	MS	F	p
Between-Subjects				
Subject/(S)	9	16.971		
Within-Subjects				
Closure (Clos)	2	15.962	9.14	0.0018***
S X Clos	18	1.746		

* $p<0.05$, ** $p<0.01$, *** $p<0.005$, and **** $p<0.001$.

employed to detect the number of occurrences of the hand to head mannerisms a driver exhibits during a specified time interval. Such a count could be used to generate a warning signal to indicate that the driver may be drowsy.

One final ANOVA analysis using the independent variables of condition and time-on-task was conducted on the 'hand to head' data. The purpose of the ANOVA was to identify a relationship of the 'hand to head' mannerisms to both condition and time-on-task driving. The results indicated a statistically significant main effect of time-on-task (F = 4.84, p < 0.0001, Table 66).

Discussion

The results of the analyses indicate that there is a highly significant relationship between all eight mannerism categories; hair, eyebrow, eyes, closure, face, mouth, neck, and body; and the independent variable of time. Of even greater interest is the highly significant relationship between eye closures and mannerism groupings of 'hand to head' movements and body position change movements. This information is the basis for future research into the instrumentation possibilities of automobile safety devices. Further research will not only clarify the relationship between driver eye closures and 'hand to head' mannerisms

TABLE 66

Two-Way Condition X Time-On-Task 'Hand to Head' ANOVA

Source	df	MS	F	p
Between-Subjects				
Subject (S)	8	173.148		
Within-Subjects				
Conditon (Cond)	1	21.441	0.88	0.3745
Cond X S	8	24.243		
Time (T)	16	30.594	4.84	0.0001****
T X S	128	6.322		
Cond X T	16	4.677	0.96	0.5051
Cond X T X S	128	4.877		

* $p<0.05$, ** $p<0.01$, *** $p<0.005$, and **** $p<0.001$.

but also can provide an opportunity to pursue detection devices for these mannerisms which demonstrate a highly significant relationship with decreased arousal behaviors.

The "other" category from the data collection instrument revealed the self stimulating behavior of three subjects singing or talking. The question generated from this observation and worthy of continuing research is: Does active subject participation decrease the frequency of eye closures and increase subject arousal. The application of this information could involve safety devices which require active driver participation and thereby improve alertness and driving performance.

Conclusions

In the driver mannerisms analysis, several variables which may be instrumented in drowsy detection devices were identified. The total number of mannerisms, in general, increased with the onset of eyelid closures. Those mannerisms which could be used for countermeasures and which when analyzed resulted in significant mean value differences for the eyelid closure categories were the number of body movements and the number of 'hand to head' mannerisms. Both of these mannerism events doubled with the onset of drowsiness.

Additional information obtained from the mannerisms analysis was the notion of developing 'active' countermeasure devices. Since a few of the drivers sang or talked to themselves to keep awake, the possibility of developing 'active' countermeasure devices may also be a feasible methodology. The 'active' approach to driver drowsiness may be used to supplement the use of a drowsy driver detection device. An 'active' countermeasure would attempt to aid the driver in maintaining a high state of arousal.

General conclusions. The fact that the low-light level CCTV camera recorded observable drowsy driver traits suggests that through telemetry a driver may be monitored. In particular, if the GM Proving Grounds would install low-light level cameras in their prototype vehicles and provide personnel to monitor the resultant telemetered picture in real-time, accidents as a result of falling asleep at the wheel might be reduced. Thus, through direct observation of the driver's driving behavior and mannerisms, the onset of drowsiness may be detected and the driver may be informed and alerted.

Recommendations and Research Topics

1. The Proving Grounds should be made aware of the results of this drowsy driver study. Serious consideration should be given to the implementation of a video telemetering system on a trial basis to test its merit in reducing accidents.
2. Research using instrumented devices to detect body movements and 'hand to head' mannerisms needs to be further investigated to determine these parameters' relationships with drowsiness.

Appendix D

LANE EXCEEDENCE ANALYSIS

by

Lenora Hardee and Walter W. Wierwille (1984)

in Skipper, Wierwille, and Hardee (1984)

LANE EXCEEDENCE ANALYSIS

The following analyses were undertaken in an attempt to associate various driving characteristics of drowsy drivers with obvious incidences of impaired performance (i. e., lane exceedences). The ultimate goal of this type of analysis was to identify driving signatures which were characteristic of drowsy drivers and which could be detected by an alerting mechanism. Thus, the following analyses represent a step toward that goal.

Initially, two magnitudes of lane exceedence were identified: 1) small exceedences, where the centerline of the vehicle exceeded the lane boundary, and 2) large exceedences, where the vehicle was completely out of lane. The FM tape recordings of the drivers' performance were then examined in fast playback, lane exceedences were identified, and the tape footages containing these exceedences were recorded at normal speed on a Sanborn 8-channel chart recorder. The recordings of these data were subsequently analyzed with respect to the following variables: oscillation, steering burst, steering velocity, and eyelid closure.

The levels of these variables were defined as follows:

Variable	Level	
Oscillation	Yes =	Oscillation in lane position present
	No =	Oscillation in lane position absent
Steering velocity prior to exceedence	Lovel1 =	Low velocity steering for 10 seconds or less
	Lovel2 =	Low velocity steering for >10 seconds
	Still1 =	Steering held still for 5 seconds or less
	Still2 =	Steering held still >5 and <10 seconds
	Still3 =	Steering held still >10 seconds
	Notstil=	Steering not held still
Steering burst	Yes =	Burst correction present
	No =	Burst correction absent
	Correct =	Correction pulse present
Magnitude of eyelid closure	1 =	Average eyelid closure of 0-70% before and during exceedence
	2 =	Average eyelid closure of 71-100% or single burst of closure $\geq$ 80% prior to exceedence or multiple bursts of closure $\geq$ 80% before and/or during exceedence

Preliminary Analyses

Prior to analyzing the chart recorded lane exceedence data, a preliminary analysis was conducted in which the total number of eyelid closures per run was correlated with the number of small exceedences per run, the number of large exceedences per run, and the total number of exceedences per run. Table 67 shows that all three of these correlations were significant (r = 0.34, p = 0.03; r = 0.51, p = 0.0009; and r = 0.46, p = 0.003, respectively). These significant correlations provided further verification that lane exceedences were associated with eyelid closures.

Four-Way Crosstab

Four-way crosstabs using three performance variables (oscillation, steering velocity, and steering burst) and eyelid closure were obtained for both large and small lane exceedences. As can be seen in Tables 68 and 69, this procedure resulted in the computation of the frequencies and percentages of lane exceedences which were associated with the eyelid closure and driving performance variables. The percentages associated with the various combinations of these four variables were relatively small, thus leading the researchers to conclude that the analysis was too detailed to allow for the development of driving stereotypes. For example, the largest percentage of occurrence of lane exceedences was only 22.2% for those drivers who exhibited oscillation, who did not hold steering still, who did not show a burst of steering input associated with lane exceedence, and who were characterized by heavy eyelid closures (Table 69).

TABLE 67

Lane Exceedence and Eyelid Closure Correlations

	Small Exceedences	Large Exceedences	Total Exceedences
Correlation	0.34	0.51	0.46
p-Value	0.03	0.0009	0.003
	N = 54	N = 33	N = 87

TABLE 68

Four-way Crosstab for Large Exceedences

OSC	STEER	BURST	CLOSURE	FREQUENCY	PERCENT
No	Lovell	Correct	2	2	6.1
No	Lovell	Yes	2	1	3.0
No	Still1	Correct	2	3	9.1
No	Still1	Yes	1	1	3.0
No	Still1	Yes	2	1	3.0
No	Still2	Yes	1	1	3.0
No	Still2	Yes	2	1	3.0
Yes	Notstil	No	1	2	6.1
Yes	Notstil	No	2	4	12.1
Yes	Still1	Correct	1	3	9.1
Yes	Still1	Correct	2	7	21.2
Yes	Still1	No	2	2	6.1
Yes	Still2	Correct	2	3	9.1
					100.0

N = 33

TABLE 69

Four-way Crosstab for Small Exceedences

OSC	STEER	BURST	CLOSURE	FREQUENCY	PERCENT
No	Lovel1	Correct	2	1	1.9
No	Lovel1	Yes	1	1	1.9
No	Lovel2	Correct	2	1	1.9
No	Still1	Correct	2	3	5.6
No	Still1	Yes	1	1	1.9
No	Still2	Correct	2	1	1.9
No	Still3	Correct	2	1	1.9
Yes	Lovel1	Correct	2	3	5.6
Yes	Lovel1	No	2	1	1.9
Yes	Lovel2	No	1	1	1.9
Yes	Notstil	Correct	2	5	9.3
Yes	Notstil	No	2	12	22.2
Yes	Still1	Correct	1	4	7.4
Yes	Still1	Correct	2	5	9.3
Yes	Still1	No	1	2	3.7
Yes	Still1	Yes	1	2	3.7
Yes	Still1	Yes	2	1	1.9
Yes	Still2	Correct	2	3	5.6
Yes	Still3	No	2	1	1.9
					100.0

N = 55

Three-Way and Two-Way Crosstabs

To account for larger percentages of lane exceedences, three-way and two-way crosstabs were obtained for both large and small lane exceedences and for the combined set of exceedences. All possible combinations of each of the four variables in question were assessed; thus, four four-way and six two-way crosstabs were obtained for large, small and combined lane exceedences. Table 70 provides an example of a three-way crosstab including the oscillation, steering velocity, and steering burst variables. This table demonstrated the increase in the percentages of associated lane exceedences which occurred when only three variables were included in the analysis (e.g., 30.3% of large lane exceedences were characterized by oscillation, steering held still less than 5 seconds, and a correction pulse as compared with the 21.2% of exceedences associated with these same variables plus eyelid closure given in Table 68).

Since these three-way and two-way crosstab analyses yielded 30 different tables of frequencies and percentages, it was necessary to further reduce the amount of data analyzed. To this end, the crosstab data were subsequently examined and only those combinations of variables associated with frequencies greater than or equal to 10% were extracted for closer examination. The results of this data reduction can be seen in Tables 71 through 76.

TABLE 70

Example of a Three-way Crosstab Including Oscillation, Steering Velocity, and Steering Burst

OSC	STEER	BURST	CLOSURE	PERCENT
No	Lovell	Correct	2	6.1
No	Lovell	Yes	1	3.0
No	Still1	Correct	3	9.1
No	Still1	Yes	2	6.1
No	Still2	Yes	2	6.1
Yes	Notstil	No	6	18.2
Yes	Still1	Correct	10	30.3
Yes	Still1	No	2	6.1
Yes	Still1	Yes	2	6.1
Yes	Still2	Correct	3	9.1
				100.0

N = 33

TABLE 71

Three-way Crosstabs Showing Frequencies that are 10 Percent or More for Combined Lane Exceedences

OSC	STEER	BURST	CLOSURE	PERCENT
Yes	Notstil	No		26.4
Yes	Stilll	Correct		21.8
No		Correct	2	13.8
Yes		Correct	2	29.9
Yes		No	1	11.5
Yes		No	2	22.9
Yes	Notstil		2	24.1
Yes	Stilll		1	14.9
Yes	Stilll		2	17.2
	Notstil	No	2	18.4
	Stilll	Correct	2	20.7

N = 87

TABLE 72

Three-way Crosstabs Showing Frequencies that are 10 Percent or More for Large Lane Exceedences

OSC	STEER	BURST	CLOSURE	PERCENT
Yes	Notstil	No		18.2
Yes	Stilll	Correct		30.3
No		Correct	2	15.2
Yes		Correct	2	30.3
Yes		No	2	18.2
No	Stilll		2	12.1
Yes	Notstil		2	12.1
Yes	Stilll		1	15.2
Yes	Stilll		2	27.3
	Notstil	No	2	12.1
	Stilll	Correct	2	30.3

N = 33

TABLE 73

Three-way Crosstabs Showing Frequencies that are 10 Percent or More for Small Lane Exceedences

OSC	STEER	BURST	CLOSURE	PERCENT
Yes	Notstil	No		31.5
Yes	Stilll	Correct		16.7
No		Correct	2	12.9
Yes		Correct	2	29.6
Yes		No	1	14.8
Yes		No	2	25.9
Yes	Notstil		2	31.5
Yes	Stilll		1	14.8
Yes	Stilll		2	11.1
	Notstil	No	2	22.2
	Stilll	Correct	2	14.8

N = 54

TABLE 74

Two-way Crosstabs Showing Frequencies that are 10 Percent or More for Combined Lane Exceedences

OSC	STEER	BURST	CLOSURE	PERCENT
No	Stilll			10.3
Yes	Notstil			32.2
Yes	Stilll			32.2
No		Correct		13.8
Yes		Correct		37.9
Yes		No		34.5
No			2	17.2
Yes			1	24.1
Yes			2	54.0
	Notstil	No		26.4
	Stilll	Correct		28.7
	Notstil		2	24.1
	Stilll		1	17.2
	Stilll		2	25.3
		Correct	2	43.7
		No	1	11.5
		No	2	22.9

N = 87

TABLE 75

Two-way Crosstabs Showing Frequencies that are 10 Percent or More for Large Lane Exceedences

OSC	STEER	BURST	CLOSURE	PERCENT
No	Still1			15.2
Yes	Notstil			18.2
Yes	Still1			42.4
No		Correct		15.2
No		Yes		15.2
Yes		Correct		39.4
Yes		No		24.2
No			2	24.2
Yes			1	21.2
Yes			2	48.5
	Notstil	No		18.2
	Still1	Correct		39.4
	Still1	Yes		12.1
	Notstil		2	12.1
	Still1		1	18.2
	Still1		2	39.4
	Still2		2	12.1
		Correct	2	45.5
		No	1	18.2
		Yes	1	12.1

N = 33

TABLE 76

Two-way Crosstabs Showing Frequencies that are 10 Percent or More for Small Lane Exceedences

OSC	STEER	BURST	CLOSURE	PERCENT
Yes	Notstil			40.7
Yes	Stilll			25.9
No		Correct		12.9
Yes		Correct		37.0
Yes		No		40.7
No			2	12.9
Yes			1	25.9
Yes			2	57.4
	Notstil	No		31.5
	Stilll	Correct		22.2
	Notstil		2	31.5
	Stilll		1	16.7
	Stilll		2	16.7
		Correct	2	42.6
		No	1	14.8
		No	2	25.9

N = 54

Development of Driving Stereotypes

The frequencies and percentages obtained from the reduced two- and three-way crosstab data were examined and two major driving stereotypes were identified. These stereotypes were characterized as follows: (1) an oscillatory buildup with a 5-12 second period prior to the exceedence and with steering either not held still or held still for 3 seconds or less, or (2) no oscillation prior to the exceedence with low or zero velocity steering followed by a correction or burst, or a steering hold for 10 seconds or less. Once these stereotypes were identified, the chart recorded data were reanalyzed, and lane exceedences were categorized accordingly. Table 77 shows the frequencies and percentages of lane exceedences characterized by these two driving stereotypes along with the magnitude of eyelid closure associated with each. These two stereotypes, regardless of eyelid closure, characterized approximately 65% of the total number of lane exceedences.

The results of the lane exceedence analysis show promise for the development of an algorithm to detect driver drowsiness. By using stereotype signatures, a detection device might be developed which continuously searches for the combination of factors shown in Table 77. Additional work remains however in determining the detection and false alarm probabilities associated with such a stereotype detection device.

Conclusions

The lane exceedence analysis contributed variables for consideration in drowsy driver detection. Through a preliminary analysis, the lane exceedence data was found to be correlated with eyelid closure. Then, when the steering velocity profiles were analyzed in detail, stereotypical responses were identified in association with the lane exceedences. Drivers when they exceeded the lane tended to display oscillatory build up prior to the exceedence or nonoscillation and steering hold prior to the exceedence followed by a correction or steering burst.

TABLE 77

Frequencies and Percentages of Lane Exceedences Associated with Two Driving Stereotypes

	Oscillatory Buildup 5-12 Second Period Steering not Still or Still 3 Sec or Less	No Oscillation Low or Zero Velocity Steering with Correction or Burst/ or Hold More Than 10 Sec
Closure Level = 2	22 or 25%	21 or 24%
Closure Level = 1	11 or 13%	3 or 3%
Total	33 or 38%	24 or 27%

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