DEVELOPMENT OF MODELS FOR DETECTION OF AUTOMOBILE DRIVER IMPAIRMENT

by

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(ABSTRACT)

Two of the leading causes of automobile accidents are driver impairment due to alcohol and drowsiness. Apparently, a relatively large percentage of these accidents occur because drivers are unaware of the degree to which they are impaired due to these sources. The purpose of this research was to develop models which could detect driver impairment due to alcohol, drowsiness, or the combination of alcohol and drowsiness, and which could be practically implemented in an automobile. Such detection models, if successfully implemented in conjunction with a system to warn an impaired driver of his or her condition, could potentially save hundreds of lives each year.

Six driver-subjects operated a computer controlled driving simulator during each of four conditions. The four conditions consisted of a control condition, an alcohol condition, a sleep-deprived condition, and a combination alcohol and sleep-deprived condition. Moderate levels of alcohol and sleep deprivation were used for this study.

Nineteen performance and behavioral measures were collected during this study. Each measure was evaluated singly and in combination with other measures to determine potential value for detection of driver

impairment. Detection models were then formulated using the most promising detection measures.

The results indicated that a useful on-board drowsiness impairment detection device is possible and practical for highway driving. This device would also, in all likelihood, provide useful detection information regardless of whether low to moderate amounts of alcohol were present in a drowsy driver. The results also showed that on-board alcohol impairment detection may be possible at moderate to high BAC.

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INTRODUCTION

Evidence exists to support the fact that two major causes of single and multiple automobile traffic accidents are alcohol and driver drowsiness or fatigue. Driving an automobile is a very complex task, requiring the operator to constantly scan the environment and respond properly to maintain control, avoid obstacles and properly interact with other vehicles. Unfortunately, while driving is complex, it is a highly overlearned task which is often taken for granted or misjudged by the driver whose driving performance is impaired to some degree.

The problem of driver drowsiness is something that affects, at some time, the majority of the drivers on the road. In fact, a survey conducted by Tilley, Erwin and Gianturca (1973) showed that drowsiness while driving affects nearly two-thirds of the driving population in general. Tilley et al. (1973) also report that "drowsiness and falling asleep at the wheel constitute statistically significant causal factors in vehicular accidents" (p. 7). It is generally agreed that drowsiness increases the likelihood of accidents, although it is difficult to pinpoint exactly how many traffic accidents or deaths are attributable to drowsiness. Estimates for highway fatalities directly attributable to fatigue or drowsiness, however, run as high as 35 percent (Kearney, 1966).

Unlike driver drowsiness, accident statistics for drivers under the influence of alcohol are well-defined. Howat and Mortimer (1978) cited the following estimates from a 1974 Department of Health, Education and

Welfare Report:

At any given time,

5%-10% of drivers on the road have Blood Alcohol Contents (BACs) of 0.01% to 0.049%

3%-10% of drivers have BACs of 0.05% to 0.099%

3% of drivers have BACs of 0.1% to 0.149%

1% of drivers have BACs of 0.15% or higher

and that drivers under the influence of alcohol are involved in:

5%-10% of the "run of the mill" accidents

10%-35% of "serious" accidents

33% of fatal multiple car accidents

55%-65% of fatal single car accidents.

Contrary to popular belief, the problems with alcohol and driving are not limited to drivers with BACs greater than 0.1%. Buttiglieri, Brunse and Case (1972) state: "Evidence is clear that the crash probability is increased at a BAC of 0.05% and that these probabilities become progressively higher at the higher BACs at a geometrically accelerating rate" (p. 310).

Information on the number of accidents caused by alcohol and drowsiness in combination is, like drowsiness, sketchy and difficult to estimate. Since it is generally agreed that drowsiness and alcohol degrade the automobile driver's ability to perform the driving task to some degree, it seems intuitively obvious that the combination of drowsiness and alcohol would cause increased performance degradation and, thereby, increased potential for accidents over either alone. The few studies that have combined the effects of alcohol and drowsiness in

driving-related tasks have found that the combined effects are antagonistic in that driver performance actually appears to improve over drowsiness alone (e.g. Huntley and Centybear 1974).

Since the problem of vehicle operation with some degree of impairment exists for whatever reason, and since this impaired performance increases property damage, injury, and death rate, possible preventative measures need to be investigated.

One approach involves detection devices that are capable of determining when a driver's performance is impaired. The idea of detection systems of this type is not new. On-board systems to alert a driver who is on the verge of falling asleep have been in existence for over 25 years. Several examples of these devices and some limitations described by Hulbert (1972) are given below:

1. Electronic Transistor Safety Alarm. Buzzer attached to the ear is activated when the head nods. Limitation: Assumes that the head nods prior to loss of alertness.
2. Button steering wheel alarm. Driver must keep button depressed or an alarm is activated. Limitation: Requires unnatural pressure, becomes tedious.
3. Alertmaster: Williams (1966). Driver depresses a pedal with the left foot. When the pedal pressure is removed, an alarm sounds. Limitation: Assumption that pedal pressure is removed before loss of driver alertness.

More recently, Nissan has developed an on-board device that measures performance degradation via driver steering behavior. The driver's

steering behavior is monitored at the outset of a trip and recorded. This is used as a baseline to which all subsequent driving behavior is compared. If any erratic behavior is detected (presumably due to drowsiness) the driver is warned accordingly. The accuracy and generalizability of this device are presently unknown. However, it should be noted that support in recent literature for a device of this type is mixed. A detailed discussion of steering reversals as a predictor of impairment appears in a later section.

Devices to detect driver impairment due to alcohol are also in existence. Thompson, Tennant and Repa (1975), categorized these devices into two classes: pre-driving tests and continuous performance monitoring (as with the drowsy driver detection systems).

Of these two categories, pre-driving tests have actually been implemented with some success. Two examples of pre-driving tests are given below:

1. Cypher-Lock. The driver must successfully enter a numerical code on a keypad in a given length of time. A driver with a higher BAC has difficulty meeting this time limit.
2. Critical Tracking Task (CTT). The driver must track a closed loop control-display system that becomes increasingly unstable with control input. The amount of time that the operator is able to maintain the target on the screen is used as the criterion. A driver with a higher BAC has greater difficulty and hence cannot maintain tracking control as long as a sober driver.

A successful continuous performance monitoring device has yet to be developed for alcohol impairment, however, a number of researchers have attempted to develop reliable measures. Thompson et al. (1975) described the following lists of general advantages and disadvantages for pre-driving tests and continuous performance monitoring devices.

PRE-DRIVING TESTS (Thompson et al. 1975)

BREATH TESTS
Advantages:
- Breath sample relatively easy to obtain
- Based on legal definition of alcohol intoxication

Disadvantages:
- Could be easy to fool unless made more complicated and discriminating
- Limited to alcohol impairment
- Present devices do not lend themselves readily to rapid automatic operation nor to low maintenance schedules

PERFORMANCE TESTS
Advantages:
- Directly sensitive to degradation in psychomotor performance
- Sensitive to degrading effects of factors such as drugs, illness, fatigue, as well as alcohol
- Not easily defeated by mechanical devices
- Can be made durable and tamper resistant

Disadvantages:
- Require some training to be effective
- May measure performance levels idiosyncratic to each driver
- Short test length may be detrimental to reliability

CONTINUOUS PERFORMANCE MONITORING (Thompson et al. 1975)

DRIVER PERFORMANCE MONITORING
Advantages:
- Sensitive to variable of prime interest, driving performance
- Does not burden driver with any additional tasks
- Sensitive to all forms of impairment
- Would catch drivers who become impaired after starting to drive

Disadvantages:
- Requires more clearly established baseline for normal performance than is presently available

PHYSIOLOGICAL MONITORING
Advantages:
- Based on detection of physiological concomitant of impairment and, therefore, hard to fool
- Sensitive to all forms of impairment
- Would catch impairment whose onset occurs while driving

Disadvantages:
- Incomplete knowledge of physiological correlates of impairment
- Present laboratory measures have not been reduced to practical application.

As can be seen from the previous list, continuous monitoring of driver performance (as well as some of the other techniques) appears to have promise for detection of alcohol impaired drivers as well as for drowsiness impaired drivers as previously discussed. The only disadvantage listed by Thompson et al. for this particular class of methodology is the requirement to establish a more clearly defined baseline for "normal" performance. If normal performance measures can be established, deviations due to impairment could potentially be used to alert the driver of a decrement in performance. Another issue concerning the practicality of an alcohol detection device is driver cooperation. The question of whether or not a driver under the influence of alcohol would heed the warning of a detection device also needs to be addressed to determine the potential usefulness of such a device.

A large number of dependent measures have been studied as predictors of driver impairment. These dependent measures can be divided into two basic categories: objective measures and subjective measures. Generally, objective measures have been shown to be better predictors of driver drowsiness impairment in general, as well as alcohol impairment. Within the category of objective measures a further categorization can be made, namely, performance measures and physiological measures.

Performance measures have shown promise both as predictors of driver impairment and in terms of practicality for automobile installation. Therefore, throughout this study performance measures were addressed in terms of potential practical use, and physiological measures were (generally) addressed for predictive value in terms of drowsiness or alcohol impairment for correlation purposes. Subjective measures, in contrast, were felt to be of less value to the current area of research and were not addressed.

Research Goals

The primary goal of this research was to explore the feasibility of driver performance and behavioral measures, both singly and in combination, to predict potentially hazardous levels of driver impairment due to drowsiness, alcohol, and the combination of drowsiness and alcohol. There were two qualifications to this statement. First, the level of alcohol that was explored was approximately 0.075% BAC, which is within the legal driving limit in most states. The reason for using a BAC at this level is twofold. First, a BAC of this level, although generally within legal limits, does cause impairment and does provide a realistic and commonly occurring event for a segment of the driving population (Buttiglieri et al., 1972). A specific example would be driving home after several drinks at a restaurant or lounge either in the early evening or late at night. The second reason for using a BAC of this level was that while it did result in impairment, subjects did not suffer undue or unnecessary hardship from alcohol aftereffects.

The second qualification is that performance and behavioral measures that were explored were limited to those that either showed promise as reliable indicants of impaired performance or could be practically installed in an automobile. Measures that indicated impaired performance but could not be practically installed in an automobile were correlated with measures that could be practically installed in an automobile. In this way, promising measures were explored despite the fact that they themselves could not be shown to directly indicate impaired performance.

The secondary goal of this research was to explore the effects of alcohol, drowsiness and the combination on driving, thereby adding to the current base of research knowledge that existed on these topics.

LITERATURE REVIEW

The literature of interest regarding the research topic at hand is divided along the dimensions of drowsiness, alcohol, and the combination of drowsiness and alcohol. Drowsiness literature is divided between sleep deprivation and task induced drowsiness or fatigue. The alcohol literature is divided into low, moderate and high alcohol doses. The experimental apparati range from driving related tasks in very low fidelity simulators to higher fidelity simulators and closed-course driving to road driving. Dependent measures range from one to eight per study with over 20 investigated in all. Often questionable statistical methods are used, such as determining significant differences through successive (as many as 15-20) univariate analyses for multiple dependent measures. (For a description of problems associated with methodology of this type see Finkelman, Wolf, and Friend (1977)).

To facilitate organization of this information, four major subheadings will be discussed. The first subheading will consist of a discussion of driver drowsiness research recently completed at Virginia Polytechnic Institute and State University (Virginia Tech). The remaining three subheadings will discuss general literature related to driver impairment due to drowsiness, alcohol, and drowsiness and alcohol in combination.

Virginia Tech Study on Driver Drowsiness

The present research was not the first study performed on the general topic of impaired driver countermeasures at Virginia Tech. A one-year research study was conducted by Skipper, Wierwille and Hardee from October 1983 to October 1984 on the topic of potential driver drowsiness countermeasures. The objectives of the study were to obtain an increased understanding of drowsy driver performance characteristics and to obtain measures which could predict driver drowsiness for use in on-board detection.

Skipper et al. utilized eyelid closure as the primary indicator of drowsiness. Eyelid closure was selected based on the results of a Duke University Study (Erwin, 1976). In this study, eight dependent measures including plethysmography, respiration rate, electroencephalography, skin electrical characteristics, electromyography, heart rate variability, eyelid position and tracking control reversals were investigated. Erwin (1976) found that eyelid closure presented the most stable physiological indicant of drowsiness in that unique characteristics can be detected during drowsiness (i.e. slow eyelid closure) and little between and no within subject variation appears to exist. Slow and lengthy eyelid closures, besides indicating drowsiness, also indicate reduced performance capability. This is true since the driver cannot monitor the road properly with eyes closed a relatively large percentage of the time (Erwin, 1976).

In the Virginia Tech study (Skipper et al., 1984), drowsiness due to both sleep deprivation and time on task was explored. Each driver was

kept awake a total of approximately 21 hours and spent one and one half hours "driving" in a high fidelity moving base simulator. During each run, low-level transient steering wheel torque and front wheel disturbances were applied to the simulation at approximately one minute intervals. The driver's task was to respond to these stimuli by applying small steering corrections to maintain the simulated vehicle's lane position.

Seventeen driver-vehicle and eyelid closure measures were collected along with driver behavior patterns for each subject. Nine of the seventeen driver-vehicle measurements were associated with the six-second interval following the introduction of the stimuli and eight were associated with the 50 second "normal driving" interval immediately preceeding the introduction of torque and disturbance stimuli.

The results of this study showed that systematic changes occurred in the measures as a function of condition (fresh vs. sleep deprived) and as a function of time on task. Results also showed that several measures were highly correlated with eyelid closure measures. These highly correlated measures included lane deviation both following a stimulus and during "normal" driving between stimuli, yaw deviation following a stimulus, and steering velocity during normal driving between stimuli.

Intervals where drivers exceeded their lane boundaries were also analyzed. These intervals were defined as being associated with impaired driving, since drivers had failed to maintain proper vehicular control. Two major trends became apparent during this analysis. The

first trend was an oscillatory buildup in lateral position (with a period of five to twelve seconds) prior to lane exceedance. The second trend was a steering wheel "hold" (without the normal control oscillations) while lateral deviation built up followed by a large steering input to correct lane position.

Videotapes of upper body movements and driver "mannerisms" were also analyzed to determine if there were any correlations with eye closures. Mannerisms were counted for each five minute interval during a run. Of the sixteen mannerisms reviewed, the results showed that the total number of mannerisms, the number of hand to head mannerisms, and the number of body movements exhibited doubled when one or more slow eye closures occurred in an interval.

The above results showed promise for the potential development of a viable detection system. Skipper and Wierwille (1985) combined the most promising performance variables from the Skipper, Wierwille and Hardee (1984) study into multivariate linear discriminant models. They found that indeed drowsiness could be predicted with some degree of success based on driving performance measures. It is also interesting to note that the most reliable drowsiness prediction was associated with the "normal" driving as opposed to stimulus presentation. (Skipper and Wierwille, 1985).

Drowsiness Impaired Drivers - General Literature

Drowsiness or fatigue, especially as it relates to driving, is a difficult and complex topic of study. As pointed out by Ryder, Malin,

and Stacy (1981) in their extensive literature review on fatigue and driving: "Despite a good deal of research, very little is known about the relationship among subjective feelings of fatigue, objective measures of performance changes, and physiological changes that underlie fatigue" (p. 15).

Given this problem, some decisions were made to focus this literature review on the objectives of the research. Several major factors influence driver fatigue. These include:

1. Time on task
2. Number of hours without sleep
3. Diurnal rhythm
4. Driving conditions (e.g. monotony).

Initially, at least, to achieve the ultimate goal of an on-board, performance related, impaired driver detection system, the driving "baseline" will have to be stable and predictable. The scenario therefore was limited to open highway driving so that the sensitivity of degradation was not lost in the "noise" of active city-type driving. Thus, the study focused on factors affecting monotonous, low-event driving.

The effect of diurnal rhythms on driver performance was studied by Lisper, Erikson, Fagerstrom and Lindholm (1979). The number of traffic accidents is not constant for every hour of the day. A marked increase occurs in the early morning hours. However, Lisper et al. found that driver performance was apparently unchanged due to changes in diurnal rhythms. They therefore concluded that time-of-day changes in accident

rates must be caused by other factors such as time on task and sleep loss.

The remaining two factors which have been shown to have an effect on driver performance, namely time on task and sleep deprivation, are the conditions of interest to this research. A detailed discussion of each separately and in combination follows.

Prolonged driving effects on drowsiness. A number of studies have been performed to attempt to determine the effect of long hours of driving on driver performance. These studies show that performance does indeed decrease with time on task, and several promising performance and physiological measures exist that could possibly predict performance impairment.

One performance measure that appears to consistently degrade with prolonged driving is lane tracking ability. Dureman and Boden (1972) found that the number of steering errors increased over time in a four hour simulator study. Consistent with this finding, Sussman, Sugarman and Knight (1971) found that for low event driving, lane position error increased over a four hour period. Similar results have also been reported by Mast, Jones, and Heimstra (1966) in a similar study.

An interesting behavioral/performance change relating to lane tracking ability has also been found to occur with prolonged driving, namely the frequency of steering reversals. General findings (e.g. Sussman et al., 1971; Sugarman and Cozad, 1972) show that frequency of small control reversals decrease with time. This finding appears to be fairly consistent for simulators, closed course and open road driving

studies (Ryder et al., 1981). Sugarman and Cozad (1972) also noted an increase in steering magnitude with this decrease in steering reversal frequency.

Another performance measure which is very popular but appears to be inconsistent with regard to time on task is velocity maintenance and, similarly, accelerator pedal reversals (Mast et al., 1966; Brown, 1966; Safford and Rockwell, 1967). This performance measure, however, besides having inconsistent results is becoming quickly outdated in the driving scenario of interest (long-term, low event, open highway) due to the increased popularity of cruise control.

A number of physiological measures have been investigated as possible predictors of driver fatigue with time on task. These include pulse rate, respiration rate, skin resistance, neck muscle tension, EEG, heart rate variability, ECG, and blood pressure (Sussman et al., 1971; Boadle, 1976; Dureman and Boden, 1972). Of these, heart rate, respiration rate (Dureman and Boden, 1972; Boadle, 1976) and EEG (Lemke, 1982) appear to be consistent indicators of the gradual onset of fatigue. While practicality of measurement while driving is in question, these measurements can potentially be used to validate other more practical measures. The exception to this may be the measure of heart rate. A device has been recently developed which unobtrusively measures heart rate through the automobile steering wheel. The reliability of the device is unknown as of this writing. However, if proven reliable, heart rate could prove to be a useful measure of driver impairment. As previously discussed, in direct comparison of the above

physiological measures to eyelid closures, Erwin (1976) found eyelid closures to be the most stable predictor of drowsiness onset.

Driving and sleep deprivation. Sleep loss has been shown to produce a decrement in driving related skills (Hulbert, 1972). Hulbert describes many of the same types of driving performance measure decrements for sleep deprivation that were previously discussed for prolonged driving. Riemersma, Sanders, Wildervanck and Gaillard (1977) found that lane position variability increased as a combined function of both sleep loss and time-on-task. A similar result was also found by Skipper et al. (1984) (as previously discussed) and Ryder et al. (1981) in an extensive literature review. Steering behavior has also been shown to change as a function of sleep loss. Drivers deprived of sleep have been shown to have lower frequency steering reversals than rested drivers (Hulbert, 1963).

Accelerator pedal reversals were found to be highly correlated with time for a twenty-four hour driving task (Safford and Rockwell, 1967); however, the results were inconsistent across subjects. Acceleration/deceleration behavior was also observed to become sluggish as a function of sleep deprivation (Hulbert 1963). As with the time-on-task research, however, velocity maintenance and accelerator behavior studies have had mixed results regarding performance degradation with sleep deprivation.

There is an interesting point to be noted regarding driver behaviors that do not relate directly to performance, but which change significantly with sleep loss and time-on-task and sleep loss in combination.

As discussed in the introduction section describing studies done at Virginia Tech, Skipper et al. noted that several behaviors, namely upper body movements, hand to head movements and general "mannerisms" change significantly as a function of sleep deprivation and time-on-task. Similar findings have been reported by Hulbert (1963) (increase in rubbing face or head, stretching, closing eyes) and Yajima, Ikeda, Oshima and Sugi (1976) (general driver restlessness). While these behaviors are not directly associated with driver performance, perhaps they could predict the onset of driver fatigue if viable measurement means could be devised (e.g. seat sensor to detect movement frequency).

Attwood and Scott (1981) studied the possibility of taking some of the more promising driver performance measures (lane position median/range and accelerator position reversal) and combining them into a multivariate prediction model of driver drowsiness. Although the study had a small number of subjects and between subject variability was high, the results were promising. Perhaps, as Attwood and Scott point out, since driving is a highly complex multi-function task, multivariate modeling is the only way to reliably determine a performance decrement due to drowsiness. Promising multivariate prediction models were also devised by Skipper and Wierwille (1985) as discussed in the section describing the studies at Virginia Tech.

Literature on Alcohol and Driver Impairment

As previously discussed in the introduction section, the objective of this research was to determine the effects and potential for

detection of drivers who are impaired with low to moderate levels of alcohol. For this purpose, "moderate" will be defined as BAC of 0.09% or less. The focus of this discussion will, as with the discussion regarding drowsiness, center on measures which are potentially valuable in predicting impairment.

There are numerous studies on the effects of alcohol on driving and driving related tasks. Alcohol has been shown to increase reaction time, decrease judgment ability, and adversely affect visual acuity. Several studies have also noted a "tunnel" vision effect, in that drivers are less responsive to stimuli in their peripheral vision causing an increased probability of accidents (Moskowitz, 1973; Kobayashi, 1974; Mortimer and Sturgis, 1974).

Alcohol has also been associated with increased concentration of attention on a single channel of a "multi-channel" task (Howat and Mortimer, 1978; Moskowitz, 1971). The effect of this one channel effect is that the channel(s) that are not the center of attention are essentially ignored. Examples of this phenomenon relating to driving behavior would be speed variation while concentration is on lane position, or steering deviation while concentration is on radio tuning, etc.

Research regarding the effect of alcohol on specific performance measures appears to support this theory of selective attention. One measure in this category is steering and steering related behavior/performance. Subjects with BACs ranging from 0.03% to 0.08% show decrements in tracking performance. (Drew, 1958; Dott and

McKelvey, 1977; Mortimer and Sturgis, 1974). Similarly, steering errors measured as deviations in lane position have been found to increase for subjects with alcohol (Allen, Jex, McRuer and DiMarco, 1975; Sugarman, Cozad and Zavola, 1973; Huntley and Perrine, 1971). Several studies indicate an increase in course steering reversals as a function of alcohol (Allen, et al., 1975; Huntley and Centybear, 1974) and a decrease in steering frequency (Mortimer and Sturgis, 1974; Allen et al., 1975) although these findings are somewhat inconsistent (Ryder et al., 1981).

It is interesting to note that the behavior of a steering wheel "hold" followed by a large steering correction to compensate for drift appears to be consistent to some degree for both drowsiness and alcohol induced performance degradation (Skipper et al. 1984, Allen et al. 1975). This behavior may be an indicant of impaired driver performance in general.

Another category of performance measures that has been frequently used for alcohol impairment studies is velocity maintenance. Specific measures have included accelerator pedal reversals, accelerator variance, and velocity variance. Of these, the most consistent results center on accelerator pedal reversals. It is generally agreed that accelerator pedal reversals increase with moderate BAC (Mortimer and Sturgis, 1979; Attwood, Williams and Madill, 1980; Howat and Mortimer, 1978).

Volumes of studies exist documenting the physiological effects of alcohol. The most prominent behavioral changes due to alcohol are

believed to be due to its effects on the central nervous system. According to Ryder et al. (1981) "In particular, the reticular activating system, which plays a critical role in the control of sleep, wakefulness, attention and arousal as well as regulating cortical activity, is thought to be the major site of alcohol affects on the central nervous system" (p. 26). In general, more recent studies of alcohol and driving impairment do not address physiological measures. This is apparently true because of the complex relationship between alcohol and physiology and its inherently large variability due to age, sex, history of use, body weight, health, and stomach contents (Ryder et al., 1981).

One physiological measure that has been recently addressed and is of interest to the current research is eye closure behavior. A study by Beideman and Stern (1977) found significant differences in eye closure duration, frequency, and ratio of long to regular closures between a no alcohol group and a group with a mean BAC of 0.073% for a simulated driving task. A similar result was also found by Erwin, Wiener and Hartwell (1975). This appears to be another potentially common measure that can be applied to either drowsiness or alcohol.

Attwood et al. (1980) tried to combine some of the most promising alcohol affected performance measures into a multivariate prediction model. Four variables showing the highest multivariate separation were used, namely, lane position, velocity variance, accelerator variance, and steering range. Where a univariate analysis showed no differences for BAC, the combined multivariate analysis did show some differences

even at moderate BACs. This led Attwood and his associates to the conclusion that measurement and therefore prediction of driver impairment due to moderate levels of alcohol may be possible, but may require several different performance measurements for prediction.

Literature on the Combined Effects of Alcohol and Drowsiness

Even though a large number of studies exist for drowsiness and alcohol effects on driving and driving related tasks individually, very few studies exist exploring the combined affects. Two relevant studies were found which addressed combined effects in a driving-type environment.

Huntley and Centybear (1974) in a closed course study, analyzed alcohol and drowsiness effects both singly and in combination. In this study, BACs of zero/0.074%/0.094% and rested/sleep deprived (29 hours awake) conditions were investigated. An interesting sleep deprivation-by-alcohol interaction was found. Alcohol was found to significantly increase the frequency of coarse steering reversals during the rested condition but not following sleep deprivation.

In a simulator study by Nelson, Ladan and Carlson (1979), drivers in three alcohol groups (0, <0.08%, >0.08%) were instructed to drive until they wanted to stop because of fatigue due to time on task. Objective measures of performance were not collected; however, heart rate was. The results showed that subjects stopped sooner with increasing BACs. Therefore, perceived fatigue was greater as alcohol level increased. Another interesting point was that heart rate was higher for the alcohol

conditions, but did not decrease over time. This raises the question of whether the physiological measure of heart rate variability which appears to have some promise for prediction of the onset of fatigue loses its reliability when alcohol is introduced.

Comparison summary: Drowsiness, alcohol and the combination.

Several objective measures appear promising for detection of both alcohol and drowsiness. However, it must be kept in mind that the studies reviewed show inconsistency in certain instances and large between subject variability for the effects of both alcohol and drowsiness.

Vehicle control degrades in terms of the objective measures of steering and velocity maintenance. Coarse steering reversals and lane position variability increase under the effects of drowsiness or alcohol; however, there appears to be an antagonistic relationship for alcohol and drowsiness combined. Huntley and Centybear (1974) found that coarse steering reversals for drivers under the combined influence of alcohol and drowsiness were not significantly different from those of rested and sober drivers. Results are mixed regarding fine steering reversals; the effect appears to be an increase in fine reversals for alcohol and a decrease in fine reversals for drowsiness (Ryder et al., 1981).

Velocity maintenance shows some promise as a predictor of driver impairment due to alcohol and drowsiness although results are somewhat mixed. As discussed in the introduction section, however, this is becoming less practical as a potential predictor for highway driving impairment due to the increased popularity of the cruise control.

Eye closures appear to be a promising predictor of both alcohol and fatigue impairment, although no research was found dealing with eye closures under a combined influence of alcohol and drowsiness. Even though current technology makes monitoring of eye closures impractical in the average car, this appears to be a valuable and reliable predictor from which additional, more practical predictors might be validated.

Driver restlessness appears to be a consistent occurrence due to fatigue; however, it was not mentioned for any of the alcohol studies reviewed. Therefore, its potential as a common predictor of impairment requires further research.

Physiological measures of heart rate, respiration rate and EEG appear to be good predictors of drowsiness onset. In at least one case, however, the effects of alcohol appeared to cancel the predictability of fatigue as measured by heart rate variability. Respiration rate and EEG measures are limited in practicality and are apparently not as reliable as eye closures for prediction and correlation purposes (Erwin, 1976). Heart rate, however, may be unobstrusively implementable in an automobile and therefore may provide useful impairment detection information.

METHODOLOGY

Experimental Design

The experimental design used for this research was a 2x3x2 factorial within subject design. This experimental design is depicted graphically in Figure 1. The factors included sleep deprivation, time-on-task, and alcohol.

The independent variable sleep deprivation had two levels, namely, rested and sleep deprived. The time-on-task independent variable had three levels. The first level was the first 30 minutes, the second level was the second 30 minutes, and the third level was the third 30 minutes. The independent variable alcohol had two levels, BACs of zero and 0.075% (as defined at the beginning of the data run).

Each of six subjects received all levels of each factor in all combinations. To control for order effects, presentation of alcohol and sleep deprivation factors were randomly assigned to four subjects and arranged in a Latin square with regard to order. The two additional subjects were randomly assigned to two conditions of a second Latin Square. A layout of the experimental design is shown in Figure 1.

There were nineteen dependent measures collected for each subject. These measures are described in detail in the data collection techniques and dependent measure definitions section.

Subjects

Six volunteer subjects participated in all experimental conditions

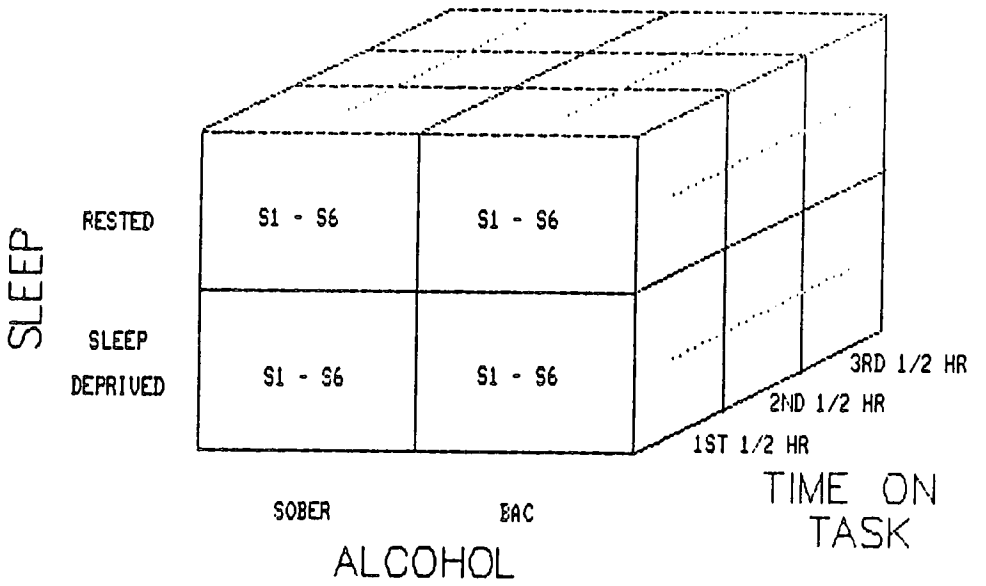


FIGURE 1. Experimental Design

and levels of this study. Subjects were screened to insure that health risks due to the effects of alcohol and sleep deprivation were minimized. Each subject was also required to fill out a questionnaire regarding drinking habits, driving habits, and sleeping habits. No subjects were used who were non-drinkers or heavy drinkers. Drivers who were not prone to drowsiness and those who exhibited pathological sleep disorders were also not used (Skipper et al., 1984). Questionnaires used for alcohol and drowsiness characteristics appear in Appendices A and B.

Three males and three females participated in the study. All subjects were at least 21 years of age. Each subject was required to have at least 20/30 distal visual acuity (with correction if necessary). Each subject was also required to have a valid driver's license, and underwent general heath, driving, and alcohol screenings as described in the procedure section.

Subjects received $4.50 per hour for their time involved with the study, including sleep deprivation and detoxification time as described in the procedure section.

Apparatus

Simulator. The simulator that was used for the study is a computer-controlled, moving-base automobile driving simulator. The simulator was programmed for handling similar to a modern, midsized, rearwheel-drive vehicle. The simulator has a high degree of fidelity

and has been validated in terms of performance measures with an instrumented automobile (Leonard and Wierwille, 1975).

The simulator has four major systems. These include a four degree-of-freedom motion platform, a roadway imaging/display system, an audio system and an analog computational system with analog-to-digital and digital-to-analog capabilities (Wierwille, 1975).

The simulator has a simulated interior consisting of a seat, brake and accelerator pedals, a dashboard with speedometer, a steering wheel and a display system.

A motion platform provides simulated vehicle motion for the roll, yaw, horizontal, and longitudinal degrees of freedom as well as simulated vehicle vibration. It is driven by closed-loop, servo-controlled, hydraulic actuators. Time delays inherent in the motion platform over and above normal vehicle delays are estimated to be 25 msec.

A roadway imaging/display produces the image of a two lane road with center strip, side markings, and additional horizontal lines to give the road the appearance of being embedded in the horizontal plane. The image is produced electronically (Tektronix 604), is presented via a black and white CRT (Setchell-Carlson 3M912), and is viewed through a Fresnel lens. The image includes a simulated automobile hood and occupies the driver's entire foveal, and a good portion of his/her peripheral field-of-view when the eyes are focused on the simulated roadway.

The audio system provides four separate simulated sounds. These simulated sounds include tire rolling resistance, engine/drivetrain

noise, tire screech on severe braking and tire squeal on severe cornering.

An analog/hybrid computational system (EAI TR48) drives the vehicle dynamics of the simulator including steering, braking, accelerator, wind gust and curvature signals. Computer outputs update motion platform position continuously. Signals are also provided to the speedometer, image generator and audio system.

The simulator equipment also includes analog-to-digital and digital-to-analog capability using two custom interfaces and two Radio Shack TRS-80 Model III microcomputers. This equipment was used to provide on-line data analysis.

Eye closure measurement -- closed circuit television. Eye closures were continuously monitored through a low light level closed-circuit television camera (RCA TC1004-U01). Recording was accomplished manually via a linear potentiometer which created an analog signal of eye closure. The camera and recording procedure were unobtrusive in that no additional lighting was required and the subject's view of the roadway image was not obstructed.

Measurement of hand removal/replacement frequency. A low-level coupling existed between conductive "antennae" on both sides of the steering wheel. When one hand was removed from the wheel, the one "antenna" had greater exposure and thereby decreased the signal coupling giving an unobtrusive, accurate and practical (in terms of potential for automobile installation) means of recording hand movement behavior.

Seat movement measurement. The frequency of seat movements (driver

"restlessness") was measured through changes in pressure as recorded by transducers in the seat backrest. The transducer signals were conditioned such that normal vibrations and vehicular movements were ignored and only larger signals indicating driver movement were measured. This provided, as with the hand movement device, an unobtrusive, accurate and practical behavior measure.

Heart rate measurement. Subject heart rate was measured via an ear plethysmograph and a Hewlett-Packard 7807C heart rate monitor.

Breathalyzer. An Intoximeter Alco Sensor-III was used to measure BAC.

Procedure

Subject selection. All potential subjects were required to complete the driver and alcohol questionnaires shown in Appendices A and B. The purpose of the driver questionnaire was to screen out potential subjects who either were not prone to drowsiness or exhibited pathological sleep disorders (Skipper et al. 1984). The purpose of the alcohol questionnaire was to screen out non-drinkers and heavy drinkers.

When subjects had been selected and notified of study participation, they were then given a Landholt C-ring vision examination. Each subject was required to have 20/30 far visual acuity or better, corrected or uncorrected, to participate in the study. This requirement ensured that roadway stimuli could be properly interpreted.

Potential subjects who qualified for the experiment based on the results of the driving and alcohol questionnaires and the vision

examination underwent a health screening contained as part of the informed consent shown in Appendix C. The purpose of this screening was to ensure that the effects of the alcohol and sleep deprivation involved in this study did not interact with other drugs and general health disorders such as diabetes, hypertension and heart disease. Potential subjects were not allowed to participate if their ability to give informed consent or to safely ingest moderate amounts of ethanol and undergo mild sleep deprivation was in question.

All data obtained through the questionnaires and health screening was confidential and handled anonymously.

Once the subject had met criteria for selection, he or she was given the instructions that appear in Appendix C.

Driving scenario. The driving scenario was 90 minutes in length. It was divided into three identical thirty-minute segments. Each segment was divided into six five-minute sections. Sections alternated between straight and curved roads to provide a realistic highway driving scenario. Subjects were instructed to drive at 55 mph. The visual scene and environment simulated night driving.

General Procedure. Each subject operated the driving simulator on four separate occasions, for ninety minutes each, under four separate conditions. The conditions consisted of the following:

1. Rested/Sober. Subjects were given a placebo beverage consisting of a diet soft drink with a trace of vodka floated on the top for taste. After an ingestion period the subject was given a breathalyzer test to verify dosage. The subject then drove

the simulator for the 90-minute scenario.

2. Rested/BAC. Subjects were given a beverage consisting of a diet soft drink and vodka, the amount of which was calculated using the equations given in Appendix D. After an ingestion period, the subject was given a breathalyzer test to verify dosage. The subject then drove the simulator through the 90-minute scenario.

3. Sleep Deprived/Sober. Subjects began driving the simulator approximately 19 hours after normal wake-up time. Thus, they had approximately 4 hours sleep deprivation (as compared with normal bedtime). Subjects were asked if their sleeping habits had been "normal" for the last several days as shown in the driving questionnaire. This was to ensure that effects due to circadian rhythm changes were minimized. The subjects' intake and state of arousal were monitored from approximately 5 pm until the designated run time, calculated from when each subject awoke that morning. The subjects were not allowed to ingest sugar, caffeine, nicotene or any other stimulants after approximately 6 pm. Subjects were given a placebo and breathalyzer test as described in condition 1 above. Subjects then drove the simulator for the 90 minute scenario.

4. Sleep Deprived/BAC. Subjects were sleep deprived as described in condition 3 above. Subjects were then administered alcohol as described in condition 2 above. Subjects then drove the simulator for the 90-minute scenario.

In the event that a subject lost control of the simulator, there was no inherent danger. The simulator simply reached a limiting excursion value and was reset. After the 90 minute scenario, the simulator motion was stopped, and the subject exited the simulator.

All subjects, regardless of BAC level, remained in the vehicle simulation lab until the detoxification level of a BAC of .03% or the equivalent amount of time (for the placebo conditions) had been reached. The subjects were then driven home, escorted to the door and asked to remain home for the remainder of that evening as a safety precaution.

Debriefing. Subjects were paid and debriefed following the fourth run.

Data Collection Techniques and Dependent Measure Definitions

The data for this experiment were collected and analyzed on-line through analog-to-digital interfaces connected to microcomputers. The data were also recorded on an FM instrumentation recorder to provide a back up in case of an interface or digital equipment failure, and in case additional analyses might be needed at a later time.

The data collection techniques used, and the associated dependent measure definitions are described below:

1. Eyelid Closure. The subject's eyes were monitored via a closed circuit TV camera and recorded on a video recorder. An experimenter tracked eyelid closure manually with a linear potentiometer, creating an analog signal of eye closure. This analog signal was sampled at 0.25 second intervals by one of the two microcomputers. The following dependent measures were

derived from the eyelid closure signal:

EYEMEAN - The mean of the eyelid closure signal, sampled over a three-minute interval.

EYEMEAS - The mean-square of the eyelid closure signal, sampled over a three-minute interval. Since the mean-square was calculated, EYEMEAS was weighted more heavily as eye closure increased.

PERCLOS - The percentage of time that the eyes were 80% to 100% closed over a three-minute interval.

2. Lane Deviation Measures. The lane position was measured as an analog signal from the simulator and was sampled at 0.25 second intervals by one of the digital microcomputers. The center of the right lane was set at zero with positively increasing values for deviations from center to the left and negatively increasing values for deviations from center to the right. The following dependent measures were derived from the lane position signal:

LANEX - The number of lane position samples in a three-minute interval which were greater than values equivalent to the centerline of the simulated vehicle exceeding either lane boundary.

LANDEVV - The variance of the lane position signal, calculated for a three-minute interval.

LANDEVSQ - The mean square of the lane position signal, calculated for a three-minute interval. Since LANDEVSQ was a mean square calculation, it was more heavily weighted with increasing deviations from the lane center.

LANDEV4 - The mean of the fourth power of the lane position signal, calculated for a three-minute interval. Since LANDEV4 was a fourth power calculation, it was very heavily weighted with increasing deviations from the lane center.

3. Steering Reversals - Steering wheel position was measured as an analog signal from the simulator and sampled at 0.15 second intervals by one of the digital microcomputers. The following dependent measures were derived from the steering wheel position signal:

SMREV - The number of times the steering wheel position increment exceeded 1° or more

after steering wheel velocity passed through zero.

LGREV - The number of times the steering wheel position increment exceeded 5° or more after steering wheel velocity passed through zero.

4. Steering Velocity - Steering wheel velocity was measured as an analog signal from the simulator and sampled at 0.15 second intervals by one of the digital microcomputers. The following dependent measures were derived from the steering velocity signal:

STEXEED - The number of times steering velocity exceeded the equivalent of 150 degrees/sec in a three-minute interval.

STVELM - Steering velocity mean calculated over a three-minute interval.

STVELV - Steering velocity variance calculated over a three-minute interval.

5. Yaw Deviation - Yaw deviation was measured as an analog signal from the simulator and sampled at 0.15 second intervals by one

of the digital microcomputers. The following dependent measures were derived from the yaw deviation signal:

YAWMEAN - Mean yaw deviation calculated over a three-minute interval.

YAWVAR - Yaw deviation variance calculated over a three minute interval.

6. Heart Rate - Heart rate was collected via an ear plethysmograph as previously discussed in the apparatus section. The heart rate signal from the plethysmograph was sampled at 0.25 second intervals by one of the digital microcomputers. The following dependent measures were derived from the heart rate signal:

HRTRTM - The heart rate mean calculated over a three-minute interval.

HRTRTV - The heart rate variance calculated over a three-minute interval.

7. Seat Movements - As previously discussed in the apparatus section. Pressure transducers in the backrest provided a signal indicating driver body movements. The dependent variable SEATMOV was derived from this signal. SEATMOV was a movement frequency measure, the amplitude of which was set such that

driver movements in the seat were recorded and vibration and related vehicle movements were ignored.

8. One Hand-on-Wheel Frequency - As previously discussed in the apparatus section, the one vs. two hand on the wheel frequency data were collected through a low power signal coupling in the steering wheel. The dependent variable HANTRAN was the frequency measure derived from this signal. HANTRAN measured the number of times a driver's hand was removed from and replaced on the steering wheel in a three-minute interval.

9. Simulated Accelerometer - A measure simulating a high pass lateral position based on a lateral accelerometer was derived from the lane position signal. This measure responded to changes in lateral position and subsequently returned to zero in a period of approximately 60 seconds, regardless of the new lane position, through a recursion equation. The dependent measure LATPOSM was derived from this signal. LATPOSM was the mean square of the incoming signal calculated over three-minute intervals. Since LATPOSM was a high-pass mean square calculation, rapid changes in lateral position were more heavily weighted than slow changes in lateral position.

Data Analysis Overview

The data analysis for this research consisted of two major parts. The first part of the analysis consisted of correlation analyses, an analysis of variance, and a stepwise discriminant analysis. The purpose of this analysis was to determine which of the dependent variables could

reliably detect driver impairment.

The second part of the analysis consisted of a linear discriminant analysis. The purpose of this discriminant analysis was, given the most reliable measures of impairment, to find an optimized linear combination of variables and to discriminate between "impaired" and "not impaired" driving observations. As will be shown, this discrimination answers a number of questions regarding the detectability of driver impairment and serves as an important step toward the ultimate goal of a vehicle-borne impaired driver detection device.

A key issue in achieving the ultimate goal of a vehicle-borne impaired driver detection device is defining impairment in quantifiable terms. Simply because a driver has been deprived of sleep, for whatever reason, does not necessarily mean that impaired driving is the result. The same is true for alcohol, particularly at the level used in this experiment (BAC = .075%). Many studies have shown that the effects of alcohol on driving performance vary greatly between subjects. It is not sufficient (scientifically although not legally) to generalize from a given BAC to a given level of impairment across subjects.

Fortunately, there is a logical and scientific solution to this problem. At this point, the distinction will be made between predictors of impairment and detectors of impairment. This distinction is based both on logic associated with the driving task and scientific evidence.

The category of impairment predictors will consist of measures associated with eye closures and lane deviations. As previously discussed in the literature review section, Erwin, et al. (1975) and

Skipper, et al. (1984) found that slow eye closures were effective indicants of drowsiness and associated task performance degradation. As Erwin and his associates also point out, a driver cannot drive safely and effectively during prolonged eye closures. Based on this statement, it is apparent that as a driver's eyes are closed more and more frequently while passing from an alert state through levels of drowsiness, the probability of an accident due to a missed visual stimulus increases.

Therefore, significant eye closures both indicate and contribute to driver impairment. While eye closures have been shown to indicate driver impairment due to drowsiness, an indicant of driver impairment due to alcohol is not as well-established. Intuitively, if a driver is unable to maintain the vehicle in a given lane, the probability of an accident is increased due to the potential for running off the road or striking another vehicle. Lane deviation and exceedence measures, therefore, would seem to be indicants of impairment due to either alcohol or drowsiness since a non-impaired driver is generally able to maintain a position within the lane.

It is difficult, however, to determine when a driver, particularly in a simulated environment where the danger of an accident is eliminated, is exceeding lane boundaries due to impairment. Factors such as a decreased sense of criticality, inattention at a curve onset or boredom cannot easily be accounted for, even when the subject is instructed to drive in the right lane. Therefore, the validity of the lane deviation and exceedance measures as impairment predictors was addressed as

part of the data analysis in this study.

The classification of variables as impairment detectors is based primarily on the practicality of automobile installation. All measures collected during this study, with the exception of the eye closure measures could be implemented in an automobile. Some measures, (e.g. heart rate or lane position) would be more difficult, expensive, or obtrusive, (given the current technology) to implement than others (e.g. steering reversals) making them less practical. Note that the lane deviation and exceedence measures could be classified either as impairment predictors or as impairment detectors based on the logic described above. Since other measures collected during this study could be more readily implemented in an automobile, and since lane measures could prove useful as impairment predictors, lane measures were treated primarily as predictors and secondarily as detectors in the data analyses.

Determination of Measure Effectiveness for Prediction. Three analytical steps were used to determine which dependent variables provided the most reliable prediction of driver impairment. The first step consisted of a correlation analysis. Two types of correlations were calculated, namely, correlations between eye measures and lane measures (both classified as impairment predictors) and correlations between impairment predictors and impairment detectors. The purpose of the correlation between eye measures and lane measures was to validate to some degree that these two independent measurement sources do in fact

indicate driver impairment. The purpose of the correlation between the impairment predictors and impairment detectors was to indicate the detectors which showed reliable trends relative to impairment.

A second analytical step used to determine the sensitivity of the various detectors was an analysis of variance (ANOVA). ANOVA's were used to determine the degree of separation of each of the measures for each of the conditions (sleep, alcohol, time-on-task) and the condition interactions. A low p-value for any given variable and condition indicated differences between levels of that condition and, perhaps more importantly for this application, a high degree of separation required for successful classification of an impaired vs. not impaired observation.

A third step used to determine the most effective detectors of impairment was the stepwise discriminant analysis. Using the most promising predictors as indicated by the correlation and ANOVA procedures, the stepwise approach was used to determine which variables provided the most useful information regarding impairment such that: 1. the measure actually provided separation in terms of impaired vs. not impaired performance, and such that 2. the information provided by the measure was to some degree independent of information provided by another measure or measures. The stepwise approach analyzes the separation provided by each variable singly and in combination with the other variables based on specified criteria. The selection of the criteria used to determine "impaired" vs. "not impaired" for the stepwise analyses will be discussed in detail in the results section.

Optimization of linear models for discrimination of impairment. Using the variables which provided the most useful information for impairment detection as determined by the analyses discussed above, a number of linear discriminant analyses were performed to determine the optimum linear classification models for impaired vs. non-impaired drivers. The linear discriminant analysis builds a model based on linear combinations of variables which maximally separate the means of the impaired vs. non-impaired groups relative to the group variance. Like the stepwise approach, pre-selected criteria are used to define the impaired vs. not impaired groups. Based on the linear discriminant model and the criteria, each observation is classified into one of four groups. For a given criterion of "impaired" vs. "not impaired" the four classification groups are as follows:

1. Correct classification as impaired

   (Hit)

2. Correct classification as not impaired

   (Correct Rejection)

3. Incorrect classification as impaired

   (False alarm)

4. Incorrect classification as not impaired

   (Miss)

The degree to which observations are correctly classified indicates the success of the linear model in terms of its ability (in this case) to correctly detect impaired performance.

RESULTS

Subject Blood Alcohol Content (BAC) Results

As previously described in the procedure section, subjects were given a breathalyzer test prior to and following each run. Although a breathalyzer test was not given at the time that the subjects reached peak BAC, interpolation from the before and after breathalyzer tests indicated that values close to the target BACs were achieved. These results and the interpolation to the peak values are described in Appendix E.

Correlation Analyses

As previously discussed in the data analysis overview section, correlations were performed between the eye measures and lane measures and between the impairment predictors and impairment detectors. The purpose of the lane measure vs. eye measure correlations was to serve as a check on the validity of the class of measures termed impairment predictors. The purpose of the correlation between the impairment predictors and the impairment detectors was to determine which of the impairment detector variables most reliably detect impairment as indicated by the degree to which they systematically change with changes in the impairment predictor measures.

Correlations were also performed on several portions of the total data set. The data were partitioned along the dimensions of sleep effects, alcohol effects, and combined effects data. For each category

of data, the rested/sober condition was included to serve as a control condition for comparison purposes. Sleep effects data consisted of the rested/sober and sleep deprived/sober portions of this data. Alcohol effects data consisted of the rested/sober and rested/BAC portions of the data. Combined effects data consisted of the rested/sober and sleep deprived/BAC portions of the data. The purpose of this division of data was to determine whether a single model concept to predict general impairment appeared promising or whether separate models would be required to detect different types of driver impairment.

Additional correlation analyses were performed with the data in several configurations, namely: three-minute intervals and six-minute intervals of data, and data corrected for individual subject means and standard deviations. The logic associated with each data configuration will be discussed in detail as each is addressed.

Correlations: Three-minute interval data

As previously discussed in the data collection section, the data for each variable were collected and reduced online via microcomputers over three-minute intervals. Depending on the variable, reduction consisted of a mean calculation, a mean-square calculation or a counter to mark discrete events (e.g. number of lane exceedences). These data reduction procedures are discussed in detail for each variable in the data collection techniques and dependent measure definitions section.

The number of observations contained in the correlation analyses varied depending on the portion of the data set in question and the

interval length. The full data set, three-minute interval correlations contained 720 observations. The partial data set (sleep effects, alcohol effects, and combined effects) three-minute interval correlations, and the full data set, six-minute interval correlations contained 360 observations. The partial data set, six-minute interval correlations contained 180 observations. Significance levels associated with the p = .001 and p = .0001 levels are shown on each table. These values are presented to give the reader a comparison reference point for the data contained in each table.

Eye measure vs. lane measure correlations. All data. Three-minute intervals. The correlations between the eye measures and lane measures for the entire data set appear in Table 1. As shown, the correlations are generally highest between the PERCLOS measure and the lane measures. Fairly high correlations also exist between EYEMEAS and the lane measures. It should be noted at this point that correlations in the range of 0.3 to 0.6 are considered encouraging for this type of research when one considers the effects of inter-subject variability and that the measures are not directly related in terms of driving performance.

Eye measure vs. lane measure correlations. Sleep effects data. Three-minute intervals. The correlations between the eye measures and lane measures for the sleep effects data (rested/sober and sleep deprived sober) are shown in Table 2. A comparison between Tables 1 and 2 reveals an increase in correlations between eye measures and lane measures when the alcohol portions of the data are not considered. It is apparent that the introduction of alcohol adds some degree of

TABLE 1 Eye Measure vs. Lane Measure Correlations. All Data. Three-Minute Intervals.

	EYEMEAN	EYEMEAS	PERCLOS
LANEX	0.21	0.41	0.58
LANEDEVV	0.20	0.37	0.53
LANEDEVSQ	0.20	0.38	0.52
LANEDEV4	0.10	0.21	0.36

R = .12, p = 0.001

R = .14, p = 0.0001

variability to the correlation data. The magnitude of the correlations in Table 2 support the validity of eye measures and lane measures as indicants of impairment due to drowsiness.

Eye measure vs. lane measure correlations. Alcohol effects data. Three-minute intervals. The correlations between the eye measures and lane measures for the alcohol effects data (rested/sober and rested/BAC) are shown in Table 3. As shown, correlations are generally much lower for the alcohol effects data than for the sleep effects data or the full data set. The exception to this is a moderate degree of correlation between PERCLOS and LANDEVSQ and LANDEV4. Examinations of the means and variances for the eye measures reveals that generally few closures occurred during this portion of the data relative to the sleep effects data. Since the range of the eye measure data is reduced, reductions in the correlations would be expected to some degree. This result indicates that eye measures may not be valid predictors of alcohol impairment. Since eye measures may not provide valid prediction, there appear to be no measures to cross validate the lane measures as alcohol impairment predictors.

Eye measure vs. lane measure correlations. Combined effects data. Three-minute intervals. The correlations between the eye measures and lane measures for the combined effects data (rested/sober, sleep deprived/BAC) are shown in Table 4. The correlations are in the 0.4 to 0.6 range for EYEMEAS and PERCLOS. The combined effects data correlations are higher than for the alcohol effects data showing some degree of impairment predictor validity. However, the correlations are

TABLE 2 Eye Measure vs. Lane Measure Correlations. Sleep Effects Data. Three-Minute Intervals.

	EYEMEAN	EYEMEAS	PERCLOS
LANEX	0.47	0.54	0.62
LANEDEVV	0.50	0.55	0.60
LANEDEVSQ	0.55	0.59	0.60
LANEDEV4	0.36	0.40	0.40

R = .17, p = 0.001

R = .20, p = 0.0001

TABLE 3 Eye Measure vs. Lane Measure Correlations. Alcohol Effects Data. Three-Minute Intervals.

	EYEMEAN	EYEMEAS	PERCLOS
LANEX	0.02	0.01	0.15
LANEDEVV	0.12	0.11	0.21
LANEDEVSQ	0.16	0.17	0.32
LANEDEV4	0.11	0.10	0.27

R = .17, p = 0.001

R = .20, p = 0.0001

TABLE 4 Eye Measure vs. Lane Measure Correlations. Combined Effects Data. Three-Minute Intervals.

	EYEMEAN	EYEMEAS	PERCLOS
LANEX	0.18	0.44	0.62
LANEDEVV	0.17	0.41	0.58
LANEDEVSQ	0.17	0.42	0.57
LANEDEV4	0.10	0.27	0.43

R = .17, p = 0.001

R = .20, p = 0.0001

lower for the combined effects data than for the sleep effects data. This reduction in correlation magnitude could have been due to variability introduced through addition of alcohol to the sleep deprived condition.

Impairment predictor vs. impairment detector correlations. All data. Three-minute intervals. The correlations between the impairment predictors (lane and eye measures) and the impairment detectors appear in Table 5. All correlations that are greater than 0.25 are underlined for ease of interpretation. The level 0.25 is highly significant ($p < 0.0001$) and was selected to highlight promising measures. As shown by Table 5, the impairment detectors that have generally high correlations with lane and eye measures include: YAWVAR, STEXEED, STVELV, LGREV, AND LATPOSM. It should be noted that the very high correlations between the lane measures and LATPOSM and YAWVAR are due in large part to the physical dependencies associated with these measures and changes in lane position. However, these measures should not be underrated as promising detectors due to this physical relationship. The measures are implementable in an automobile (in some form) and show correlations with eye measures as well as lane measures.

Impairment predictor vs. impairment detector correlations. Sleep effects data. Three-minute intervals. The correlations between the impairment predictors and impairment detectors for the sleep effects data (rested/sober, sleep deprived/sober) are shown in Table 6. Again, correlations greater than 0.25 are highlighted with an underline. The table shows that correlations are higher for the sleep effects data than

TABLE 5 Impairment Predictor vs. Impairment Detector Correlations. All Data. Three-Minute Intervals.

	EYEMEAN	EYEMEAS	PERCLOS	LANEX	LANDEVV	LANDEVSQ	LANDEV4
YAWMEAN	0.15	0.18	-0.05	-0.14	-0.18	-0.18	-0.26
YAWVAR	0.24	0.42	0.55	0.82	0.91	0.87	0.76
STEXCEED	0.16	0.27	0.37	0.43	0.50	0.46	0.41
STVELM	-0.12	-0.13	-0.14	-0.07	-0.09	-0.09	-0.09
STVELV	0.21	0.27	0.30	0.28	0.31	0.26	0.20
SMREV	0.08	0.05	0.01	0.01	0.02	-0.01	-0.04
LGREV	0.24	0.31	0.30	0.29	0.30	0.25	0.13
SEATMOV	0.22	0.31	0.12	0.13	0.17	0.17	0.06
HRTRTM	-0.05	-0.18	-0.28	-0.23	-0.22	-0.22	-0.14
HRTRTV	0.07	0.02	<0.01	0.04	0.07	0.09	-0.01
HANTRAN	-0.04	-0.05	-0.01	0.03	0.08	0.04	-0.01
LATPOSM	0.21	0.40	0.55	0.91	0.99	0.96	0.83

R = .12, p = 0.001
R = .14, p = 0.0001

TABLE 6 Impairment Predictor vs. Impairment Detector Correlations. Sleep Effects Data. Three-Minute Intervals.

	EYEMEAN	EYEMEAS	PERCLOS	LANEX	LANDEVV	LANDEVSQ	LANDEV4
YAWMEAN	0.21	0.17	0.04	0.08	0.05	0.04	0.04
YAWVAR	0.51	0.56	0.58	0.72	0.82	0.72	0.63
STEXCEED	0.37	0.41	0.50	0.53	0.53	0.48	0.44
STVELM	-0.15	-0.14	-0.13	-0.02	-0.06	-0.05	-0.09
STVELV	0.35	0.39	0.46	0.47	0.47	0.42	0.40
SMREV	0.08	0.10	0.06	0.12	0.18	0.14	0.11
LGREV	0.37	0.40	0.43	0.47	0.51	0.43	0.39
SEATMOV	0.39	0.37	0.20	0.16	0.26	0.35	0.09
HRTRTM	-0.12	-0.18	-0.22	-0.17	-0.16	-0.25	-0.12
HRTRTV	0.16	0.14	0.11	0.18	0.29	0.22	0.20
HANTRAN	-0.09	-0.09	<0.01	0.04	0.12	0.04	0.04
LATPOSM	0.51	0.55	0.60	0.81	0.99	0.89	0.75

R = .17, p = 0.001
R = .20, p = 0.0001

for the entire data set. The impairment detectors showing the highest correlations include: YAWVAR, STEXEED, STVELV, LGREV, SEATMOV, and LATPOSM.

Impairment predictor vs. impairment detector correlations. Alcohol effects data. Three-minute intervals. The correlations between the impairment predictors and impairment detectors for the alcohol effects data (rested/sober, rested/BAC) are shown in Table 7. The correlations are generally much lower between impairment predictors and impairment detectors for the alcohol effects data than for the full data set or the sleep effects data. The exceptions to this are HRTRTV, YAWVAR, and LATPOSM which showed relatively high correlations with the lane measures. Generally, the correlations between the eye measures and impairment detectors are low for the alcohol effects data.

Impairment predictor vs. impairment detector correlations. Combined effects data. Three-minute intervals. The correlations between the impairment predictors and impairment detectors for the combined effects data (rested/sober, sleep deprived/BAC) are shown in Table 8.

The correlations are generally lower for the combined effects data than for the sleep effects data. The impairment detectors showing the highest correlations with the impairment predictors include: YAWVAR, STEXEED, STVELV, HRTRTM, LATPOSM, and LGREV.

Correlations: Six-minute interval data

All data collected and reduced over three-minute intervals were combined into six-minute intervals. This was accomplished by taking a mean

TABLE 7 Impairment Predictor vs. Impairment Detector Correlations. Alcohol Effects Data. Three-Minute Intervals.

	EYEMEAN	EYEMEAS	PERCLOS	LANEX	LANDEVV	LANDEVSQ	LANDEV4
YAWMEAN	0.33	0.31	-0.17	<0.01	-0.02	<0.01	<0.01
YAWVAR	0.05	0.03	0.05	0.27	0.67	0.49	0.45
STEXCEED	-0.01	-0.02	-0.01	0.07	0.02	0.01	0.03
STVELM	-0.10	-0.08	-0.17	-0.02	-0.03	-0.06	-0.06
STVELV	-0.04	-0.07	-0.09	-0.04	-0.03	-0.06	-0.06
SMREV	-0.10	-0.12	-0.22	-0.07	0.02	-0.11	-0.10
LGREV	-0.02	-0.05	-0.07	0.07	0.18	0.09	0.08
SEATMOV	0.20	0.23	0.11	-0.01	0.09	0.07	0.03
HRTRTM	0.20	0.14	0.05	0.03	-0.06	0.06	0.04
HRTRTV	0.04	0.03	0.36	0.29	0.33	0.45	0.37
HANTRAN	-0.09	-0.11	-0.04	0.04	0.12	0.08	0.08
LATPOSM	0.13	0.11	0.21	0.52	0.98	0.82	0.77

R = .17, p = 0.001
R = .20, p = 0.0001

TABLE 8 Impairment Predictor vs. Impairment Detector Correlations. Combined Effects Data. Three-Minute Intervals.

	EYEMEAN	EYEMEAS	PERCLOS	LANEX	LANDEVV	LANDEVSQ	LANDEV4
YAWMEAN	0.12	0.13	0.12	-0.22	-0.28	-0.29	-0.35
YAWVAR	0.18	0.41	0.56	0.86	0.94	0.92	0.83
STEXCEED	0.10	0.21	0.31	0.43	0.52	0.49	0.46
STVELM	-0.13	-0.17	-0.18	-0.12	-0.13	-0.13	-0.13
STVELV	0.19	0.22	0.24	0.30	0.34	0.30	0.27
SMREV	0.05	-0.02	-0.09	-0.06	-0.06	-0.08	-0.08
LGREV	0.20	0.25	0.20	0.27	0.27	0.24	0.14
SEATMOV	0.15	0.26	0.06	0.18	0.22	0.20	0.11
HRTRTM	0.03	-0.12	-0.27	-0.27	-0.27	-0.26	-0.18
HRTRTV	0.22	0.13	-0.03	0.02	0.05	-0.04	-0.01
HANTRAN	-0.06	-0.09	-0.07	-0.01	<0.01	-0.01	-0.03
LATPOSM	0.18	0.43	0.60	0.92	0.99	0.98	0.86

R = .17, p = 0.001
R = .20, p = 0.0001

of the data for two three-minute intervals for each variable, such that three-minute intervals one and two became six-minute interval one; three-minute intervals three and four became six-minute interval two; and so on. This was performed in order to determine whether data collected over a longer interval provided greater reliability for impairment prediction and detection. Presentation of the six-minute interval data will be the same as for the three-minute interval data, namely correlations between eye measures and lane measures and between impairment predictors and impairment detectors for the full data set, sleep effects data, alcohol effects data and combined effects data.

Eye measure vs. lane measure correlations. Six-minute intervals. All data. The correlations between the eye measures and lane measures for the entire data set combined into six-minute intervals appear in Table 9. The correlations are generally highest between PERCLOS and the lane measures, with EYEMEAS and the lane measures showing relatively high correlations also. All correlations shown in Table 9 are higher than the corresponding three-minute interval correlations.

Eye measure vs. lane measure correlations. Six-minute intervals. Sleep effects data. The correlations between the eye measures and lane measures for the sleep effects data (rested/sober, sleep deprived/sober) appear in Table 10. The table shows that the correlations are all higher for the six-minute interval data than for the corresponding three-minute interval data (Table 2). Of particular interest is the general magnitude of the correlations shown in Table 10, which are the highest seen thus far. Note that several correlations

TABLE 9 Eye Measure vs. Lane Measure Correlations. All Data. Six-Minute Intervals.

	EYEMEAN	EYEMEAS	PERCLOS
LANEX	0.28	0.47	0.71
LANEDEVV	0.28	0.46	0.68
LANEDEVSQ	0.29	0.47	0.68
LANEDEV4	0.17	0.32	0.56

R = .17, p = 0.001

R = .20, p = 0.0001

TABLE 10 Eye Measure vs. Lane Measure Correlations. Sleep Effects Data. Six-Minute Intervals.

	EYEMEAN	EYEMEAS	PERCLOS
LANEX	0.55	0.63	0.78
LANEDEVV	0.55	0.61	0.70
LANEDEVSQ	0.61	0.65	0.71
LANEDEV4	0.46	0.53	0.68

R = .24, p = 0.001

R = .28, p = 0.0001

between PERCLOS and the lane measures are greater than 0.7.

Eye measures vs. lane measure correlations. Six-minute intervals. Alcohol effects data. The correlations between the eye measures and lane measures for the alcohol effects data (rested/sober, rested/BAC) appear in Table 11. The correlations between lane measures and eye measures are generally lower for the alcohol effects data than for any other category of data. The correlations for the six-minute interval alcohol effects data are, however, generally slightly higher than the correlations for the three-minute interval alcohol effects data shown in Table 3.

Eye measure vs. lane measure correlations. Six-minute intervals. Combined effects data. The correlations between the eye measures and lane measures for the six-minute combined effects data (rested/sober, sleep deprived/BAC) appear in Table 12. As shown, correlations between PERCLOS and several of the lane measures are in the 0.7 to 0.8 range while the correlations between EYEMEAS and several of the lane measures are in the 0.5 range. In comparing the six-minute interval combined effects data (Table 4), the six-minute data again show consistently higher correlations.

Impairment predictor vs. impairment detector correlations. Six-minute intervals. All data. The correlations between the impairment predictors and impairment detectors for the entire six-minute interval data set appear in Table 13. As with the three-minute interval data, correlations greater than 0.25 are highlighted to show the most promising impairment detectors. As shown, impairment detectors exhibit-

TABLE 11 Eye Measure vs. Lane Measure Correlations. Alcohol Effects Data. Six-Minute Intervals.

	EYEMEAN	EYEMEAS	PERCLOS
LANEX	0.05	0.04	0.23
LANEDEVV	0.14	0.14	0.32
LANEDEVSQ	0.19	0.21	0.40
LANEDEV4	0.15	0.14	0.35

R = .24, p = 0.001

R = .28, p = 0.0001

TABLE 12 Eye Measure vs. Lane Measure Correlations. Combined Effects Data. Six-Minute Intervals.

	EYEMEAN	EYEMEAS	PERCLOS
LANEX	0.25	0.51	0.77
LANEDEVV	0.25	0.51	0.77
LANEDEVSQ	0.26	0.53	0.77
LANEDEV4	0.18	0.41	0.69

R = .24, p = 0.001

R = .28, p = 0.0001

TABLE 13 Impairment Predictor vs. Impairment Detector Correlations.
All Data. Six-Minute Intervals.

	EYEMEAN	EYEMEAS	PERCLOS	LANEX	LANDEVV	LANDEVSQ	LANDEV4
YAWMEAN	0.22	0.21	-0.07	-0.12	-0.16	-0.15	-0.25
YAWVAR	0.33	0.51	0.71	0.86	0.92	0.88	0.77
STEXCEED	0.27	0.38	0.55	0.53	0.56	0.53	0.48
STVELM	-0.13	-0.16	-0.18	-0.12	-0.14	-0.14	-0.13
STVELV	0.32	0.34	0.42	0.33	0.32	0.28	0.23
SMREV	0.13	0.08	0.02	-0.01	-0.03	-0.07	-0.06
LGREV	0.36	0.37	0.39	0.34	0.33	0.28	0.17
SEATMOV	0.30	0.38	0.14	0.20	0.23	0.24	0.08
HRTRTM	-0.06	-0.19	-0.30	-0.25	-0.25	-0.25	-0.19
HRTRTV	0.08	0.03	<0.01	0.06	0.09	0.12	-0.01
HANTRAN	-0.02	-0.04	0.01	0.05	0.10	0.06	-0.01
LATPOSM	0.29	0.47	0.69	0.93	0.996	0.97	0.82

R = .17, p = 0.001
R = .20, p = 0.0001

ing high correlations with the impairment predictors include: YAWVAR, STEXCEED, STVELV, LGREV, HRTRTM, and LATPOSM. As was discussed with the three-minute interval data, it should be noted that the high correlations between LATPOSMS, YAWVAR, and some of the lane measures are due, at least in part, to physical dependencies between variables based on steering and lane position. The correlations shown in Table 13 are generally higher than the corresponding three-minute interval correlations shown in Table 5. The same variables described in the discussion of the three-minute data appear promising, but in addition to those, the six-minute interval data show that perhaps two additional variables should be considered in subsequent analyses, namely HRTRTM and SEATMOV.

Impairment predictor vs. impairment detector correlations. Six-minute intervals. Sleep effects data. The correlations between the impairment predictors and impairment detectors for the sleep effects data (rested/sober, sleep deprived/sober) appear in Table 14. As shown, impairment detectors yielding the highest general correlation with the impairment predictors are: YAWVAR, STEXCEED, STVELV, LGREV, SEATMOV, and LATPOSM. HRTRTM and HRTRTV also show consistent correlations, although they are generally not as high as some of the other variables. In comparison with the corresponding three-minute interval data (Table 6) the six-minute intervals consistently provided higher correlations.

Impairment predictor vs. impairment detector correlations. Six-minute intervals. Alcohol effects data. The correlations between the impairment predictors and impairment detectors for the alcohol

TABLE 14 Impairment Predictor vs. Impairment Detector Correlations. Sleep Effects Data. Six-Minute Intervals.

	EYEMEAN	EYEMEAS	PERCLOS	LANEX	LANDEVV	LANDEVSQ	LANDEV4
YAWMEAN	0.25	0.20	0.05	0.07	0.04	0.02	0.03
YAWVAR	0.57	0.62	0.68	0.79	0.85	0.74	0.70
STEXCEED	0.42	0.48	0.62	0.66	0.60	0.57	0.54
STVELM	-0.17	-0.16	-0.16	-0.06	-0.11	-0.12	-0.11
STVELV	0.40	0.45	0.57	0.55	0.49	0.43	0.49
SMREV	0.12	0.14	0.11	0.14	0.13	0.06	0.12
LGREV	0.45	0.49	0.55	0.60	0.54	0.45	0.51
SEATMOV	0.47	0.45	0.23	0.26	0.37	0.48	0.16
HRTRTM	-0.12	-0.18	-0.23	-0.19	-0.17	-0.27	-0.16
HRTRTV	0.19	0.17	0.15	0.22	0.36	0.30	0.24
HANTRAN	-0.10	-0.09	0.03	0.07	0.14	0.04	0.08
LATPOSM	0.55	0.61	0.70	0.84	0.99	0.89	0.78

R = .24, p = 0.001
R = .28, p = 0.0001

effects data (rested/sober, rested/BAC) appear in Table 15. With few exceptions, the eye measures do not show consistent correlations with the impairment detectors for the alcohol effects data. The variables YAWVAR, HRTRTV, and LATPOSMS show the most promise as impairment detectors for alcohol. In a comparison between the three-minute alcohol effects correlations in Table 7 and the six-minute alcohol effects correlations, the six-minute correlations are again generally higher.

Impairment predictor vs. impairment detector correlations. Six-minute intervals. Combined effects data. The correlations between the impairment predictors and impairment detectors for the combined effects data (rested/sober, sleep deprived/BAC) appear in Table 16. As shown, the variables YAWVAR, STEXCEED, STVELV, LGREV, SEATMOV, HRTRTM, and LATPOSM show relatively high and consistent correlations with eye measures and lane measures. The variable STVELM also shows consistent correlations with both eye measures and lane measures, although these correlations are not as high as with some of the other variables. Again, the correlations for the six-minute interval data were consistently higher than for the corresponding three-minute interval data. In the case of the combined effects data the variable SEATMOV in particular appeared more promising as a detector when the six-minute interval data were considered as opposed to the three-minute interval data.

Correlations: Data Corrected for Individual Differences

The issue of whether or not a baseline of driving behavior data is required at the beginning of a drive for subsequent comparison was dis-

TABLE 15 Impairment Predictor vs. Impairment Detector Correlations. Alcohol Effects Data. Six-Minute Intervals.

	EYEMEAN	EYEMEAS	PERCLOS	LANEX	LANDEVV	LANDEVSQ	LANDEV4
YAWMEAN	0.40	0.38	-0.19	-0.04	-0.06	-0.03	-0.05
YAWVAR	0.08	0.07	0.16	0.26	0.68	0.50	0.46
STEXCEED	-0.02	-0.07	0.01	0.02	-0.02	-0.01	0.01
STVELM	-0.08	-0.06	-0.20	-0.05	-0.11	-0.15	-0.13
STVELV	-0.05	-0.09	-0.09	-0.08	-0.13	-0.12	-0.12
SMREV	-0.09	-0.13	-0.21	-0.13	-0.14	-0.26	-0.21
LGREV	<0.01	-0.03	0.01	0.04	0.08	0.03	0.05
SEATMOV	0.24	0.25	0.12	-0.04	0.14	0.10	0.03
HRTRTM	0.20	0.15	0.05	0.04	-0.06	0.07	0.06
HRTRTV	0.04	0.03	0.47	0.41	0.39	0.52	0.41
HANTRAN	-0.10	-0.11	0.05	0.01	0.11	0.08	0.06
LATPOSM	0.15	0.14	0.31	0.55	0.98	0.83	0.80

R = .24, p = 0.001
R = .28, p = 0.0001

TABLE 16 Impairment Predictor vs. Impairment Detector Correlations. Combined Effects Data. Six-Minute Intervals.

	EYEMEAN	EYEMEAS	PERCLOS	LANEX	LANDEVV	LANDEVSQ	LANDEV4
YAWMEAN	0.19	0.16	-0.17	-0.21	-0.25	-0.26	-0.33
YAWVAR	0.28	0.52	0.75	0.90	0.95	0.93	0.84
STEXCEED	0.20	0.32	0.52	0.53	0.59	0.56	0.55
STVELM	-0.14	-0.21	-0.24	-0.18	-0.19	-0.19	-0.18
STVELV	0.32	0.29	0.34	0.33	0.34	0.31	0.29
SMREV	0.10	-0.03	-0.14	-0.11	-0.14	-0.15	-0.13
LGREV	0.35	0.30	0.27	0.31	0.30	0.27	0.19
SEATMOV	0.22	0.31	0.08	0.26	0.28	0.26	0.13
HRTRTM	0.04	-0.12	-0.29	-0.30	-0.31	-0.31	-0.24
HRTRTV	0.27	0.16	-0.02	0.04	0.07	0.05	-0.02
HANTRAN	-0.05	-0.09	-0.07	<0.01	0.01	-0.01	-0.04
LATPOSM	0.26	0.52	0.77	0.95	0.996	0.98	0.86

R = .24, p = 0.001
R = .28, p = 0.0001

cussed in the data analysis overview section. Such a baseline measure, if implemented, has the potential advantage of reducing inter-subject variability while also increasing the reliability of impairment detection.

To test whether a baseline measure would increase reliability, two methods were implemented. For both methods, the baseline was calculated using the second through sixth intervals of the first segment of the rested/sober run. As indicated earlier, a segment was thirty minutes in length and a run consisted of three segments. The first three-minute interval of data was not used because it appeared during the data runs that there was a brief initial "settling in" period while the subject was regaining the "feel" of the simulator. This "settling in" is probably similar to the experience of driving a new or infrequently driven automobile.

The first method consisted of subtracting the mean of an individual subject's baseline data from all subsequent data values for each variable. For the second method, the baseline mean was subtracted from the data as with the first method, but in addition, each value was divided by the standard deviation of the baseline measure, giving a result similar to standardizing the data. The data were divided by the standard deviation only if four out of the five baseline intervals for any given variable were different, otherwise, only the mean was subtracted as with the first method above. The resulting correlations are described below for each method in the same way that the correlations have been described previously, namely, all data, sleep

effects data, alcohol effects data, and combined effects data. However, only the correlations between the impairment predictors and impairment detectors will be described, since the primary purpose of this baseline approach is to see if detection reliability can be improved.

Impairment predictor vs. impairment detector, mean corrected correlations. Three-minute intervals. All data. The mean corrected correlations between the impairment predictors and impairment detectors for the entire data set appear in Table 17. A comparison between Table 17 and the corresponding "uncorrected" correlations shown in Table 1 shows very little change for the most part. A few of the correlation values increased and a few of the correlation values decreased, but in the majority of cases, the magnitude of the change was small.

Impairment predictor vs. impairment detector, mean corrected correlations. Three-minute intervals. Sleep effects data. The mean corrected correlations between the impairment predictors and impairment detectors for the sleep effects data (rested/sober, sleep deprived/sober) appear in Table 18. In a comparison of Table 18 with the corresponding uncorrected sleep effects data shown in Table 6, it is again seen that some of the correlations changed due to the mean correction. However, as with the full data set, the changes were relatively small and inconsistent.

Impairment predictor vs. impairment detector, mean corrected correlations. Three-minute intervals. Alcohol effects data. The mean corrected correlations between the impairment predictors and impairment detectors for the alcohol effects data (rested/sober, rested/BAC) are

TABLE 17 Impairment Predictor vs. Impairment Detector Mean Corrected Correlations. All Data. Three-Minute Intervals.

	EYEMEAN	EYEMEAS	PERCLOS	LANEX	LANDEVV	LANDEVSQ	LANDEV4
YAWMEAN	0.01	0.01	0.07	0.03	0.05	-0.01	-0.15
YAWVAR	0.23	0.41	0.56	0.82	0.90	0.86	0.76
STEXCEED	0.15	0.26	0.37	0.43	0.50	0.45	0.41
STVELM	-0.18	-0.20	-0.10	-0.04	-0.05	-0.05	-0.08
STVELV	0.12	0.19	0.31	0.29	0.33	0.28	0.21
SMREV	-0.08	-0.10	0.05	0.08	0.15	0.09	0.01
LGREV	0.15	0.25	0.34	0.29	0.30	0.25	0.13
SEATMOV	0.25	0.33	0.12	0.13	0.17	0.17	0.06
HRTRTM	-0.16	-0.20	-0.18	-0.07	-0.07	-0.03	-0.03
HRTRTV	0.05	0.01	-0.01	0.05	0.08	0.12	<0.01
HANTRAN	0.02	0.09	0.07	0.04	0.04	0.01	0.02
LATPOSM	0.25	0.42	0.55	0.90	0.99	0.96	0.83

R = .12, p = 0.001
R = .14, p = 0.0001

TABLE 18 Impairment Predictor vs. Impairment Detector Mean Corrected Correlations. Sleep Effects Data. Three-Minute Intervals.

	EYEMEAN	EYEMEAS	PERCLOS	LANEX	LANDEVV	LANDEVSQ	LANDEV4
YAWMEAN	0.04	0.02	0.17	0.18	0.31	0.13	0.12
YAWVAR	0.41	0.51	0.62	0.72	0.83	0.72	0.64
STEXCEED	0.30	0.38	0.50	0.51	0.53	0.45	0.43
STVELM	-0.26	-0.23	-0.08	0.02	-0.01	-0.03	-0.06
STVELV	0.19	0.31	0.48	0.47	0.52	0.41	0.40
SMREV	-0.12	-0.06	0.09	0.14	0.31	0.17	0.13
LGREV	0.21	0.33	0.48	0.48	0.53	0.43	0.41
SEATMOV	0.42	0.39	0.20	0.16	0.22	0.31	0.08
HRTRTM	-0.23	-0.31	-0.28	-0.22	-0.22	-0.20	-0.23
HRTRTV	0.11	0.13	0.11	0.19	0.27	0.27	0.20
HANTRAN	-0.05	<0.01	0.06	0.06	0.07	0.04	0.05
LATPOSM	0.51	0.56	0.60	0.80	0.99	0.89	0.75

R = .17, p = 0.001
R = .20, p = 0.0001

shown in Table 19. In a comparison between Table 19 and the corresponding uncorrected alcohol effects data set shown in Table 7, any changes due to the mean correction are generally small and inconsistent. Note, however, the increases in correlations between SMREV and EYEMEAN, EYEMEAS, and LANDEVV for the mean corrected case. In this isolated instance, perhaps additional investigation into a possible baseline is warranted if the variable SMREV can be shown to be a reliable detector of alcohol impairment.

Impairment predictor vs. impairment detector, mean corrected correlations. Three-minute intervals. Combined effects data. The mean corrected correlations between the impairment predictors and impairment detectors for the combined effects data set are shown in Table 20. In the comparison of Table 20 with the corresponding uncorrected data of Table 8, there are in general few changes of any magnitude. Note that in the mean corrected case, the correlations between HRTRTM and YAWMEAN and the impairment predictors actually decreased substantially in several instances.

Impairment predictor vs. impairment detector, normalized data correlations. Three-minute intervals. All data. The normalized data correlations between the impairment predictors and impairment detectors for the entire data set appear in Table 21. In the comparison between Table 21 and the corresponding uncorrected data in Table 5, it is shown that many of the higher correlations seen in the uncorrected data were reduced to some extent by normalizing the data. On the whole, the changes in the correlations due to normalization were inconsistent.

TABLE 19 Impairment Predictor vs. Impairment Detector Mean Corrected Correlations. Alcohol Effects Data. Three-Minute Intervals.

	EYEMEAN	EYEMEAS	PERCLOS	LANEX	LANDEVV	LANDEVSQ	LANDEV4
YAWMEAN	0.02	0.02	-0.03	0.12	0.28	0.21	0.18
YAWVAR	-0.03	-0.06	0.09	0.30	0.71	0.51	0.49
STEXCEED	-0.02	-0.02	0.02	0.09	0.08	0.06	0.07
STVELM	-0.21	-0.17	-0.11	0.02	0.06	0.02	<0.01
STVELV	-0.21	-0.19	-0.03	0.01	0.07	0.04	0.02
SMREV	-0.35	-0.33	-0.11	0.03	0.29	0.09	0.08
LGREV	-0.21	-0.17	-0.04	0.07	0.19	0.11	0.09
SEATMOV	0.21	0.23	0.12	-0.03	0.08	0.04	0.01
HRTRTM	0.02	0.08	0.09	0.16	0.02	0.20	0.11
HRTRTV	-0.02	<0.01	0.21	0.31	0.34	0.48	0.38
HANTRAN	-0.15	-0.11	-0.10	-0.08	-0.13	-0.18	-0.13
LATPOSM	0.21	0.15	0.16	0.54	0.98	0.82	0.80

R = .17, p = 0.001
R = .20, p = 0.0001

TABLE 20 Impairment Predictor vs. Impairment Detector Mean Corrected Correlations. Combined Effects Data. Three-Minute Intervals.

	EYEMEAN	EYEMEAS	PERCLOS	LANEX	LANDEVV	LANDEVSQ	LANDEV4
YAWMEAN	0.01	<0.01	-0.01	-0.04	-0.06	-0.11	-0.25
YAWVAR	0.20	0.41	0.57	0.85	0.93	0.91	0.83
STEXCEED	0.10	0.21	0.30	0.43	0.52	0.47	0.46
STVELM	-0.17	-0.21	-0.15	-0.10	-0.09	-0.09	-0.11
STVELV	0.12	0.16	0.25	0.31	0.37	0.32	0.28
SMREV	-0.08	-0.17	-0.04	0.03	0.07	0.03	-0.02
LGREV	0.15	0.21	0.24	0.27	0.27	0.24	0.15
SEATMOV	0.19	0.29	0.06	0.18	0.22	0.21	0.11
HRTRTM	-0.11	-0.07	-0.05	-0.03	-0.02	-0.01	<0.01
HRTRTV	0.18	0.11	-0.01	0.02	0.05	0.06	<0.01
HANTRAN	-0.06	-0.01	<0.01	0.02	<0.01	<0.01	<0.01
LATPOSM	0.22	0.45	0.59	0.92	0.99	0.98	0.86

R = .17, p = 0.001
R = .20, p = 0.0001

TABLE 21 Impairment Predictor vs. Impairment Detector Standardized Correlations. All Data. Three-Minute Intervals.

	EYEMEAN	EYEMEAS	PERCLOS	LANEX	LANDEVV	LANDEVSQ	LANDEV4
YAWMEAN	0.02	0.18	0.07	0.11	0.08	0.13	0.11
YAWVAR	0.29	0.44	0.57	0.49	0.71	0.54	0.43
STEXCEED	0.22	0.33	0.37	0.24	0.45	0.29	0.23
STVELM	-0.19	-0.22	-0.10	0.01	-0.04	-0.01	-0.02
STVELV	0.14	0.16	0.23	0.14	0.20	0.11	0.07
SMREV	0.05	0.03	0.06	0.07	0.14	0.09	0.01
LGREV	0.20	0.22	0.34	0.19	0.20	0.11	0.06
SEATMOV	0.21	0.27	0.30	0.20	0.20	0.24	0.14
HRTRTM	-0.17	-0.25	-0.27	-0.11	-0.04	-0.03	-0.04
HRTRTV	-0.02	0.02	0.02	0.10	0.02	0.10	0.02
HANTRAN	0.18	0.28	0.08	<0.01	0.02	-0.04	0.02
LATPOSM	0.33	0.52	0.52	0.74	0.99	0.92	0.75

R = .12, p = 0.001
R = .14, p = 0.0001

Impairment predictor vs. impairment detector, normalized data correlations. Three-minute intervals. Sleep effects data. The normalized data correlations between the impairment predictors and impairment detectors for the sleep effects data (rested/sober, sleep deprived/sober) appear in Table 22. In the comparison between Table 22 and the corresponding uncorrected sleep effects correlations shown in Table 6, the changes due to normalization were inconsistent. A number of correlations such as YAWVAR and EYEMEAS decreased while several others such as HRTRTM and EYEMEAN increased.

Impairment predictor vs. impairment detector, normalized correlations. Three-minute intervals. Alcohol effects data. The normalized data correlations between the impairment predictors and impairment detectors for the alcohol effects data (rested/sober, rester/BAC) appear in Table 23.

The comparison between Table 23 and the corresponding uncorrected alcohol effects data (Table 7) shows that the results due to data normalization are again inconsistent. Note the large decrease in correlations between YAWVAR and the lane measures.

Impairment predictor vs. impairment detector normalized correlations. Three-minute intervals. Combined effects data. The normalized data correlations between the impairment predictors and impairment detectors for the combined effects data (rested/sober, sleep deprived/BAC) appear in Table 24. In the comparison between Table 24 and the corresponding non-normalized data shown in Table 8, changes in the correlations due to normalization were again inconsistent. Several

TABLE 22 Impairment Predictor vs. Impairment Detector Standardized Correlations. Sleep Effects Data. Three-Minute Intervals.

	EYEMEAN	EYEMEAS	PERCLOS	LANEX	LANDEVV	LANDEVSQ	LANDEV4
YAWMEAN	0.20	0.18	0.17	0.01	0.28	0.14	0.05
YAWVAR	0.34	0.33	0.60	0.70	0.62	0.50	0.60
STEXCEED	0.37	0.37	0.50	0.42	0.47	0.29	0.30
STVELM	-0.25	-0.23	-0.08	0.03	-0.02	-0.03	-0.05
STVELV	0.24	0.25	0.46	0.43	0.44	0.27	0.33
SMREV	0.04	0.04	0.09	0.11	0.27	0.13	0.10
LGREV	0.26	0.26	0.51	0.49	0.44	0.31	0.37
SEATMOV	0.27	0.26	0.20	0.15	0.25	0.29	0.08
HRTRTM	-0.31	-0.30	-0.30	-0.31	-0.22	-0.23	-0.29
HRTRTV	-0.04	-0.03	0.09	0.13	0.06	0.12	0.08
HANTRAN	0.26	0.28	0.11	-0.02	-0.02	-0.08	-0.05
LATPOSM	0.54	0.51	0.53	0.72	0.99	0.90	0.69

R = .17, p = 0.001
R = .20, p = 0.0001

TABLE 23 Impairment Predictor vs. Impairment etector Standardized Correlations. Alcohol Effects Data. Three-Minute Intervals.

	EYEMEAN	EYEMEAS	PERCLOS	LANEX	LANDEVV	LANDEVSQ	LANDEV4
YAWMEAN	-0.03	-0.04	-0.03	0.16	0.30	0.30	0.26
YAWVAR	-0.07	-0.08	0.07	0.21	0.44	0.34	0.29
STEXCEED	<0.01	-0.03	0.02	0.06	0.06	0.05	0.04
STVELM	-0.24	-0.20	-0.11	0.03	0.04	0.01	0.01
STVELV	-0.13	-0.11	-0.02	0.01	0.04	0.01	-0.01
SMREV	-0.12	-0.12	-0.09	0.04	0.22	0.08	0.05
LGREV	-0.16	-0.13	<0.01	0.02	0.08	0.03	0.01
SEATMOV	0.19	0.18	0.12	-0.01	0.09	0.04	0.02
HRTRTM	-0.26	-0.23	0.06	0.14	0.02	0.08	0.02
HRTRTV	-0.07	-0.06	0.19	0.23	0.22	0.28	0.16
HANTRAN	0.06	0.07	-0.02	-0.07	-0.19	-0.20	-0.13
LATPOSM	0.30	0.21	0.17	0.51	0.98	0.87	0.82

R = .17, p = 0.001
R = .20, p = 0.0001

TABLE 24 Impairment Predictor vs. Impairment Detector Standardized Correlations. Combined Effects Data. Three-Minute Intervals.

	EYEMEAN	EYEMEAS	PERCLOS	LANEX	LANDEVV	LANDEVSQ	LANDEV4
YAWMEAN	-0.03	-0.09	-0.01	0.14	-0.02	0.07	-0.01
YAWVAR	0.27	0.56	0.55	0.44	0.82	0.62	0.48
STEXCEED	0.16	0.32	0.30	0.20	0.48	0.31	0.24
STVELM	-0.17	-0.22	-0.15	-0.03	-0.08	-0.04	-0.04
STVELV	0.19	0.20	0.19	0.07	0.25	0.12	0.07
SMREV	0.03	-0.02	-0.03	<0.01	0.07	0.02	-0.04
LGREV	0.19	0.22	0.22	0.07	0.18	0.08	0.03
SEATMOV	0.21	0.37	0.06	0.32	0.27	0.33	0.22
HRTRTM	-0.18	-0.14	-0.02	-0.02	0.02	<0.01	<0.01
HRTRTV	0.06	0.02	0.04	0.11	0.02	0.08	0.05
HANTRAN	0.15	0.32	0.06	0.04	0.04	-0.01	-0.02
LATPOSM	0.31	0.64	0.57	0.77	0.99	0.93	0.77

R = .17, p = 0.001
R = .20, p = 0.0001

increases in correlations did appear, however. Most notably the correlations between some of the eye measures and SEATMOV, HANTRAN, and LATPOSM increased in magnitude with data standardization.

Correlation Summary

Four major issues noted in the correlation analysis results are summarized below:

1. The six-minute correlations appeared to be the most reliable in all instances when compared to the three-minute correlations.
2. The baseline manipulations caused inconsistent results and only showed advantages in isolated instances.
3. A number of variables showed promise for detection for each of the four data sets used (all data, sleep effects data, alcohol effects data, and combined effects data). These variables are summarized in Table 25.
4. Eye measures and lane measures showed high correlations for all sets of data with the exception of the alcohol effects data.

Analysis of Variance (ANOVA)

The analysis of variance (ANOVA) technique was used as the second step in the determination of the reliability of each dependent measure for detection of impairment. ANOVAs are generally used to determine whether or not two or more samples come from a single population or from different populations. In most instances, a criterion probability level is set, usually 0.05 or 0.01, such that if the probability of the

TABLE 25 Summary of Potentially Reliable Impairment Detectors Based on the Correlation Analysis.

Type of Impairment			
Alcohol	Drowsiness	Combined Effects	General (All Data)
YAWVAR	YAWVAR	YAWVAR	YAWVAR
HRTRTV	STEXEED	STEXEED	STEXEED
LATPOSM	STVELVAR	STVELVAR	STVELVAR
	LGREV	LGREV	LGREV
	SEATMOV	SEATMOV	HRTRTM
	HRTRTM	LATPOSM	
	HRTRTV	STVELM	

samples coming from the same population (as given by the ANOVA) falls below the specified criterion, then the samples are judged to be different.

For the current analysis, the judgement of whether or not the levels of the sleep, alcohol, and time-on-task conditions are different from one another as indicated by a single variable or combinations of variables is of interest, but is secondary in terms of importance. The ANOVAs for each variable have been used to determine which variables show the greatest sensitivity for detection based on the degree of separation for a given condition. A low p-value associated with a given variable for a given condition indicates that the variable is sensitive to some degree to differences between levels of the condition, and therefore could potentially be used to discriminate between the levels.

Generally, when multiple dependent measures are collected for an analysis of this type, a multivariate analysis of variance (MANOVA) is initially conducted. The MANOVA takes all dependent measures into account to determine whether differences exist between levels of a given condition. The advantage to this approach is that a determination can be made as to whether any differences exist when all variables are considered. If no differences in the MANOVA are found, any differences found in subsequent univariate tests would be due to chance associated with running multiple tests at a given probability level. (For example, if twenty univariate ANOVAs are run, by chance at least one in twenty would be likely to be significant at the $p<0.05$ level). If, on the other hand, the MANOVA is found to be significant, univariate ANOVAs

could be run in order to find where the differences are found with greater assurance that some of the differences associated with the individual variables are not due chance.

A MANOVA was not conducted as part of this analysis for the following reasons. First, there were a large number of dependent variables collected for this study, while only six subjects were used. The small number of subjects was necessary due to both the high cost associated with each subject and the experimenter time required. Note that 24 separate runs were made for this experiment, 12 of which required three experimenters to remain awake almost an entire night. The largest number of variables that can be analyzed with the MANOVA technique is $n-1$, which for this case, is equal to five. Therefore, to analyze all of the variables, multiple MANOVAs would have had to be run, thus limiting to some degree the protection afforded by the MANOVA as discussed above.

Second, when the number of variables in the MANOVA model is close to the number of subjects for which the data were collected, statistical power is lost. This creates a trade-off dilemma between wanting to maintain a reasonably powerful test but wanting to run as few MANOVAs as possible. In order to maintain reasonable statistical power, as many as six MANOVAs would be required in this instance.

For the reasons stated above, only univariate ANOVAs were calculated for this analysis. Since a MANOVA was not performed, and since there were a large number of variables collected for this research, the ANOVA results will not be described in terms of significant differences, but will only be treated as indicators of the degree of separation associ-

ated with each variable for each of the three conditions and the interactions.

For a variable to be considered as a potentially reliable detector, a p-value of less than 0.20 will be used as a criterion value. The value 0.20 was selected because it indicates separation (with 80% confidence) which could prove useful in a multivariate model, and because it eliminates some of the larger p-values for which differences are most likely to be due to chance.

The types of impairment detection will be considered in much the same way as was done for the correlation analysis, namely general impairment (all data), drowsiness impairment, alcohol impairment and combined-effects impairment. The ANOVA summary tables will be summarized for the impairment predictors followed by the impairment detectors. The terms "very low," "low," and "within criterion," will be used qualitatively throughout the following summary to denote order of magnitude differences in the p-values under consideration.

Impairment Predictor ANOVAs--Eye Measures

EYEMEAN. The ANOVA summary table for the variable EYEMEAN appears as Table 26. The p-value for the segment (time-on-task) condition was very small, the p-value for the sleep condition was small and the p-values for the sleep by segment and alcohol by sleep by segment interactions were within the criterion of 0.20. This indicates that EYEMEAN is sensitive to sleep, time-on-task and the interaction.

EYEMEAS. The ANOVA summary table for the variable EYEMEAS appears

TABLE 26 Analysis of Variance Summary Table for the Variable EYEMEAN

Source	df	SS	F	p
Alcohol	1	4336.71	1.76	0.2424
Alcohol x subject	5	12343.16		
Sleep	1	127150.75	20.54	0.0062
Sleep x subject	5	30945.39		
Segment	2	127708.58	22.80	0.0002
Segment x subject	10	28011.77		
Alcohol x sleep	1	106.72	0.11	0.7590
Alcohol x sleep x subject	5	5079.06		
Alcohol x segment	2	3129.66	1.23	0.3334
Alcohol x segment x subject	10	12737.71		
Sleep x segment	2	20135.61	3.19	0.0849
Sleep x segment x subject	10	31576.34		
Alcohol x sleep x segment	2	7463.66	3.58	0.0674
Alcohol x sleep x segment x subject	10	10435.72		

as Table 27. The p-value for the segment (time-on-task) condition was very low and the p-values for the sleep condition and the sleep by segment interaction were low. This indicates that EYEMEAS is sensitive to sleep, time-on-task and the interaction of sleep and time-on-task.

PERCLOS. The ANOVA summary table for the variable PERCLOS appears as Table 28. The results shown are similar to the other eye measures, in that the conditions sleep and segment (time-on-task) and the sleep by segment interaction have small p-values.

It is apparent that the impairment due to "drowsiness" as referenced throughout this study and measured through eye closures occurs in large part from the interaction of sleep deprivation and time-on-task induced fatigue. This point is illustrated in Figure 2. As the figure shows, the most pronounced effect in terms of an impaired driver is not due to the sleep condition alone (as indicated by the relatively small difference between sleep conditions for the first segment) or time-on-task alone (as indicated by the slope of the line for the rested condition) but by the interaction of sleep deprivation and time-on-task.

Impairment Predictor ANOVAs--Lane Measures

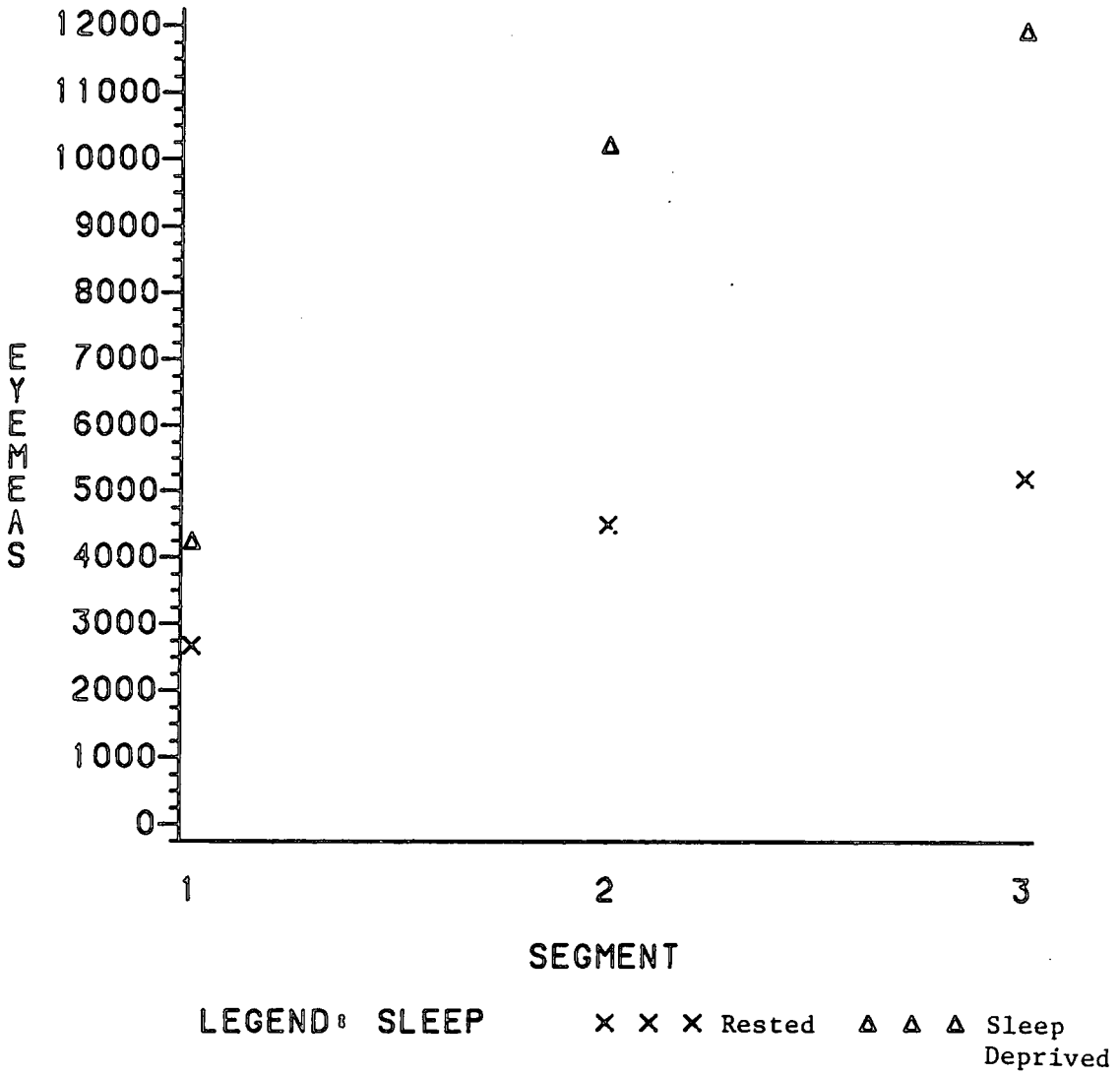
LANEX. The ANOVA summary table for the variable LANEX appears as Table 29. The p-value for the segment (time-on-task) condition was low and the p-values for the sleep condition and sleep by segment interaction were within the criterion of $p<0.20$. This reflects a pattern similar to that which was found for the eye closures, although it is not as pronounced. The degree of separation relating to the alcohol condi-

TABLE 27 Analysis of Variance Summary Table for the Variable EYEMEAS

Source	df	SS	F	p
Alcohol	1	52780676	0.48	0.5211
Alcohol x subject	5	554868270		
Sleep	1	3933643090	16.50	0.0097
Sleep x subject	5	1192069661		
Segment	2	3438868019	24.59	0.0001
Segment x subject	10	699140200		
Alcohol x sleep	1	8636760	0.14	0.7221
Alcohol x sleep x subject	5	304813190		
Alcohol x segment	2	39356046	0.37	0.6981
Alcohol x segment x subject	10	528058100		
Sleep x segment	2	897480564	6.06	0.0189
Sleep x segment x subject	10	740730776		
Alcohol x sleep x segment	2	88609867	0.81	0.4727
Alcohol x sleep x segment x subject	10	548021376		

TABLE 28 Analysis of Variance Summary Table for the Variable PERCLOS

Source	df	SS	F	p
Alcohol	1	3.63	0.06	0.8148
Alcohol x subject	5	297.67		
Sleep	1	1645.49	4.11	0.0984
Sleep x subject	5	2000.70		
Segment	2	701.47	4.28	0.0454
Segment x subject	10	819.63		
Alcohol x sleep	1	0.21	< 0.01	0.9549
Alcohol x sleep x subject	5	290.76		
Alcohol x segment	2	18.25	0.29	0.7576
Alcohol x segment x subject	10	319.75		
Sleep x segment	2	575.64	3.35	0.0772
Sleep x segment x subject	10	860.18		
Alcohol x sleep x segment	2	21.31	0.31	0.7370
Alcohol x sleep x segment x subject	10	338.50		



* Note: For a discussion of the measure EYEMEAS, see the data analysis overview and dependent measure definitions section.

Weighted Eye Closure (Mean Square)

SLEEP	F (1,5) = 16.50, p = .010
SEGMENT	F (2,10) = 24.59, p = .0001
SLEEP X SEGMENT	F (2,10) = 6.06, p = .019

Figure 2. EYEMEAS vs. SEGMENT means plotted by sleep level.

TABLE 29 Analysis of Variance Summary Table for the Variable LANEX

Source	df	SS	F	p
Alcohol	1	3199.72	1.71	0.2481
Alcohol x subject	5	9366.20		
Sleep	1	11663.05	2.85	0.1520
Sleep x subject	5	20438.64		
Segment	2	10192.01	4.54	0.0394
Segment x subject	10	11212.89		
Alcohol x sleep	1	1934.46	0.87	0.3929
Alcohol x sleep x subject	5	11072.88		
Alcohol x segment	2	2012.40	1.48	0.2744
Alcohol x segment x subject	10	6818.70		
Sleep x segment	2	7623.23	2.85	0.1049
Sleep x segment x subject	10	13381.91		
Alcohol x sleep x segment	2	1025.10	0.69	0.5222
Alcohol x sleep x segment x subject	10	7387.57		

tion and alcohol interactions did not fall within the criterion value of $p<0.20$.

LANDEVV. The ANOVA summary table for the variable LANDEVV appears as Table 30. The p-values for the segment (time-on-task) condition and the sleep by segment interaction were low, and the p-value for the sleep condition was within the criterion value of $p<0.20$. This is a similar pattern to that described in the eye measures discussion. Note that the alcohol condition and alcohol by segment interaction separation fell just outside the criterion. This is the first indication of any alcohol related separation shown to this point.

LANDEVSQ. The ANOVA summary table for the variable LANDEVSQ appears as Table 31. The p-value for the segment condition was low and the p-values for the alcohol and sleep conditions and the alcohol by segment and sleep by segment interactions were within the criterion value of $p<0.20$. Again, the pattern associated with the sleep/time-on-task interaction was apparent, although it is not as pronounced as it was with the eye measures. In addition to this, however, LANDEVSQ shows separation for the alcohol condition and the alcohol by segment interaction.

LANDEV4. The ANOVA summary table for the variable LANDEV4 appears as Table 32. Only the segment condition was within the criterion value of 0.20 for LANDEV4.

The pattern of the drowsiness/time-on-task interaction noted for the eye measures was also apparent for several of the lane measures (LANEX, LANDEVV, and LANDEVSQ). This is illustrated by Figure 3 for LANDEVSQ.

TABLE 30 Analysis of Variance Summary Table for the Variable LANDEVV

Source	df	SS	F	p
Alcohol	1	406138	2.03	0.2140
Alcohol x subject	5	1002685		
Sleep	1	1171730	2.95	0.1465
Sleep x subject	5	1985533		
Segment	2	1387040	7.13	0.0119
Segment x subject	10	972243		
Alcohol x sleep	1	193518	1.02	0.3585
Alcohol x sleep x subject	5	946852		
Alcohol x segment	2	223250	1.87	0.2036
Alcohol x segment x subject	10	595564		
Sleep x segment	2	748678	3.62	0.0658
Sleep x segment x subject	10	1035295		
Alcohol x sleep x segment	2	104797	0.73	0.5050
Alcohol x sleep x segment x subject	10	715812		

TABLE 31 Analysis of Variance Summary Table for the Variable LANDEVSQ

Source	df	SS	F	p
Alcohol	1	548495	2.33	0.1870
Alcohol x subject	5	1174566		
Sleep	1	1714130	3.27	0.1303
Sleep x subject	5	2620596		
Segment	2	1505422	6.72	0.0141
Segment x subject	10	1119643		
Alcohol x sleep	1	63915	0.24	0.6457
Alcohol x sleep x subject	5	1337464		
Alcohol x segment	2	332603	2.23	0.1586
Alcohol x segment x subject	10	746898		
Sleep x segment	2	840782	2.70	0.1155
Sleep x segment x subject	10	1557379		
Alcohol x sleep x segment	2	149463	0.74	0.4997
Alcohol x sleep x segment x subject	10	1004128		

TABLE 32 Analysis of Variance Summary Table for the Variable LANDEV4

Source	df	SS	F	p
Alcohol	1	3.374×10^{13}	1.47	0.2801
Alcohol x subject	5	1.150×10^{14}		
Sleep	1	5.140×10^{13}	1.82	0.2350
Sleep x subject	5	1.410×10^{14}		
Segment	2	5.497×10^{13}	1.96	0.1915
Segment x subject	10	1.402×10^{14}		
Alcohol x sleep	1	2.959×10^{13}	1.24	0.3155
Alcohol x sleep x subject	5	1.190×10^{14}		
Alcohol x segment	2	3.373×10^{13}	1.37	0.2977
Alcohol x segment x subject	10	1.230×10^{14}		
Sleep x segment	2	5.003×10^{13}	1.73	0.2258
Sleep x segment x subject	10	1.443×10^{14}		
Alcohol x sleep x segment	2	3.035×10^{13}	1.21	0.3374
Alcohol x sleep x segment x subject	10	1.250×10^{14}		

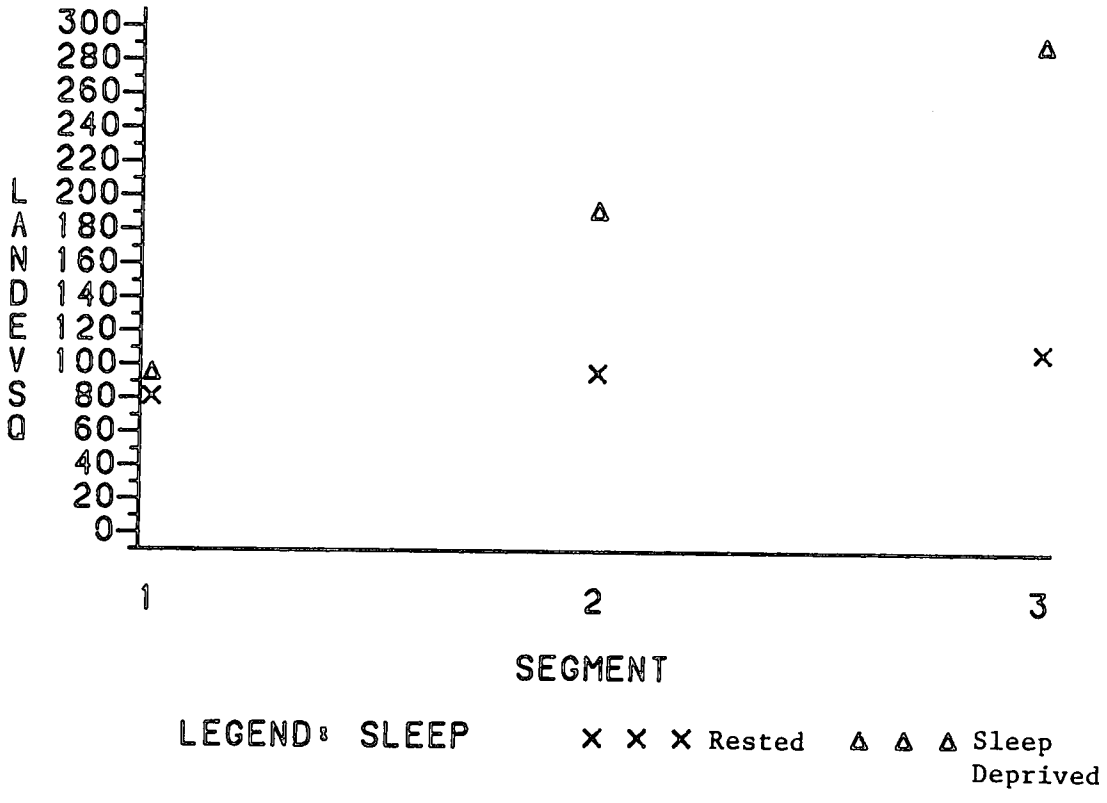
As shown in Figure 3, the p-values associated with this finding were not as low as for the eye measures and therefore must be interpreted with caution. However, the pattern associated with the interaction of sleep and time-on-task is the same.

Unlike the eye measures, the variable LANDEVSQ showed some degree of separation for the alcohol and alcohol by segment interaction. This finding is illustrated in Figure 4. The variable LANDEVSQ appears to be the most reliable general predictor of impairment in terms of separation across both the drowsiness and alcohol conditions. Since it did separate for both drowsiness and alcohol, and could potentially be implemented in an automobile, it was considered as an impairment detector in subsequent analyses. (For further discussion on impairment predictors vs. impairment detectors, see the data analysis overview section.)

Impairment Detectors

YAWMEAN. The ANOVA summary table for the variable YAWMEAN appears as Table 33. A very low p-value exists for the segment (time-on-task) condition. The p-value for the sleep condition was also within the criterion value of 0.20. YAWMEAN appears to have potential as a drowsiness detector.

YAWVAR. The ANOVA summary table for the variable YAWVAR appears as Table 34. A low p-value exists for the segment (time-on-task) condition. The p-values for the sleep condition and sleep by segment interaction were also within the criterion $p<0.20$. YAWVAR appears to have potential as a drowsiness detector. The pattern of drowsiness/time-

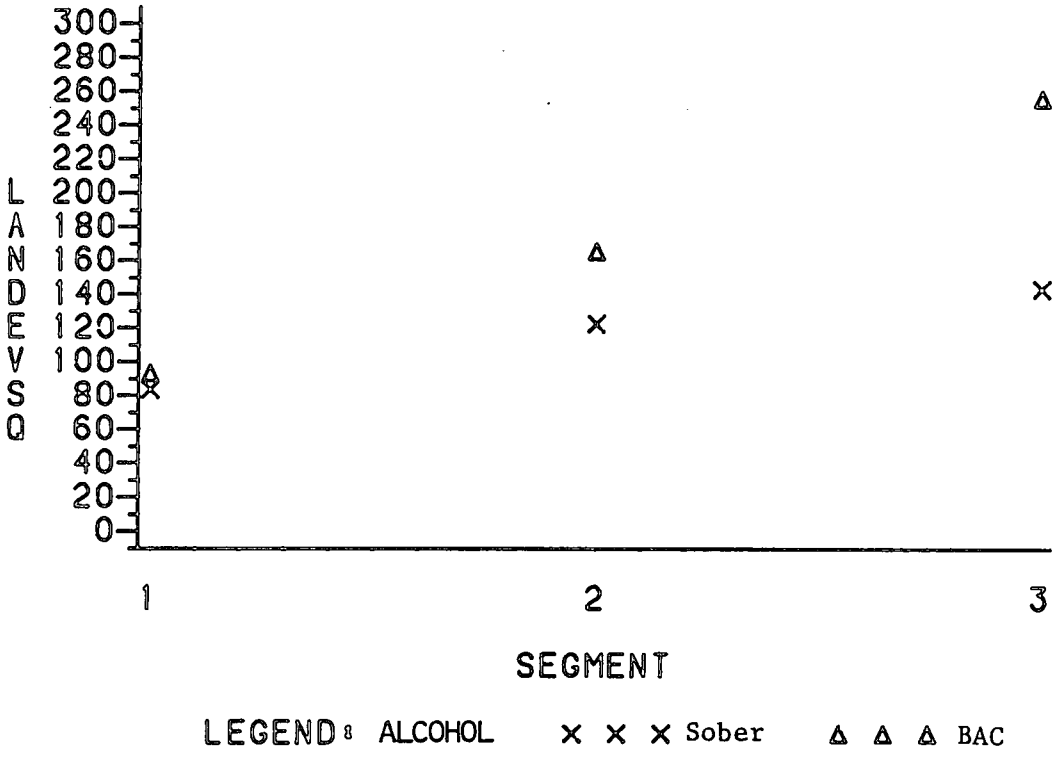


* Note: For a discussion of the measure LANDEVSQ, see the data analysis overview and dependent measure definitions section.

Weighted Lane Deviation (Mean Square)

SLEEP	F (1,5) = 3.27, p = .130
SEGMENT	F (2,10) = 6.72, p = .014
SLEEP X SEGMENT	F (2,10) = 2.70, p = .116

Figure 3. LANDEVSQ vs. SEGMENT means plotted by sleep level.



* Note: For a discussion of the measure LANDEVSQ, see the data analysis overview and dependent measure definitions section.

Weighted Lane Deviation (Mean Square)

ALCOHOL	F (1,5) = 2.33, p = .1870
SEGMENT	F (2,10) = 6.72, p = .0141
ALCOHOL X SEGMENT	F (2,10) = 2.23, p = .1586

Figure 4. LANDEVSQ vs. SEGMENT means plotted by alcohol level.

TABLE 33 Analysis of Variance Summary Table for the Variable YAWMEAN

Source	df	SS	F	p
Alcohol	1	0.0039	< 0.01	0.9379
Alcohol x subject	5	2.9392		
Sleep	1	0.2982	3.61	0.1159
Sleep x subject	5	0.4130		
Segment	2	0.8641	35.67	0.0001
Segment x subject	10	0.1211		
Alcohol x sleep	1	0.0503	0.16	0.7094
Alcohol x sleep x subject	5	1.6151		
Alcohol x segment	2	0.0096	1.25	0.3275
Alcohol x segment x subject	10	0.0382		
Sleep x segment	2	0.0230	1.29	0.3186
Sleep x segment x subject	10	0.0895		
Alcohol x sleep x segment	2	0.0200	2.00	0.1856
Alcohol x sleep x segment x subject	10	0.0499		

TABLE 34 Analysis of Variance Summary Table for the Variable YAWVAR

Source	df	SS	F	p
Alcohol	1	10694.71	0.74	0.4290
Alcohol x subject	5	71974.84		
Sleep	1	138382.68	3.77	0.1097
Sleep x subject	5	183383.85		
Segment	2	141106.07	8.08	0.0082
Segment x subject	10	87294.23		
Alcohol x sleep	1	13516.53	0.72	0.4360
Alcohol x sleep x subject	5	94339.88		
Alcohol x segment	2	12791.60	1.11	0.3668
Alcohol x segment x subject	10	57586.14		
Sleep x segment	2	74843.78	4.44	0.0417
Sleep x segment x subject	10	84326.81		
Alcohol x sleep x segment	2	7801.33	0.55	0.5945
Alcohol x sleep x segment x subject	10	71165. 31		

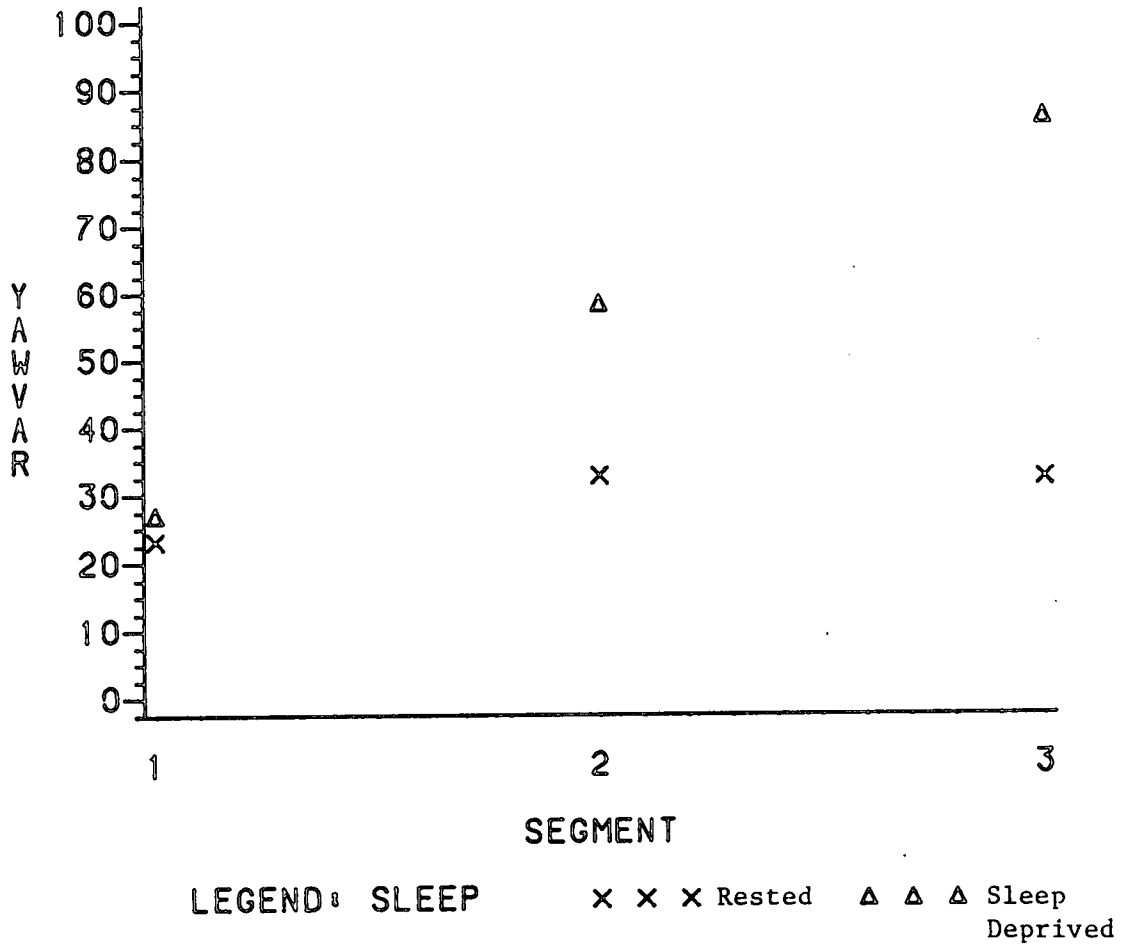
on-task interaction was similar to the eye and lane measures. This pattern is illustrated in Figure 5.

STEXEED. The ANOVA summary table for the variable STEXEED appears as Table 35. The p-values for the sleep and segment conditions and the sleep by segment interactions were within the criterion value of $p<0.20$. STEXEED shows some potential as a drowsiness detector.

STVELM. The ANOVA summary table for the variable STVELM appears as Table 36. A very low p-value exists for the segment (time-on-task) condition with the p-values for the alcohol and sleep conditions and the alcohol by sleep interaction falling within the criterion value of $p<0.20$. STVELM shows potential as an alcohol, drowsiness and general impairment detector.

STVELVAR. The ANOVA Summary Table for the variable STVELVAR appears as Table 37. Low p-values exist for both the segment (time-on-task) condition and the sleep by segment interaction. The p-values for the sleep condition and alcohol by sleep interaction also fall within the criterion value of $p<0.20$, but the alcohol condition does not. STVELVAR shows potential as a drowsiness detector, exhibiting the sleep/time-on-task pattern seen previously. This pattern is illustrated for STVELVAR in Figure 6.

SMREV. The ANOVA Summary Table for the variable SMREV appears as Table 38. Low p-values exist for the segment (time-on-task) condition and for the alcohol by sleep and alcohol by segment interactions. A p-value just greater than the criterion value of 0.20 also exists for the alcohol condition. SMREV thus shows some potential as an alcohol detec-



* Note: For a discussion of the measure YAWVAR, see the data analysis overview and dependent measure definitions section.

Yaw Variance

SLEEP	F (1,5) = 3.77, p = .110
SEGMENT	F (2,10) = 8.08, p = .008
SLEEP X SEGMENT	F (2,10) = 4.44, p = .042

Figure 5. YAWVAR vs. SEGMENT means plotted by sleep level.

TABLE 35 Analysis of Variance Summary Table for the Variable STEXEED

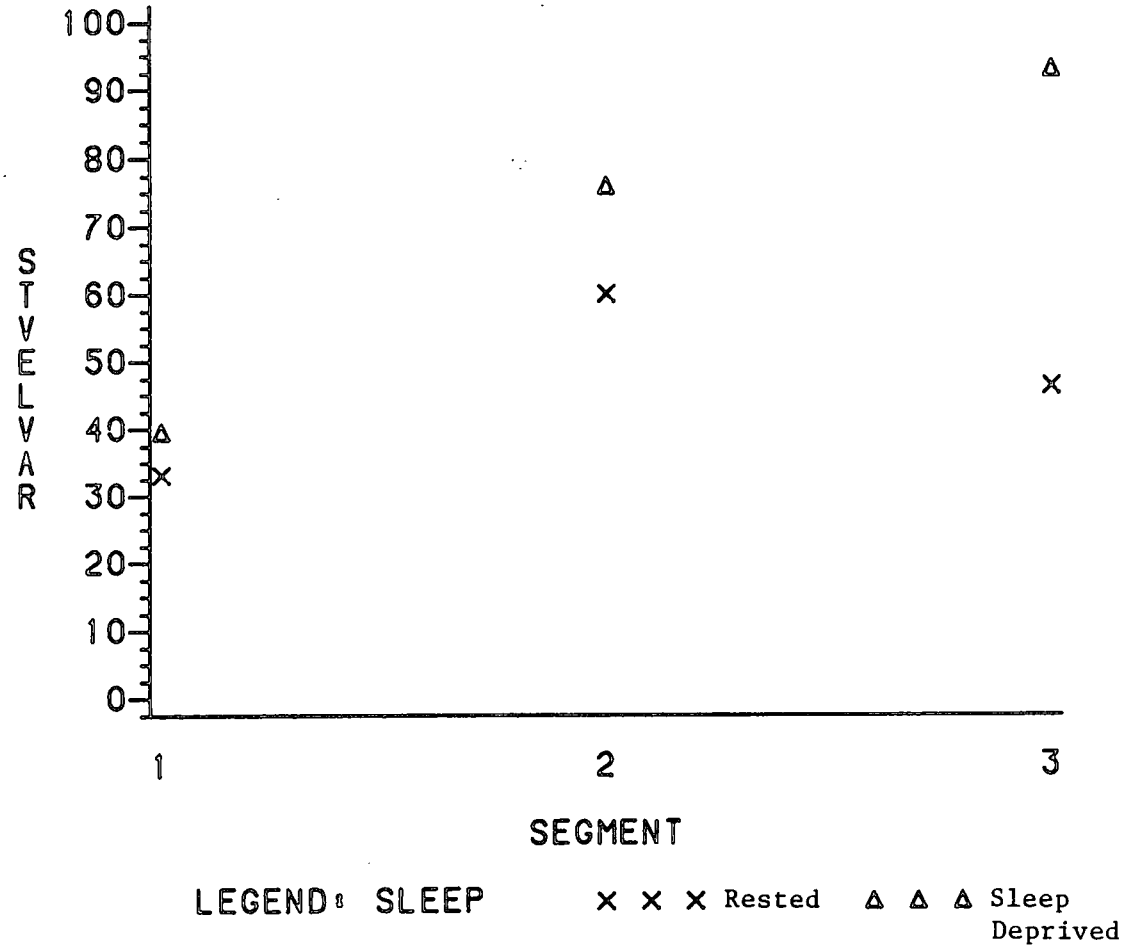
Source	df	SS	F	p
Alcohol	1	0.0347	0.01	0.9440
Alcohol x subject	5	31.84		
Sleep	1	212.33	2.46	0.1776
Sleep x subject	5	431.71		
Segment	2	143.45	2.91	0.1008
Segment x subject	10	246.33		
Alcohol x sleep	1	1.01	0.09	0.7818
Alcohol x sleep x subject	5	59.23		
Alcohol x segment	2	14.25	1.15	0.3543
Alcohol x segment x subject	10	61.79		
Sleep x segment	2	116.60	2.46	0.1353
Sleep x segment x subject	10	237.08		
Alcohol x sleep x segment	2	11.86	1.05	0.3853
Alcohol x sleep x segment x subject	10	56.43		

TABLE 36 Analysis of Variance Summary Table for the Variable STVELM

Source	df	SS	F	p
Alcohol	1	0.3351	2.75	0.1584
Alcohol x subject	5	0.0610		
Sleep	1	0.0437	2.72	0.1600
Sleep x subject	5	0.0803		
Segment	2	0.1355	42.20	0.0001
Segment x subject	10	0.0161		
Alcohol x sleep	1	0.0227	4.85	0.0789
Alcohol x sleep x subject	5	0.0234		
Alcohol x segment	2	0.0039	1.44	0.2823
Alcohol x segment x subject	10	0.0135		
Sleep x segment	2	0.0028	0.77	0.4899
Sleep x segment x subject	10	0.0185		
Alcohol x sleep x segment	2	0.0016	0.49	0.6278
Alcohol x sleep x segment x subject	10	0.0169		

TABLE 37 Analysis of Variance Summary Table for the Variable STVELVAR

Source	df	SS	F	p
Alcohol	1	0.05	< 0.01	0.9965
Alcohol x subject	5	13163.45		
Sleep	1	96208.65	2.45	0.1783
Sleep x subject	5	196377.60		
Segment	2	168920.88	5.45	0.0251
Segment x subject	10	155115.23		
Alcohol x sleep	1	11470.79	2.31	0.1888
Alcohol x sleep x subject	5	24794.25		
Alcohol x segment	2	4749.25	1.18	0.3455
Alcohol x segment x subject	10	20051.35		
Sleep x segment	2	53617.61	4.65	0.0374
Sleep x segment x subject	10	57680.78		
Alcohol x sleep x segment	2	7330.69	1.08	0.3770
Alcohol x sleep x segment x subject	10	34024.63		



* Note: For a discussion of the measure STVELVAR, see the data analysis overview and dependent measure definitions section.

Steering Velocity Variance

SLEEP	F (1,5) = 2.45, p = .180
SEGMENT	F (2,10) = 5.45, p = .025
SLEEP X SEGMENT	F (2,10) = 4.65, p = .037

Figure 6. STVELVAR vs. SEGMENT means plotted by sleep level.

TABLE 38 Analysis of Variance Summary Table for the Variable SMREV

Source	df	SS	F	p
Alcohol	1	23816.50	2.14	0.2035
Alcohol x subject	5	55674.71		
Sleep	1	310.73	0.08	0.7857
Sleep x subject	5	18868.04		
Segment	2	62907.25	7.10	0.0120
Segment x subject	10	44273.15		
Alcohol x sleep	1	39738.61	5.97	0.0584
Alcohol x sleep x subject	5	33293.00		
Alcohol x segment	2	5233.84	3.56	0.0679
Alcohol x segment x subject	10	7347.23		
Sleep x segment	2	7153.17	0.99	0.4037
Sleep x segment x subject	10	35960.03		
Alcohol x sleep x segment	2	1139.31	0.14	0.8699
Alcohol x sleep x segment x subject	10	40315.56		

tor and perhaps as a combined effects detector.

LGREV. The ANOVA Summary Table for the variable LGREV appears as Table 39. Low p-values exist for the sleep and segment (time-on-task) conditions and for the sleep by segment interaction. LGREV shows potential for drowsiness detection and shows the same pattern of sleep/time-on-task interaction as seen previously. A plot of LGREV vs. time-on-task by sleep illustrates this pattern again, and is shown in Figure 7.

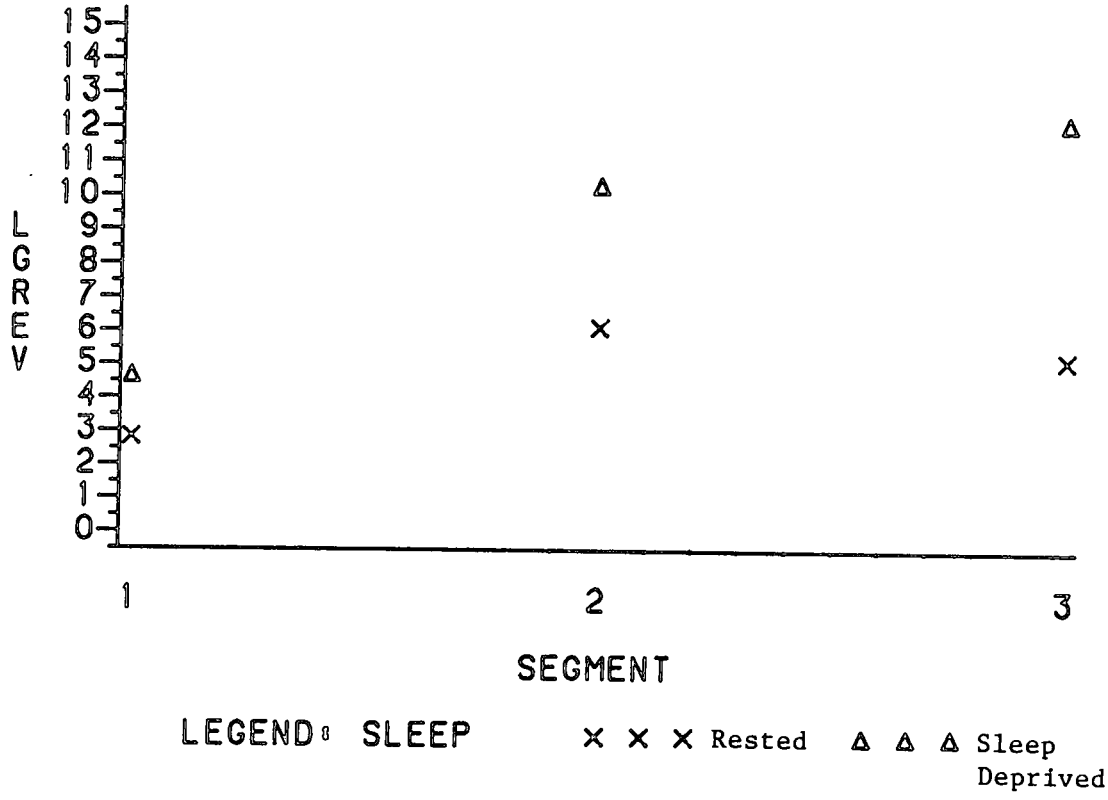
SEATMOV. The ANOVA Summary Table for the variable SEATMOV appears as Table 40. A very low p-value exists for the segment condition and low p-values exist for the sleep condition and sleep by segment interaction. SEATMOV shows potential for drowsiness detection. A plot of SEATMOV vs. segment by sleep condition appears in Figure 8.

HRTRTM. The ANOVA Summary Table for the variable HRTRTM appears as Table 41. Low p-values exist for all three conditions as well as for the sleep by segment and alcohol by sleep by segment interaction. HRTRTM shows potential for general impairment detection as well as drowsiness, alcohol, and combined effects detection. Plots of HRTRTM vs. segment by sleep and HRTRTM vs. segment by alcohol illustrate this potential for detection, and appear in Figures 9 and 10, respectively.

HRTRTV. The ANOVA Summary Table for the variable HRTRTV appears as Table 42. Low p-values exist for the segment (time-on-task) condition and the sleep by segment interaction. No other main effects or interactions show much separation, however. Therefore, HRTRTV does not show much potential for detection.

TABLE 39 Analysis of Variance Summary Table for the Variable LGREV

Source	df	SS	F	p
Alcohol	1	28.80	0.88	0.3907
Alcohol x subject	5	163.23		
Sleep	1	3423.47	4.50	0.0875
Sleep x subject	5	3807.03		
Segment	2	3639.01	5.21	0.0282
Segment x subject	10	3492.91		
Alcohol x sleep	1	215.61	1.35	0.2983
Alcohol x sleep x subject	5	800.73		
Alcohol x segment	2	65.16	1.67	0.2361
Alcohol x segment x subject	10	194.66		
Sleep x segment	2	821.60	5.92	0.0202
Sleep x segment x subject	10	694.25		
Alcohol x sleep x segment	2	87.39	0.69	0.5249
Alcohol x sleep x segment x subject	10	635.23		



* Note: For a discussion of the measure of LGREV, see the data analysis overview and dependent measure definitions section.

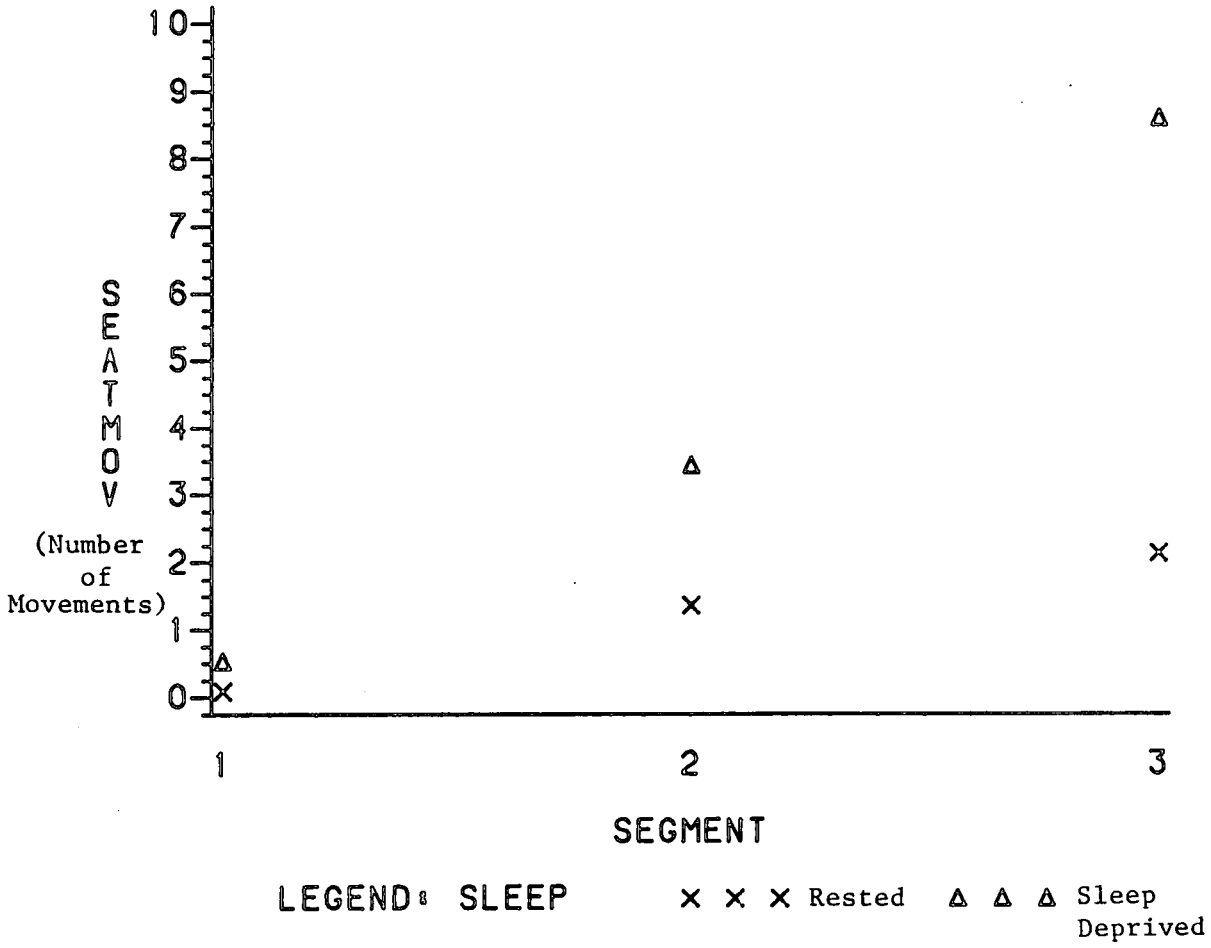
Large Steering Reversals

SLEEP	F (1,5) = 4.50, p = .088
SEGMENT	F (2,10) = 5.21, p = .028
SLEEP X SEGMENT	F (2,10) = 5.92, p = .020

Figure 7. LGREV vs. SEGMENT means plotted by sleep level.

TABLE 40 Analysis of Variance Summary Table for the Variable SEATMOV

Source	df	SS	F	p
Alcohol	1	78.01	0.83	0.4027
Alcohol x subject	5	467.15		
Sleep	1	1611.01	6.39	0.0526
Sleep x subject	5	1260.11		
Segment	2	3102.81	13.43	0.0015
Segment x subject	10	1154.79		
Alcohol x sleep	1	165.31	0.95	0.3734
Alcohol x sleep x subject	5	865.85		
Alcohol x segment	2	5.31	0.06	0.9396
Alcohol x segment x subject	10	423.46		
Sleep x segment	2	1167.66	6.34	0.0167
Sleep x segment x subject	10	921.04		
Alcohol x sleep x segment	2	47.16	0.37	0.6971
Alcohol x sleep x segment x subject	10	630.31		



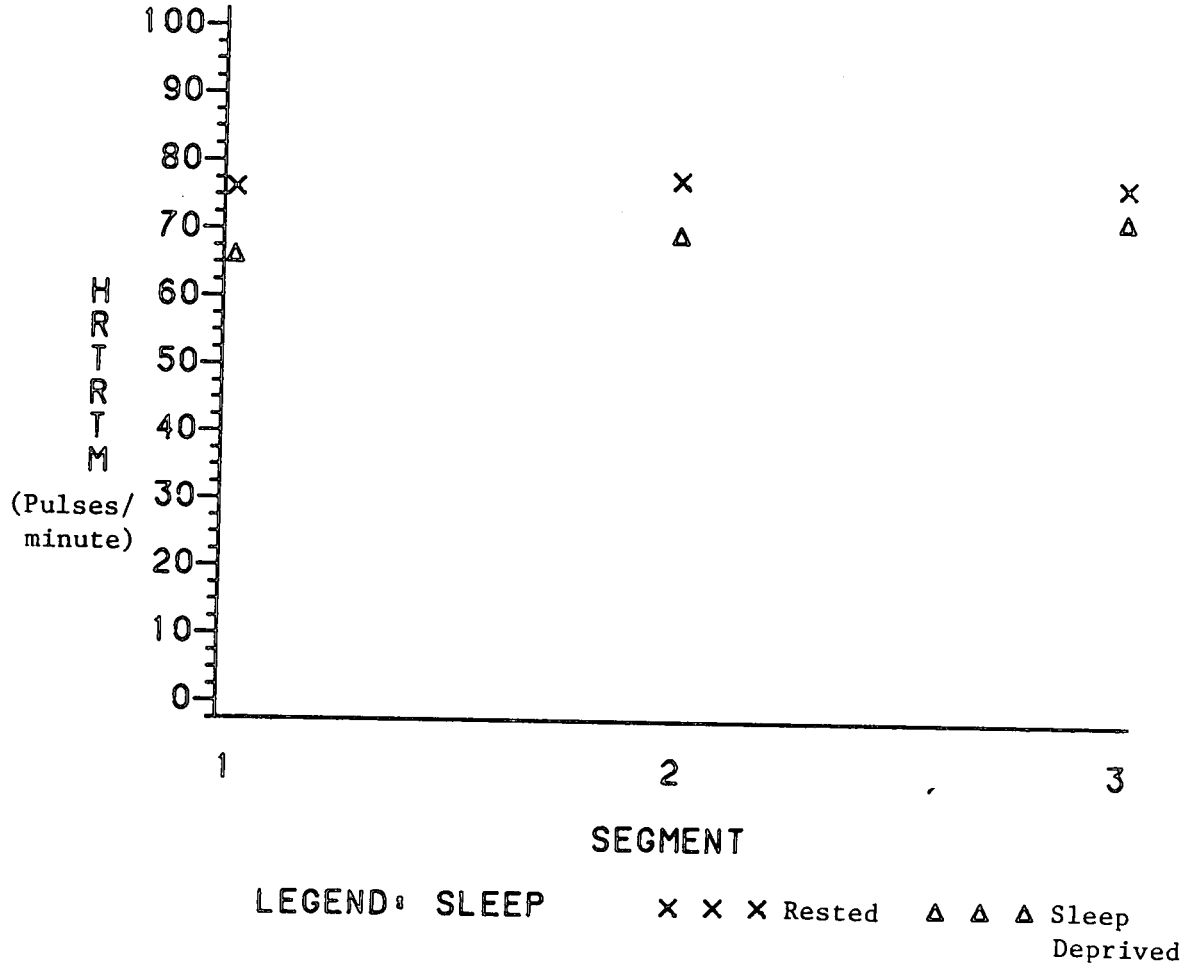
Seat Movements

SLEEP	F (1,5) = 6.39, p = .053
SEGMENT	F (2,10) = 13.43, p = .002
SLEEP X SEGMENT	F (2,10) = 6.34, p = .017

Figure 8. SEATMOV vs. SEGMENT means plotted by sleep level.

TABLE 41 Analysis of Variance Summary Table for the Variable HRTRTM

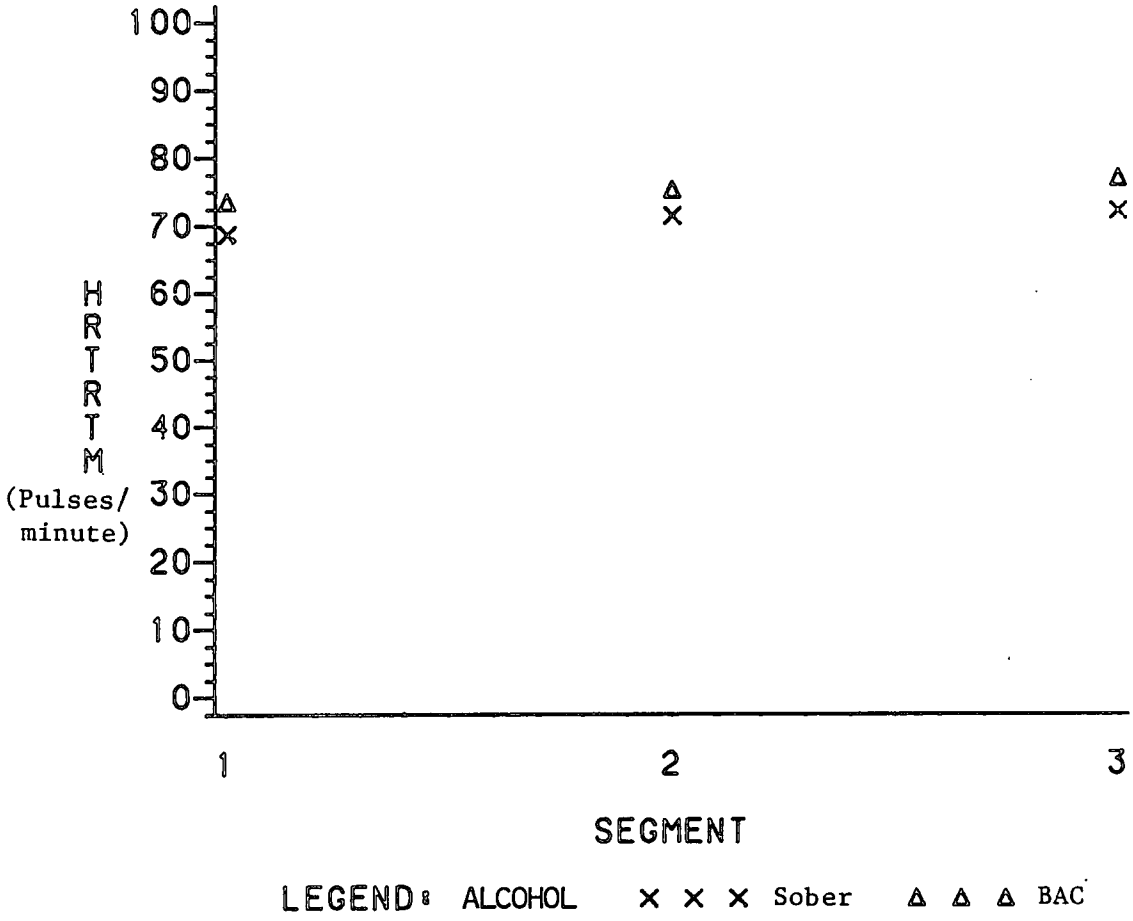
Source	df	SS	F	p
Alcohol	1	3673.90	9.51	0.0273
Alcohol x subject	5	1931.21		
Sleep	1	10430.95	7.11	0.0445
Sleep x subject	5	7334.59		
Segment	2	1590.73	10.02	0.0041
Segment x subject	10	794.04		
Alcohol x sleep	1	1048.23	1.92	0.2244
Alcohol x sleep x subject	5	2729.27		
Alcohol x segment	2	39.54	0.79	0.4818
Alcohol x segment x subject	10	251.48		
Sleep x segment	2	742.16	3.62	0.0657
Sleep x segment x subject	10	1025.61		
Alcohol x sleep x segment	2	176.59	3.23	0.0826
Alcohol x sleep x segment x subject	10	273.07		



Heart Rate Mean

SLEEP	F (1,5) = 7.11, p = .045
SEGMENT	F (2,10) = 10.02, p = .044
SLEEP X SEGMENT	F (2,10) = 3.62, p = .066

Figure 9. HRTRTM vs. SEGMENT means plotted by sleep level.



Heart Rate Mean

SLEEP	F (1,5) = 9.51, p = .027
SEGMENT	F (2,10) = 10.02, p = .044
SLEEP X SEGMENT	F (2,10) = 0.79, p = .482

Figure 10. HRTRTM vs. SEGMENT means plotted by alcohol level.

TABLE 42 Analysis of Variance Summary Table for the Variable HRTRTV

Source	df	SS	F	p
Alcohol	1	29011.49	0.89	0.3899
Alcohol x subject	5	163834.68		
Sleep	1	1772.16	0.04	0.8499
Sleep x subject	5	223132.91		
Segment	2	38191.88	7.74	0.0093
Segment x subject	10	24667.48		
Alcohol x sleep	1	19490.39	0.74	0.4298
Alcohol x sleep x subject	5	132180.79		
Alcohol x segment	2	328.00	0.26	0.7788
Alcohol x segment x subject	10	6397.61		
Sleep x segment	2	7312.19	8.08	0.0082
Sleep x segment x subject	10	4526.37		
Alcohol x sleep x segment	2	1311.56	1.29	0.3161
Alcohol x sleep x segment x subject	10	5064.05		

HANTRAN. The ANOVA Summary Table for the variable HANTRAN appears as Table 43. Low p-value exists for the segment (time-on-task) condition. The p-value for the alcohol condition fell just outside the 0.20 criterion. Since no other conditions or interactions show separation, HANTRAN shows only marginal potential for alcohol detection.

LATPOSM. The ANOVA Summary Table for the variable LATPOSM appears as Table 44. Low p-values exist for the segment condition and the sleep by segment interaction. Additionally, the p-value for the sleep condition is within the criterion of 0.20. LATPOSMS shows potential for use as a drowsiness detector. It should also be noted that the alcohol condition and alcohol by segment interaction fall just outside the criterion level. LATPOSM was, therefore, used as an alcohol discriminator as well as a drowsiness discriminator in subsequent analyses.

Analysis of Variance--Summary

The analysis of variance technique was used to determine the degree of separation across each condition and the interactions. This separation information gave an indication of the potential for each variable to reliably detect impairment due to alcohol, drowsiness, the combined effects of alcohol and drowsiness and general driver impairment due to any of the above sources. These results are summarized in Table 45.

Stepwise Discriminant Analysis

The third step used in determination of dependent variable reliability was the stepwise discriminant analysis. The major advantage of the

TABLE 43 Analysis of Variance Summary Table for the Variable HANTRAN

Source	df	SS	F	p
Alcohol	1	10404.40	1.87	0.2296
Alcohol x subject	5	27806.46		
Sleep	1	87.50	0.01	0.9108
Sleep x subject	5	31529.79		
Segment	2	42148.02	4.11	0.0498
Segment x subject	10	51280.05		
Alcohol x sleep	1	7087.61	1.08	0.3457
Alcohol x sleep x subject	5	32716.71		
Alcohol x segment	2	1393.34	0.59	0.5725
Alcohol x segment x subject	10	11807.03		
Sleep x segment	2	52.69	0.01	0.9877
Sleep x segment x subject	10	21229.35		
Alcohol x sleep x segment	2	1193.56	0.47	0.6401
Alcohol x sleep x segment x subject	10	12787.64		

TABLE 44 Analysis of Variance Summary Table for the Variable LATPOSM

Source	df	SS	F	p
Alcohol	1	271400	2.03	0.2134
Alcohol x subject	5	667999		
Sleep	1	925488	3.37	0.1259
Sleep x subject	5	1374103		
Segment	2	1053073	7.34	0.0109
Segment x subject	10	717166		
Alcohol x sleep	1	118625	0.94	0.3758
Alcohol x sleep x subject	5	628129		
Alcohol x segment	2	137435	1.77	0.2201
Alcohol x segment x subject	10	388670		
Sleep x segment	2	548005	3.78	0.0599
Sleep x segment x subject	10	724887		
Alcohol x sleep x segment	2	72291	0.76	0.4913
Alcohol x sleep x segment x subject	10	474278		

TABLE 45 Summary of Potentially Sensitive Impairment Detectors Based on the Analysis of Variance

Type of Impairment			
Alcohol	Drowsiness	Combined Effects	General
STVELM	YAWMEAN	STVELM	STVELM
SMREV	YAWVAR	STVELVAR	HRTRTM
HRTRTM	STEXEED	SMREV	
LATPOSM	STVELM	HRTRTM	
LANDEVSQ	STVELVAR		
HANTRAN	LGREV		
	SEATMOV		
	HRTRTM		
	LATPOSM		
	LANDEVSQ		

stepwise approach over the univariate analysis of variance approach is that it considers combinations of dependent variables, thereby accounting for any redundancy of information provided by two or more variables. This was particularly important for this analysis since many of the dependent variables are physically related to some degree (e.g. steering velocity, steering exceedance and steering velocity variance).

The stepwise discriminant analysis uses the following six steps to determine which dependent variables provide useful, independent information to a linear discriminant model.

1. A criterion for discrimination and a threshold value for model entry and removal are specified. The criterion for discrmination is simply a rule used for classification of observations. The rules established for classification of observations as "impaired" or "not impaired" will be discussed later in this section. The threshold value for model entry and removal is the p-value specified as "significant" in order for the variable to remain in the model. The p-value selected for this analysis was p=0.20. This value was selected because it gave indication of which variables provide useful independent information (with 80 percent confidence) while providing a criterion for entry and removal that was not so stringent that the stepwise approach would consider only a portion of the variables for entry into the model.
2. An F value is calculated for each variable individually. This is the F value associated with the specified criterion for dis-

crimination (i.e. "impaired" vs. "not impaired").

3. The variable with the largest F value greater than the criterion for entry is entered into the model.
4. The F for removal is computed. This is a partial F test on each variable in the model given the information from all other variables in the model (Note that with only one variable in the model this is equal to the F to enter). If the partial F is below the threshold for removal, the variable is taken out of the model.
5. The F to enter is computed for each variable not in the model. This is the partial F for each variable outside the model given the information from the variables in the model.
6. Steps 4 and 5 are repeated until no variables can be entered or removed.

The variables remaining in the stepwise model are those which provide a degree of independent information based on the criterion selected ($p = 0.20$ for this analysis) for the discriminator ("impaired" vs. "not impaired") specified.

The criterion for "impairment" was treated differently for alcohol and drowsiness. As previously discussed in the data analysis overview section, it makes intuitive sense to use lane deviation measures as the criterion variables for alcohol impairment, especially when consideration is given to the large inter-subject variability associated with alcohol ingestion. However, based on the results presented for the correlation and ANOVA analyses, it appears as though the lane measures

may not reliably indicate alcohol impairment at the BAC used in this study. Therefore, for alcohol impairment, the following criterion will be used:

If BAC then impaired. If sober than not impaired.

Also, as discussed in the data analysis overview section, eye measures have proved to be reliable indicators of drowsiness in previous studies (Erwin et al. 1976; Skipper et al. 1984) and in addition have face value in that a driver cannot drive effectively if proper eye scanning behavior is not maintained. This result was also supported by the findings presented in the correlation and ANOVA sections. The eye measures EYEMEAS and PERCLOS have been shown to be the most reliable based on these results, and therefore the criterion for drowsiness impairment was based on these measures.

For selection of a criterion for EYEMEAS, the results summarized by Figure 2 were used. Based on Figure 2 it seems apparent that an EYEMEAS of 5000 or less indicated an unimpaired driver while values of 9000 or more indicated some degree of impairment. In an analysis of this type, it is important not to select a criterion that is too low, because the resulting discriminant anlaysis would have a high false alarm rate making an alerting device potentially bothersome. It is also important, for safety reasons, that the miss rate is sufficiently low to effectively detect an impaired driver. Therefore, a criterion for EYEMEAS was selected such that neither miss nor false alarm rates would have been exceptionally high. From Figure 2, the criterion point of EYEMEAS = 7000 was chosen based on this logic.

For the establishment of a criterion for PERCLOS, intuition was used to some degree. PERCLOS is the percentage of time that the eyes are 80% to 100% closed. A driver cannot respond properly to stimuli in the driving environment in this condition and therefore is impaired by definition. Based on this premise, a small level of PERCLOS was appropriate for a criterion level. A PERCLOS value of 2% over a three-minute interval means that the eyes are essentially closed for three to four seconds. This value seemed appropriate in that higher values would increase the probability of an accident while lower values would substantially increase the false alarm rate.

Based on the logic above, the following rule was established for classification of drowsiness impairment:

If PERCLOS is greater than 2

or EYEMEAS is greater than 7000, then impaired.

ELSE not impaired.

The criteria for the general impairment model and combined effects impairment model were derived based on the knowledge that both alcohol and drowsiness needed to be considered. Therefore, for both the combined effects impairment model and the general impairment model both the alcohol criterion and the drowsiness criteria were used as criteria as stated above.

The variables found to be reliable in either the correlation analysis or the ANOVA results were placed in a stepwise discriminant model for the corresponding four types of impairment, namely alcohol, drowsiness, combined effects, and general. The stepwise results are

summarized below.

Stepwise Model--Alcohol Impairment

From the ANOVA and correlation analyses, the following variables showed potential as alcohol impairment detectors.

Correlation analysis	ANOVA
YAWVAR	STVELM
HRTRTV	SMREV
LATPOSM	HRTRTM
	LATPOSM
	HANTRAN

Each of the above variables was entered into the stepwise discriminant model. The variables were entered in groups of five or less, since as previously discussed in the ANOVA section, there are only five degrees of freedom (number of subjects minus one) available for the multivariate calculations. Through a successive elimination based on redundancy of information between variables, the variables shown to be important by the stepwise approach given the criteria described previously were: SMREV, HRTRTM, LANDEVSQ, and HANTRAN.

Stepwise Model--Drowsiness Impairment

From the ANOVA and correlation analyses, the following variables showed potential as drowsiness impairment detectors:

Correlation Analysis	ANOVA
YAWVAR	YAWMEAN
STEXEED	YAWVAR
STVELVAR	STEXEED
LGREV	STVELM
SEATMOV	STVELV

LATPOSM	LGREV
HRTRTM	SEATMOV
HRTRTV	LATPOSM
	LANDEVSQ
	HRTRTM

The variables were entered five at a time, and through successive elimination by the stepwise approach, the following variables were shown to contain a significant amount of independent information: YAWMEAN, YAWVAR, STEXEED, SEATMOV, and LANDEVSQ.

Stepwise Model--Combined Effects Impairment

From the ANOVA and correlation analyses, the following variables showed potential as combined effects impairment detectors:

Correlation analysis	ANOVA
YAWVAR	STVELM
STEXEED	STVELVAR
STVELVAR	SMREV
LGREV	HRTRTM
SEATMOV	
HRTRTM	
LATPOSM	
STVELM	

The variables were entered five at a time, and through the process of successive elimination by the stepwise approach, the following variables were shown to contain a significant amount of independent information: LGREV, SMREV, and SEATMOV.

Stepwise Model--General Impairment

From the ANOVA and correlation analyses, the following variables showed potential as general impairment predictors:

Correlation analysis	ANOVA
YAWVAR	STVELM
STEXCEED	HRTRTM
STVELVAR	
LGREV	
HRTRTM	
LATPOSM	

The variables were entered five at a time and through the process of elimination performed by the stepwise approach, the following variables were shown to contain a significant amount of independent information:

YAWVAR, LGREV, HRTRTM, LATPOSM, STVELM.

Through the process of combining information into stepwise models, it was discovered that several of the variables had a high degree of redundant information. These variables are YAWVAR, LATPOSMS, and LANDEVSQ; and LGREV and YAWMEAN. In the discussion section, several combinations of these variables will be modeled. While the modeling of these additional variables may be less than optimal to some degree, the information will be included so that trade-offs between such factors as ease of implementation can be considered.

Linear Discriminant Analysis

A linear discriminant analysis uses information provided in a set of specified measures to derive a linear function for optimal classification of observations based on specified criteria. For this analysis, classification of a driver as "impaired" or "not impaired" was the goal. The criteria for classification were the same as was described in the stepwise discriminant analysis and are summarized below:

ALCOHOL

If BAC then impaired, else not impaired.

DROWSINESS

If PERCLOS > 2 or EYEMEAS > 7000, then impaired, else not impaired.

GENERAL AND COMBINED EFFECTS

If BAC or PERCLOS > 2 or EYEMEAS > 7000, then impaired, else not impaired.

These classification rules determine the actual classification as impaired or not impaired. The linear discriminant function determines the predicted classification as impaired or not impaired based on information provided in the specified variables. The effectiveness of the linear discriminant function is determined by the number of misclassified observations. The correct and incorrect classifications are generally presented in a matrix format called a confusion matrix. The confusion matrix format is shown below:

		Predicted	
		Impaired	Not Impaired
Actual	Impaired	Correct (Hit)	Incorrect (Miss)
	Not Impaired	Incorrect (False Alarm)	Correct (Correct Rejection)

Costs associated with a miss or a false alarm can be specified for this type of analysis. While it is important for driver safety considerations to have a low miss rate for a model of this type, it is also important not to have a false alarm rate that is too high. In actual

use, a high false alarm rate could cause a driver to become annoyed with an impairment detection device and disconnect it or ignore it altogether. Therefore, equal costs were assigned to a miss and a false alarm for this analysis.

Prior probabilities of observations can also be specified for an analysis of this type. Although the probability of an impaired observation was less likely than a non-impaired observation (except for the case of alcohol) the prior probabilities were set equally at 0.5. A model of this type has no information regarding the state of a driver prior to data collection. Therefore, equal prior probabilities provide the most accurate and conservative estimation in that the model depends only on the data collected for use in classification.

The results of the discriminant analyses for the four categories of impairment (alcohol, drowsiness, combined effects, and general) and the two data collection interval lengths (three-minute interval data and six-minute interval data) are presented in Tables 46 through 53. Contained in each table is the confusion matrix showing the number of observations per cell, the marginal observation totals, the percentages associated with the miss and false alarm rates, the apparent error rate (APER) and the standardized canonical coefficients associated with each variable in the model. The APER is an overall indicator of the success of the discriminant function. It is calculated by taking the sum of the miss and false alarm totals divided by the total number of observations. As a reference, a general rule of thumb for interpreting this type of analysis is that an APER of 20% or less is considered "good" discrimination. It should be noted that some statistical bias is present in

the APER when the number of cell observations differ a great deal from one another. In the case of unequal observations, the miss and false alarm percentages provide the most conservative estimate of discriminant model success.

The standardized canonical coefficients give a relative indication of the importance of each variable to the linear discriminant function. A variable with a canonical coefficient of large relative magnitude (either positively or negatively) indicates that a relatively large portion of the multivariate separation used for discrimination was derived from information contained in that variable.

Alcohol impairment discriminant analysis. Three-minute interval data. The discriminant analysis results for the three-minute interval alcohol data appear in Table 46. The confusion matrix shows that 57 of the 180 impaired observations (31.67%) were misclassified (misses) and that 33 of the 180 non-impaired observations (18.33%) were misclassified (false alarms) giving an APER for the three-minute alcohol data of 25.0%. As also shown in Table 46, the standardized canonical coefficients indicated that HRTRTM was the most important variable in the linear discriminant function.

Alcohol impairment discriminant analysis. Six-minute interval data. The discriminant analysis results for the six-minute alcohol data appear in Table 47. The confusion matrix shows that 29 of 90 impaired observations (32.22%) were misclassified (misses) and that 13 of the 90 non-impaired observations were misclassified (false alarms) giving an APER for the six-minute alcohol data of 23.3%. As also shown in Table 47, the standardized canonical coefficients indicated that HRTRTM was the most important variable in the linear discriminant function. In

TABLE 46 Alcohol Impairment Discriminant Analysis. Three-minute interval data.

		Predicted: Impaired	Predicted: Not Impaired	
Actual	Impaired	123	57 (31.67%)	180
	Not Impaired	33 (18.33%)	147	180
		156	204	360

APER = 25.0%

Model Variables:	Standardized Canonical Coefficients
HRTRTM	.9766
HANTRAN	-.6152
LANDEVSQ	.5485
SMREV	-.5062

TABLE 47 Alcohol Impairment Discriminant Analysis. Six-minute interval data

		Predicted: Impaired	Predicted: Not Impaired	
Actual	Impaired	61	29 (32.22%)	90
	Not Impaired	13 (14.44%)	77	90
		74	106	180

APER = 23.3%

Model Variables:	Standardized Canonical Coefficients
HRTRTM	1.0517
HANTRAN	- .6868
SMREV	- .5570
LANDEVSQ	.4752

comparison of the discriminant analyses for the three-minute alcohol data (Table 46) and the six-minute alcohol data (Table 47), the overall discriminability as indicated by the APER, and the false alarm percentage slightly favor the six-minute data. The miss percentage, however, slightly favored the three-minute data over the six-minute data.

Drowsiness impairment discriminant analysis. Three-minute interval data. The discriminant analysis results for the three-minute sleep data appear in Table 48. The confusion matrix shows that 33 of the 101 impaired observations (32.67%) were misclassified (misses) and that 19 of the 259 non-impaired observations (7.34%) were misclassified (false alarms) giving an APER for the three-minute sleep data of 14.44%. As also shown in Table 48, the standardized canonical coefficients indicated that LANDEVSQ and SEATMOV were the most important variables in the linear discriminant function.

Drowsiness impairment discriminant analysis. Six-minute interval data. The discriminant analysis results for the six-minute sleep data appear in Table 49. The confusion matrix shows that 16 of the 48 impaired observations (33.33%) were misclassified (misses) and that 7 of the 132 non-impaired observations were misclassified (false alarms) giving an APER for the six-minute sleep data of 12.8%. As also shown in Table 49, the standardized canonical coefficients indicated that YAWVAR, SEATMOV, and LANDEVSQ were the most important variables in the linear discriminant function. In comparison of the discriminant analyses for the three-minute sleep data (Table 48) and the six-minute sleep data (Table 49), the overall discriminability as indicated by the APER shows

TABLE 48 Drowsiness Impairment Discriminant Analysis. Three-minute interval data.

		Predicted: Impaired	Predicted: Not Impaired	
Actual	Impaired	68	33 (32.67%)	101
	Not Impaired	19 (7.34%)	240	259
		87	273	360

APER = 14.44%

Model Variables:	Standardized Canonical Coefficients
LANDEVSQ	.6024
SEATMOV	.5060
STEXEED	.3100
YAWMEAN	.2878
YAWVAR	.2189

TABLE 49 Drowsiness Impairment Discriminant Analysis. Six-minute interval data.

		Predicted: Impaired	Predicted: Not Impaired	
Actual	Impaired	32	16 (33.33%)	48
	Not Impaired	7 (5.3%)	125	132
		39	141	180

APER = 12.8%

Model Variables:	Standardized Canonical Coefficients
YAWVAR	.4781
SEATMOV	.4476
LANDEVSQ	.4258
YAWMEAN	.3620
STEXEED	.3086

that the six-minute data provided slightly better discrimination. The comparison also shows that the false alarm percentage was lower for the six-minute data, but the miss percentage was lower for the three-minute data.

Combined effects impairment discriminant analysis. Three-minute interval data. The discriminant analysis results for the three-minute combined effects data appear in Table 50. The confusion matrix shows that 75 of the 197 impaired observations (38.07%) were misclassified (misses) and that 52 of the 163 non-impaired observations (31.90%) were misclassified (false alarms) giving an APER for the three-minute combined effects data of 35.3%. As also shown in Table 50, the standardized canonical coefficients indicated that LGREV and SMREV were the most important variables in the linear discriminant function.

Combined effects impairment discriminant analysis. Six-minute interval data. The discriminant analysis results for the six-minute combined effects data appear in Table 51. The confusion matrix shows that 35 of the 90 impaired observations (38.89%) were misclassified (misses) and that 28 of the 90 non-impaired observations (31.11%) were misclassified (false alarms) giving an APER for the six-minute combined effects data of 35.0%. As also shown in Table 51, the standardized canonical coefficients indicate that LGREV and SMREV were the most important variables in the linear discriminant function. In comparison of the discriminant analyses for the three-minute combined effects data (Table 50) and the six-minute combined effects data (Table 51) no appreciable differences exist between APERs, false alarm rate or miss

TABLE 50 Combined Effects Impairment Discriminant Analysis. Three-minute interval data.

		Predicted: Impaired	Predicted: Not Impaired	
Actual	Impaired	122	75 (38.07%)	197
	Not Impaired	52 (31.90%)	111	163
		174	186	360

APER = 35.3%

Model Variables:	Standardized Canonical Coefficients
LGREV	1.0981
SMREV	- .9462
SEATMOV	.3926

TABLE 51 Combined Effects Impairment Discriminant Analysis. Six-minute interval data.

		Predicted: Impaired	Predicted: Not Impaired	
Actual	Impaired	55	35 (38.89%)	90
	Not Impaired	28 (31.11%)	62	90
		83	97	180

APER = 35.0%

Model Variables:	Standardized Canonical Coefficients
LGREV	1.1506
SMREV	- .9429
SEATMOV	.3028

rates for the combined effects data.

General impairment discriminant analysis. Three-minute interval data. The discriminant analysis results for the three-minute general impairment data appear in Table 52. The confusion matrix shows that 212 of the 461 impaired observations (45.99%) were misclassified (misses) and that 64 of the 258 non-impaired observations (24.71%) were misclassified (false alarms) giving an APER for the six-minute general impairment data of 38.0%. As also shown in Table 52, the standardized canonical coefficients indicate that LATPOSM, LGREV, and HRTRTM were the most important variables in the linear discriminant function.

General impairment discriminant analysis. Six-minute interval data. The discriminant analysis results for the six-minute general impairment data appear in Table 53. The confusion matrix shows that 97 of the 208 impaired observations (47.63%) were misclassified (misses) and that 37 of the 152 non-impaired observations (24.34%) were misclassified (false alarms) giving an APER for the six-minute general impairment data of 37.2%. As also shown in Table 53, the standardized canonical coefficients indicated that LATPOSM, LGREV, and HRTRTM were the most important variables in the linear discriminant function. A comparison of the discriminant analyses for the three-minute general impairment data (Table 52) and the six-minute general impairment data (Table 52) indicates that only small differences exist between the APERs, false alarm rates and miss rates.

TABLE 52 General Impairment Discriminant Analysis. Three-minute interval data.

		Predicted: Impaired	Predicted: Not Impaired	
Actual	Impaired	249	212 (45.99%)	461
	Not Impaired	64 (24.71%)	195	259
		313	407	720

APER = 38.0%

Model Variables:	Standardized Canonical Coefficients
LATPOSM	.6746
LGREV	.5045
HRTRTM	.4688
STVELM	- .3063

TABLE 53 General Impairment Discriminant Analysis. Six-minute interval data.

		Predicted: Impaired	Predicted: Not Impaired	
Actual	Impaired	111	97 (47.63%)	208
	Not Impaired	37 (24.34%)	115	152
		148	212	360

APER = 37.2%

Model Variables:	Standardized Canonical Coefficients
LATPOSM	.6286
LGREV	.5736
HRTRTM	.4126
STVELM	- .2990

DISCUSSION AND ADDITIONAL RESULTS

Summary of Impairment Detection

As shown in the Results Section, of the four impairment detection models derived (general, alcohol, drowsiness, and combined effects) two detection models, namely alcohol and drowsiness, proved successful to some degree. The drowsiness model showed discriminability with an APER in the range of 12 to 14%. While the drowsiness model miss rate was in the range of 30%, this rate is still low enough for a device to be of practical use even with no further improvements.

The alcohol model showed discriminability with an APER in the range of 23%. While the discriminability for the alcohol model was not as good as for the drowsiness model, it is still very promising when one considers the moderate level of alcohol administered and the inherently large inter-subject variability associated with alcohol. At a BAC closer to the legal limit for driving (e.g. 0.09% BAC), discriminability would probably improve.

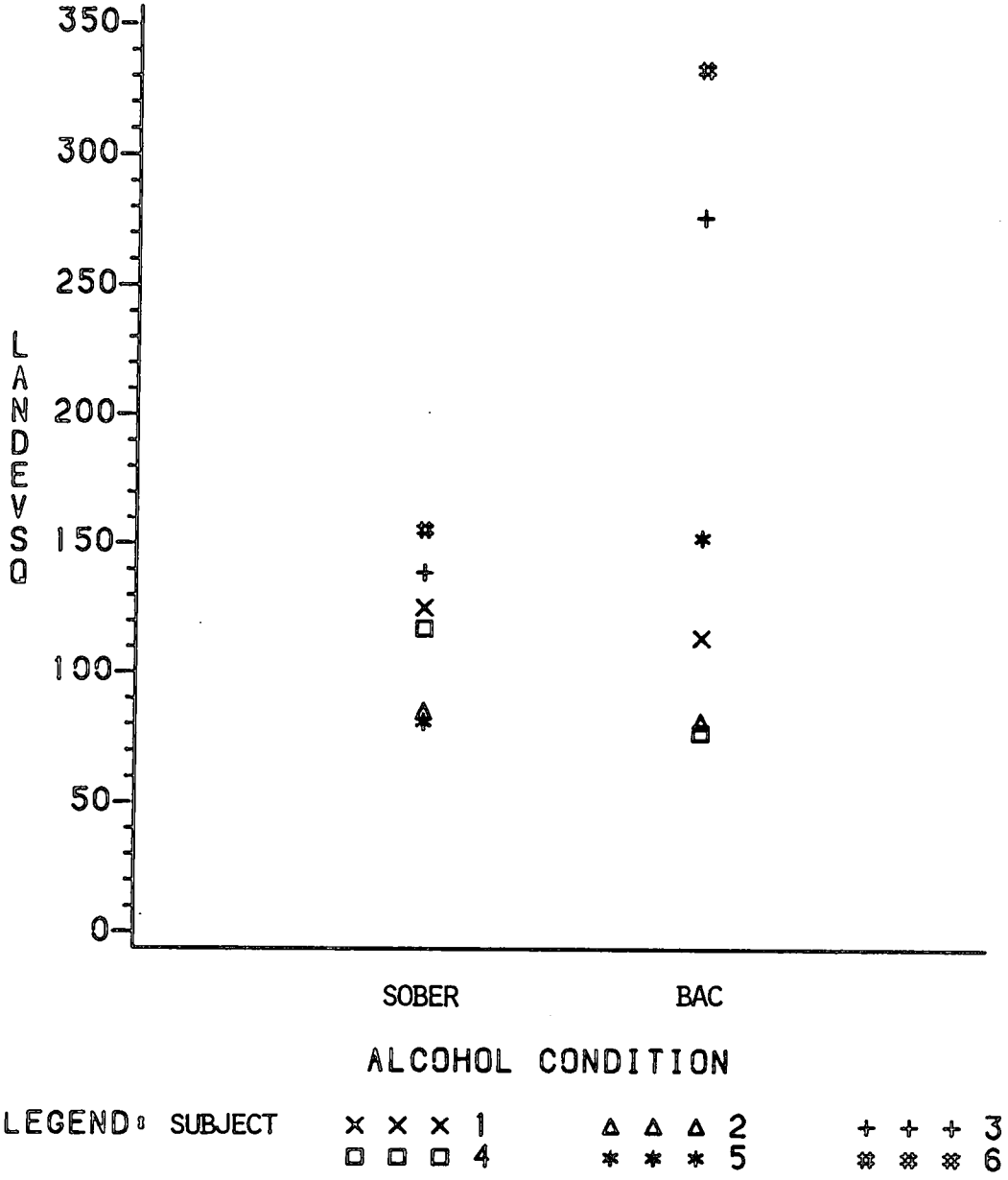
Eye Measures and Lane Measures as Impairment Predictors

The use of eye measures and lane measures as predictors of impairment was discussed several times in previous sections. As with the two previous studies cited (Erwin et al., 1976; Skipper et al., 1984) the results indicated that the eye measures in general, and in particular the EYEMEAS and PERCLOS measures, were reliable indicators of impairment due to drowsiness. To a lesser degree, the results also showed that the eye measures proved reliable as indicators of impairment due to the com-

bination of alcohol and drowsiness. In this instance, it appeared as though the introduction of alcohol added variability to the data which lessened the reliability of prediction to some extent, but not enough to render the eye measures useless for impairment prediction.

For alcohol impairment alone, the eye measures showed very little promise regarding impairment prediction. This is contrary to some degree to results found by Beideman and Stern (1977) and Erwin, Wiener, and Hartwell (1975) which showed a relationship between closure duration, frequency and ratio of long to regular closures, and alcohol for a tracking task supposedly indicative of driving.

The lane measures showed some degree of reliability for impairment prediction based on correlations with the eye measures for the sleep effects and combined effects data. However, especially in the case of the combined effects data, the lane measures contained too much variability to be relied upon exclusively for impairment prediction. Although this did not affect the drowsiness-impaired data since eye measures could be used for prediction, it did detract from the result of the alcohol impairment analysis. Due to the inherent inter-subject variability that exists for alcohol impairment at a given level, grouping observations as "impaired" or "not impaired" based on whether or not a subject has ingested alcohol is not an optimum criterion. This inter-subject variability was present in this study and is illustrated in Figure 11 for the variable LANDEVSQ. It was hoped that the lane measures would prove to be more reliable criteria of driver impairment due to alcohol than BAC, however, that could not be shown to be the case.



* Note: For a discussion of the measure LANDEVSQ, see the data analysis overview and dependent measure definitions section.

Figure 11. LANDEVSQ vs. ALCOHOL means plotted by subject.

The Effect of Time-on-Task

As shown by the analysis of variance, the most pronounced effect in the majority of the variables was time on task. It is interesting to note that regardless of condition, the subjects' driving did not generally show significant signs of impairment until at least 20 to 30 minutes into the run. Although the levels of sleep deprivation and alcohol were moderate for this experiment, it is still surprising that the initial driving was largely unaffected. It seems apparent that the driver who is moderately impaired due to drowsiness or drowsiness and alcohol becomes a real danger only after some time on the road.

Interval Length for Detection

As shown in the correlation analysis section and to a lesser degree in the discriminant analysis section, the six-minute interval data were more reliable in some instances for impairment detection than the three-minute interval data. Based on the point discussed in the previous section, namely that subjects did not show impairment until 20 or 30 minutes into the run, six-minute intervals appear to be of sufficient resolution to detect and alert a driver of degraded performance prior to the driver becoming dangerously impaired. The exception to this may perhaps be impairment due to alcohol alone, since as shown in the analysis of variance section, alcohol impairment did not generally change much with time-on-task. This question relates back to the concept of the pre-drive detection device vs. the on-board device discussed in the literature review section. That is, if a driver is sig-

nificantly impaired due to alcohol alone, a device limiting access to the roadway should be considered as opposed to an alerting device which is activated after the driver is on the road.

The Onset of Drowsiness

As previously mentioned, the onset of drowsiness, whether alcohol is introduced or not, takes 20 to 30 minutes as opposed to a shorter period of time as one might expect. An interesting phenomenon regarding drowsiness onset was noted during data collection and analysis. Drivers exhibited cyclic bouts of drowsiness. Early in the run the cycles were of short duration and were apparently not difficult to overcome. However, as the run continued, the bouts of drowsiness were more severe and more difficult to overcome. This phenomenon is illustrated in Figure 12.

Although not specifically investigated as such, it appears as though detection of drowsiness impairment is occurring during only the majority of "down" cycles shown in Figure 12. If initial detection is occurring during the first one or two cycles, then indeed the most dangerous driver impairment could be avoided through a detection device.

Baseline Comparison vs. Absolute Detection

As shown by the individual subject-corrected correlations, a baseline apparently is not required for successful drowsiness impairment detection. The drowsiness detection model proved (although it has not been validated with a second set of data) that on-board drowsiness detection is indeed feasible without a baseline measure. The alcohol

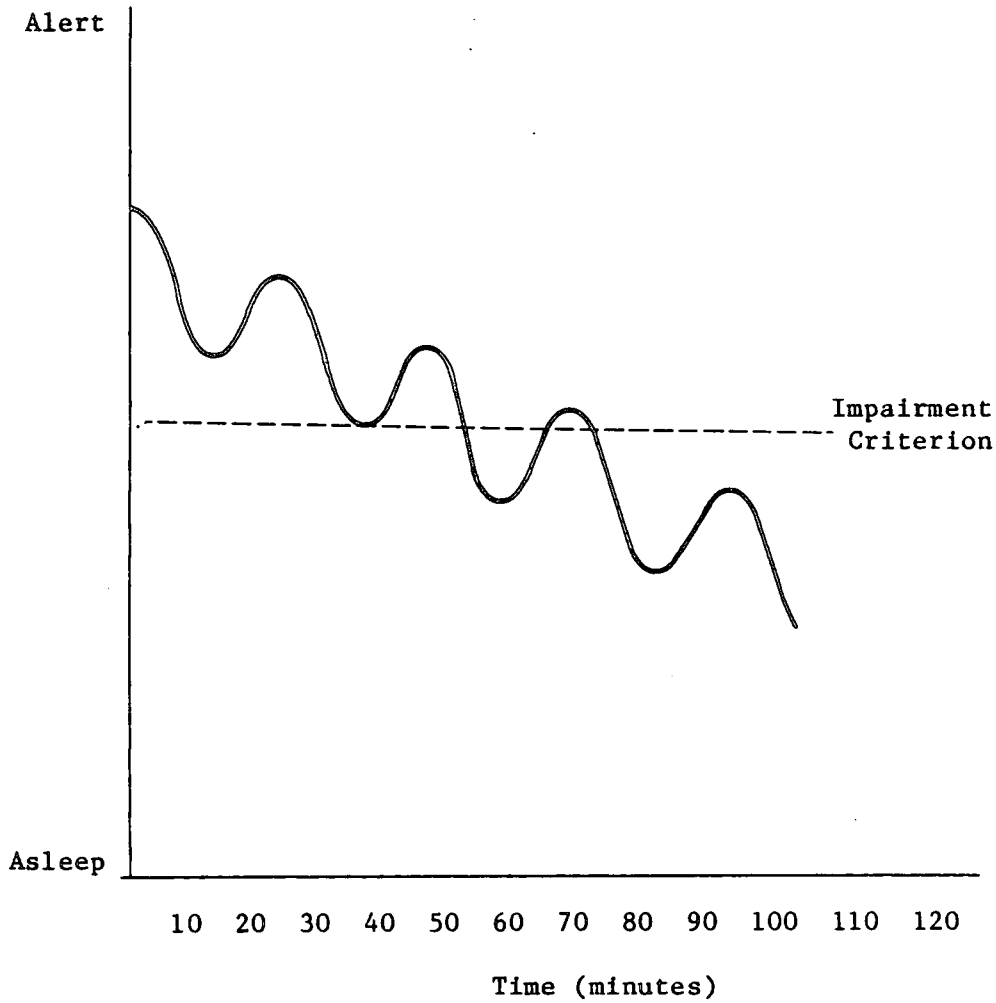


Figure 12. Illustration of the Pattern of Drowsiness Onset for a Sleep Deprived Driver.

detection model also showed promise without a baseline, especially considering the moderate levels of alcohol administered.

Further investigation into a baseline measure could, however, increase the probability of detection for a general impairment detection model. It seems possible that this type of detection could benefit from a properly implemented baseline in spite of the negative results seen in the correlation analysis. Perhaps this issue warrants further study.

Optimized Discriminant Models

Although the procedure undertaken in the results section has apparently determined the optimum linear functions for discrimination, several issues such as simplicity and ease of implementation, and optimization of the criteria for impairment have not been addressed. It is obvious that some measures are easier or cheaper to implement than others. Therefore, several "less than optimal" models were created and show interesting results.

Confusion matrices for a drowsiness model using the variables LATPOSMS, STEXEED, STVELVAR, LGREV, and SEATMOV for both three-minute interval data and six-minute interval data are shown in Tables 54 and 55, respectively.

In a comparison between the "less than optimized" six-minute interval drowsiness model and the optimized six-minute interval drowsiness model confusion matrix in Table 49, only one less correct classification is present in the "less than optimized" model, despite the fact that three of the variables are different. This result is due to the simi-

TABLE 54 Drowsiness Impairment Discriminant Analysis. Three-minute interval data. Model II

		Predicted: Impaired	Predicted: Not Impaired	
Actual	Impaired	63	38 (37.62%)	101
	Not Impaired	21 (8.11%)	238	259
		84	276	360

APER = 16.39%

Model Variables:	Standardized Canonical Coefficients
SEATMOV	.6239
LATPOSM	.5414
STEXEED	.3054
LGREV	.1623
STVELVAR	.1204

TABLE 55 Drowsiness Impairment Discriminant Analysis. Six-minute interval data. Model II

		Predicted: Impaired	Predicted: Not Impaired	
Actual	Impaired	31	17 (35.42%)	48
	Not Impaired	7 (5.3%)	125	132
		38	142	180

APER = 13.3%

Model Variables:	Standardized Canonical Coefficients
SEATMOV	.5911
LATPOSM	.4590
LGREV	.4459
STEXEED	.3542
STVELVAR	- .0314

larity of some of the measures discussed in the results section.

A second "less than optimal" model was created for drowsiness and is shown in Table 56. Although the model contains only two variables (LATPOSM and SEATMOV), misclassification did not change much as evidenced by the miss, false alarm, and APER percentages when compared to the optimized drowsiness model. This finding illustrates that, for drowsiness detection at least, a model does not necessarily have to be complex to be successful.

The concept of optimized criteria for classification was mentioned in the results section, but not fully described. The criteria for the determination of drowsiness impairment (PERCLOS > 2 or EYEMEAS > 7000) were chosen a priori as conservative estimates. It should be noted that there is a trade-off, however, between miss and false alarm rates to some degree as the criteria are changed. Tables 57 and 58 illustrate this point. In a comparison between the "relaxed" criteria of Table 57 (PERCLOS > 3 or EYEMEAS > 9000) and the corresponding "conservative" criteria model of Table 50, there is an improvement in the miss, false alarm, and APER percentages with the relaxed criteria. An even greater improvement appears in Table 53 when only the PERCLOS > 2 criterion is used. Although the original criteria for impairment are optimal for the given circumstances, perhaps further investigation into whether or not these criteria are too stringent is warranted. In any case, should a model prove too sensitive to be practical once implemented, there is room for adjustment while maintaining discriminability.

TABLE 56 Drowsiness Impairment Discriminant Analysis. Six-minute interval data. Model III

		Predicted: Impaired	Predicted: Not Impaired	
Actual	Impaired	31	17 (35.42%)	48
	Not Impaired	13 (9.85%)	119	132
		44	136	180

APER = 16.7 %

Model Variables:	Standardized Canonical Coefficients
LATPOSM	.9742
SEATMOV	.4920

TABLE 57 Drowsiness Impairment Discriminant Analysis. Relaxed Criterion (PERCLOS > 3 or EYEMEAS > 9000). Six-minute interval data.

		Predicted: Impaired	Predicted: Not Impaired	
Actual	Impaired	28	10 (26.32%)	38
	Not Impaired	6 (4.23%)	136	142
		34	146	180

APER = 8.9%

Model Variables:	Standardized Canonical Coefficients
STEXEED	.5741
SEATMOV	.5320
LATPOSM	.3431
LGREV	.3212
STVELVAR	.1036

TABLE 58 Drowsiness Impairment Discriminant Analysis. Relaxed Criterion (PERCLOS > 2 only). Six-minute interval data.

		Predicted: Impaired	Predicted: Not Impaired	
Actual	Impaired	20	8 (28.57%)	28
	Not Impaired	4 (2.63%)	148	152
		24	156	180

APER = 6.7%

Model Variables:	Standardized Canonical Coefficients
LATPOSM	.7692
STEXEED	.6218
STVELVAR	.4152
SEATMOV	.2460
LGREV	- .0292

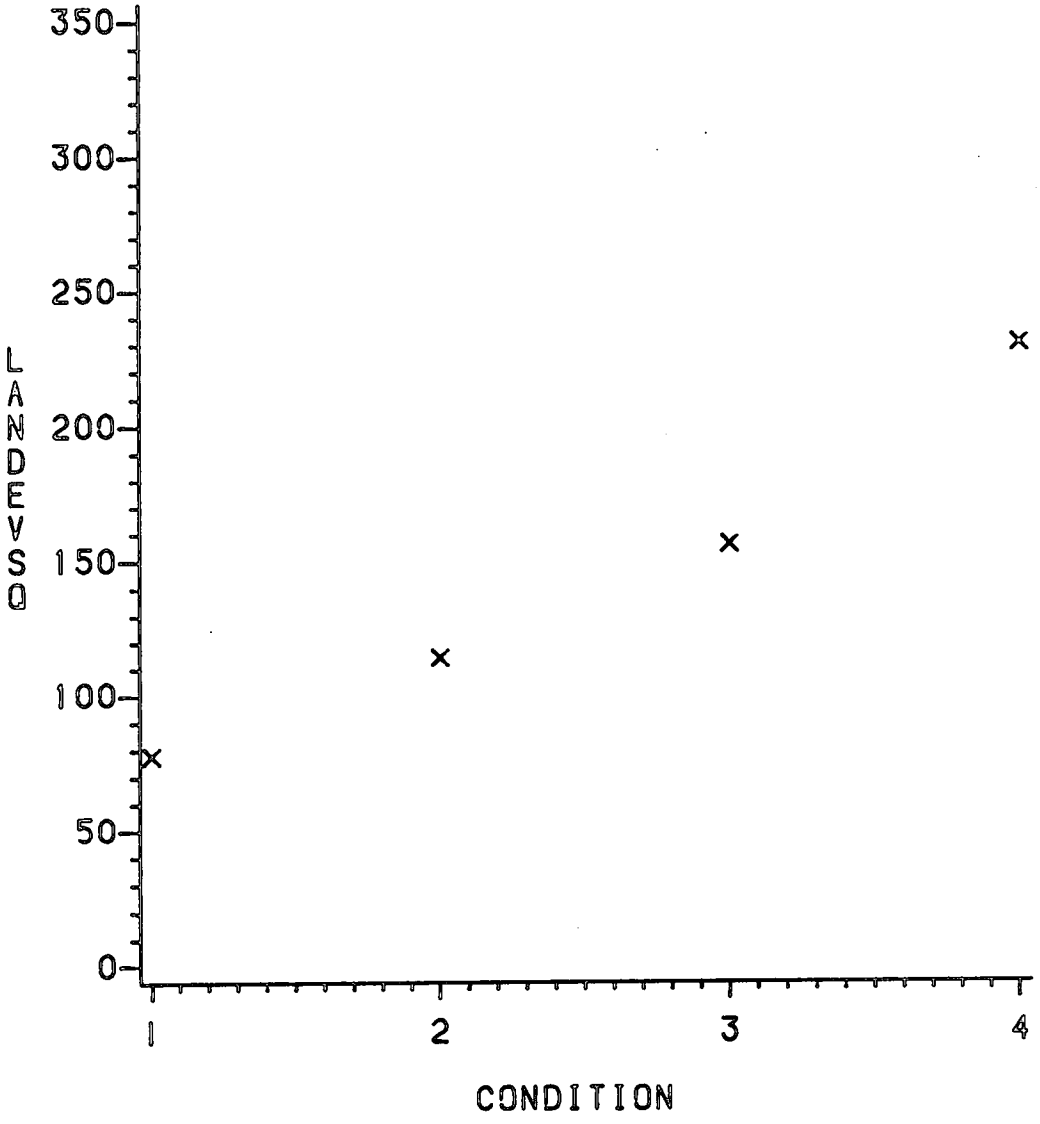
Combined Effects Impairment

As discussed in the Literature Review Section, several studies (e.g. Huntley and Centybear, 1974) found an improvement in driving performance for drivers who were influenced by alcohol and drowsiness in combination over drivers who were influenced by drowsiness alone. The results of this study found no such effect and that, if anything, perhaps the opposite was true. Although no significant differences were found between the sleep deprived/sober and sleep deprived/BAC conditions for any of the dependent variables, the trend shown was, almost without exception, that the mean of the sleep deprived/BAC observations showed greater driver impairment than the mean of the sleep deprived sober observations. This trend is illustrated in Figure 13.

Given the success of the drowsiness model, the question still remains as to whether or not the introduction of alcohol would adversely affect the detectability of drowsiness impaired driver performance. To answer this question, the drowsiness model was applied to the combined effects data. The resulting discriminant analysis is shown in Table 59. As shown, the APER for the combined effects data using the drowsiness model and criteria is 18.9%. Although the miss percentage was somewhat high (42.11%), the drowsiness model still shows the ability to provide useful detection even when alcohol is present in a drowsy driver.

Model Validation

The next logical step in the refinement of the drowsiness and



Legend: 1 = Rested/Sober, 2 = Rested/BAC, 3 = Sleep Deprived/Sober, 4 = Sleep Deprived/BAC

* Note: For a discussion of the measure LANDEVSQ, see the data analysis overview and dependent measure definitions section.

Figure 13. LANDEVSQ vs. Condition.

TABLE 59 Combined Effects Discriminant Analysis Using Drowsiness Model II. Six-minute interval data.

		Predicted: Impaired	Predicted: Not Impaired	
Actual	Impaired	33	24 (42.11%)	57
	Not Impaired	10 (8.13%)	113	123
		43	137	180

APER = 18.9%

Model Variables:	Standardized Canonical Coefficients
LATPOSMS	.6233
LGREV	.4621
SEATMOV	.3890
STVELVAR	.0847
STEXEED	.0592

alcohol models is validation of detection with a different set of data than the data on which the models were derived. While the models appear very promising, this validation would give an accurate estimation of how well drowsiness and alcohol impairment could be detected by an actual device.

CONCLUSIONS AND RECOMMENDATIONS

Conclusions

The results of the experiment indicate that a useful on-board drowsiness detection device is possible and practical for highway driving. Drowsiness models formulated in this research study would, in all likelihood, provide reasonably reliable drowsiness impairment detection. The drowsiness models would also, in all likelihood, provide useful detection information regardless of whether low to moderate amounts of alcohol were present in a drowsy driver. The results also show that on-board alcohol impairment detection may be possible at moderate to high BAC.

Recommendations

Because of the promise shown in detecting impaired drivers, it is recommended that work be continued which is directed toward refining, proving, and implementing a detection system. Specific recommendations include the following:

1. Further work should be done on drowsy driver detection models using nonlinear and other optimization techniques. The objective of this work would be to develop accurate detection models that are as easy as possible to implement and relatively insensitive to individual differences.

2. The detection models should be checked in the same simulation using new subjects as a form of validation. The models should also be checked in a modified simulation, where an attempt is

made to create a different but realistic scenario. The purpose of the second simulation is to test detection capabilities in a different but typical environment, thereby further checking validity.

3. Work should begin on human factors design of a warning system for the driver, once drowsiness has been detected.

4. In regard to alcohol impairment, testing should continue at higher BACs (at or near 0.1%), to determine whether or not detection accuracies can be improved.

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APPENDICES

APPENDIX A

Driving Questionnaire

To be filled in by experimenter:

Subject Number: _____

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

Complete the following items:

1. Year of Birth _____

2. Check one: Male _____ Female _____

3. Occupation: _____

Circle the correct response to the following:

4. Marital Status: Married Single Divorced

Separated Widowed

5. Do you smoke? Yes No

6. If you are a smoke, do you smoke:

Lightly Moderately Heavily

7. Do you have a valid drivers license? Yes No

If yes, do you wear contact lenses? Yes No

8. Do you ordinarily wear glasses while driving? Yes No

If yes, do you wear contact lenses? Yes No

9. What are your normal sleeping hours?

Retire _____ Awake _____

10. On the average, what is your depth of sleep?

Restless Light Moderate Deep Very Deep

Sleeping Habits

Check the blank that is most appropriate

	Never	Almost Never	Occasion-ally	Moder-ately Often	Very Often
1. Do you normally fall asleep during the day?	_____	_____	_____	_____	_____
2. How often do you fall asleep watching TV?	_____	_____	_____	_____	_____
3. How often do you fall asleep reading?	_____	_____	_____	_____	_____
4. Do you fall asleep after lunch?	_____	_____	_____	_____	_____
5. Do you fall asleep after dinner?	_____	_____	_____	_____	_____
6. How often do you take daily naps?	_____	_____	_____	_____	_____

Driving Habits

Check the blank that is most appropriate

	Never	Almost Never	Occasion-ally	Moder-ately Often	Very Often
7. How often have you experienced drowsiness while driving?	_____	_____	_____	_____	_____
8. How often have you driven for more than three hours at a time?	_____	_____	_____	_____	_____
9. How often have you had trouble staying awake in situations other than driving?	_____	_____	_____	_____	_____

10. Estimate 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

11. 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.

12. When I drive when I am tired: (Check one)

_____a. My driving is the same as when I am rested.
_____b. My driving is not as good as when I am rested.
_____c. I occasionally dose or nod off.
_____d. I often doze or nod off.

APPENDIX B

Alcohol Questionnaire

To be filled in by experimenter:

Subject Number: _____

Visual Acuity: _____

Weight: _____

The following questionnaire is designed to provide the experimenters with information regarding alcohol and caffeine consumption. All answers will be confidential and will be treated anonymously.

1. How much of the following do you consume per week?

   a) Beer (number of cans, bottles, glasses) _____ per week

   b) Wine (white, red, rose) _____ glasses per week

   c) Fortified Wine (port or sherry) _____ glasses per week

   d) Hard (distilled) liquor (whiskey, gin, etc.) _____ ounces per week.

2. During the course of a week, on which days do you usually consume alcoholic beverages? (Circle all days that apply)

   Mon. Tue. Wed. Thu. Fri. Sat. Sun.

3. Indicate the percentage of your alcohol consumption associated with each of the days you may have circled in question 2; writing the correct percentage values in the spaces provided for monring, afternoon, and evening. (Remember that the total of these percentages should equal 100 for the entire week.)

	Mon.	Tue.	Wed.	Thu.	Fri.	Sat.	Sun.
Morning	____	____	____	____	____	____	____
Afternoon	____	____	____	____	____	____	____
Evening	____	____	____	____	____	____	____

4. How much coffee do you drink?

   a) Morning _____ cups per day

   b) Afternoon _____ cups per day

   c) Evening _____ cups per day

5. If you are female, on what date did your last menstrual period begin?

APPENDIX C

Instructions and Informed Consent

The purpose of this study is to investigate the effects of alcohol and drowsiness on driving behavior and performance. The study is being conducted at the Vehicle Simulation Laboratory, Department of Industrial Engineering and Operations Research, Virginia Polytechnic Institute and State University, Blacksburg, VA 24061, telephone number 961-7962. The research team consists of Tom Dingus, Lenora Hardee, and Julie Skipper, who are graduate students in Industrial Engineering and Operations Research; and Dr. Walter W. Wierwille, (Principle Investigator), Professor of Industrial Engineering and Operations Research.

Your task for this study is to drive an automobile simulator in a simulator highway driving scenario. Please drive in the right lane and maintain your speed at 55 mph for the entire driving time. You will be required to wear the lap seatbelt provided at all times during the driving scenario.

You have the right to discontinue driving at any time for any reason. However, for you own safety it is important that you do not disconnect your lap belt or attempt to exit the simulator until the motion platform has been stopped. You may select either of the two procedures listed below if you wish to exit the simulator.

1. a) Inform the experimenter of your wish to stop.
   b) Remain seated while the experimenter stops the simulator.
   c) Upon instructions from the experimenter, disconnect the lap belt and exit the simulator <u>allowing the experimenter to</u>

assist you in doing so.

2. a) Inform the experimenter of your wish to stop.

   b) Press the emergency stop button on the dash.

   c) Remain seated with lap belt attached until the experimenter can assist you in exiting.

While it is your right to stop at any time, please complete the driving scenario if you can. We cannot use any of your data if you do not complete all of the runs.

You will drive the simulator on four separate occasions. On all four occasions you will be given a drink consisting of varying amounts of vodka and a diet soft-drink mixer. You will then be given a breathalyzer test, similar to one used by many law enforcement organizations. Upon completion of this test you will drive the automobile simulator for approximately two hours.

Prior to each session, a member of the research team will pick you up at your residence. After the session, you will remain with a member of the research team until the majority of the alcohol has worn off. During this time you can read, watch TV, or listen to music. After the majority of the alcohol has worn off, you will be driven hom. It is important that you stay home for the remainder of that evening, so that all alcohol effects will have worn off before you attempt any type of activity.

Two of the four sessions will be run in the early evening, and two will be run late at night. A specific schedule will be set up for you by a member of the research team. For the early evening sessions, it is important that you do not eat anything for three hours prior to your

scheduled arrival time at the vehicle simulation lab. It is also important that you get a reasonable amount of sleep the night before these sessions. After the session, dinner will be purchased for you at a local fast-food restaurant.

For the late night sessions, you will also be picked up and driven to the Vehicle Simulation lab in the early evening. Dinner will again be purchased for you at a fast-food restaurant. After dinner we will take you to the building in which the Vehicle Simulation lab is located. During the time between dinner and the start of your experimental run, you can read, study, watch TV, or listen to music. Also, during this time period, you will not be permitted to smoke, or drink any coffee or soft drinks. These stimulants would affect the results of the experiment. You will remain awake throughout the evening into the early morning hours. A member of the research team will awaken you if you should doze off. Sometime in the early morning hours (approximately 2 AM) the driving session will begin.

If you happen to fall asleep during the driving session, one of the members of the research team will wake you. You are in no danger in the simulator if you run off the road; however, you should try and remain awake during the driving task. Please try to keep driving even though you may be tired.

Data will be recorded during each driving scenario. The data will be analyzed such that your identity remains anonymous. The experiment is not design to test driving skill, but rather to obtain information on the influences of alcohol and drowsiness on driving. Please try to drive normally.

After completing the study, you will be paid at the rate of $4.50 per hour. You will be paid for all time spent in performing the experiment, including evening hours spent prior to the session with an experimenter, the session itself, and time spent after the session waiting for the alcohol effects to dissipate.

If you have any questions about the experiment or your rights as a participant, feel free to ask. We will answer your questions as honestly as possible. Anwers to some questions may have to wait until all experimental sessions have been completed to avoid affecting the outcome. Please do not discuss the experiment with anyone until after all data for all participants have been collected. Data collection is expected to be completed by May 15, 1985.

There are certain risks associated with this experiment. These risks include the following:

1. A health threat exists if you are not generally in good health or if you have a medical history of diabetes, hypertension, heart disease, or any other serious illness.
2. A potential health threat exists if you have not informed the experimenter of any prescription, non-prescription, or illegal drugs that you are currently taking.
3. A risk of injury exists if you attempt to leave the driving simulator before its motion has stopped and without assistance from a member of the research team.

4. There is the possibility that there would be some interference in your activities on the day following each experimental session.

PARTICIPANT'S INFORMED CONSENT

The purpose of this document is to obtain your consent to participate in this experiment, to inform you of your rights and obligations as a participant, and to insure that you understand all risks associated with this experiment.

Rights of Participation

(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.

(2) You have the right to be informed of the overall results of the experiment. If, after participation, you wish to receive summary information about 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 when it becomes available.

Inherent Risks

(1) A health threat exists for this experiment if you are not generally in good health, or if you have a medical history of diabetes, hypertension, heart disease, or any other serious illness.

(2) A health risk exists from the combined effects of alcohol and certain prescription, non-prescription, and illegal drugs.

(3) A risk of injury is present if you attempt to exit the simulator prior to the simulator motion being stopped or without the help of one of the experimenters.

(4) While under the influence of alcohol you may experience blurred vision, dizziness, nausea, loss of balance, and difficulty with speech.

(5) There may be some interference in your activities on the day following each experimental session.

Obligations

(1) You will be required to refrain from eating any foods or drinking any liquids (except water) for at least three (3) hours prior to each experimental session.

(2) You will be required to abstain from drinking any alcohol for twenty-four (24) hours perior to each experimental session.

(3) For the late night sessions you will be required to refrain from smoking cigarettes, ingesting sugar, caffeine, or any other stimulatns from six o'clock in the evening until after the experimental session.

(4) You will be required to remain under observation until your blood alcohol content (as indicated by a breathalyzer test) is reduced to 0.03% or less.

(5) After each session, you will be driven to your residence by a member of the research team. Under no circumstances will you be allowed to drive or walk home yourself.

(6) It is your responsibility as a participant to advise a member of the research team of any medical problems that arise during the course of this study. In the unlikely event that you suffer injury, we will not offer care or compensation other than first aid.

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

Your signature below indicates that you have read and understand the above stated rights and inherent health risks, that the information you have provided on the attached questionnaire regarding your health and any medication or drugs that you are currently taking is true to the best of your knowledge, and that you consent to participate in the study as described. If you include your printed name and address below, a summary of the experimental results will be sent to you.

Signature	
Date	Printed Name and Address
Witness Date	Vehicle Simulation Lab IEOR Department Virginia Tech Blacksburg, VA 24061 961-7962

HEALTH, MEDICATION, AND DRUG QUESTIONNAIRE

1. Are you in good general health? Yes No

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

   _____

   _____

   _____

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

Diabetes	Yes	No
Hypertension	Yes	No
Heart Disease	Yes	No
Any other serious illness	Yes	No

3. List any prescription drugs you are currently taking.

   _____

   _____

4. List any non-prescription drugs you are currently taking.

   _____

   _____

5. Do you drink alcoholic beverages (Beer, Wine, Fortified Wine or Liquor)? Yes No

6. Are you taking any drugs of any kind other than those listed in 3, 4, or 5 above? Yes No

_____ _____

Signature Witness

_____ _____

Date Witness

APPENDIX D

Alcohol Dosage Calculations

Two alcohol dosage levels will be used for this study, zero, and 0.075% BAC. (Both levels are at present within legal limits for driving in the State of Virginia.) These levels will be attained by administering a dosage of vodka mixed with a diet soft drink. The vodka used will be 80 proof (40% pure ethanol).

For both conditions, the total drink volume will be held constant with respect to body weight. The total drink volume will be determined by taking the participant's body weight in pounds, dividing it by 50, and multiplying the quotient by four. This gives four ounces of liquid per 50 pounds of body weight. (Barbre and Price, 1982). For the zero BAC condition, a small amount of vodka will be floated on top of the drink for taste. This will serve as the placebo (0% BAC) condition.

For the 0.075% BAC condition, the vodka dosage will be based on the subject's gender and body weight. For female subjects, 0.573 milliliters of pure ethanol per kilogram of body weight will be administered in accordance with formula (1) below (Barbre and Price 1982).

(1) $\% \text{ BAC} = 0.166d - 0.0803d^2 + 0.0348d^3$

where d is equal to milliliters of pure ethanol per kilogram of body weight. For male subjects, 0.746 milliliters of pure ethanol per kilogram of body weight will be administered in accordance with formula (2) below (Radwan, Price, and Tergou, 1983).

(2) $\% \text{ BAC} = .031941d + 16522d^2 - .09782d^3$

where d is again equal to milliliters of pure ethanol per kilogram of body weight.

The amounts of pure ethanol calculated above for females and males will be divided by 0.4 to give milliliters of vodka per kilogram of body weight.

The beverage will be consumed steadily over a 20-minute period, and will give a BAC close to the desired level of 0.075%. This level will start to decrease in approximately fifteen minutes after consumption and continue to decrease with time.

APPENDIX E

Breathalyzer Results

Each subject was given a breathalyzer test at the beginning and end of each run. As discussed in the procedure section, the subject was given 20 minutes to finish drinking the mixed drink. The subject was then given a breathalyzer test and started the run approximately 10 to 15 minutes after the drink was finished. The time between when the drink was finished and the run started varied slightly because the subject went to the restroom, which took varying amounts of time for each subject. Since, at the time of the first breathalyzer test, the alcohol was still being absorbed into the blood stream, this time difference caused greater variability in the test results prior to the run than the test results taken after the run. This difference in variability is illustrated in Table 60.

Table 60 shows the breathalyzer results for the BAC = 0.075% condition. All of the breathalyzer readings for the BAC = 0.000% conditions were 0.006% or less and therefore are not shown.

It is estimated that the subjects' BACs reached peak value approximately 15 to 20 minutes into the data run. Therefore, the exact peak value cannot be reported. However, extrapolation of the results was performed and is shown in Figure 14. Intervals equal to ± 1 of the breathalyzer tests taken before and after the runs as well as a hypothetical mean BAC curve are shown in Figure 14.

TABLE 60 Breathalyzer results for the BAC = 0.075% condition.

	Rested		Sleep Deprived	
Subject	Before	After	Before	After
1	.036	.036	.040	.040
2	.048	.035	.034	.031
3	.055	.040	.056	.035
4	.073	.035	.049	.039
5	.066	.037	.065	.040
6	.043	.032	.037	.042
$\bar{x}$ =	.054	.036	.054	.038
σ =	.014	.003	.015	.004

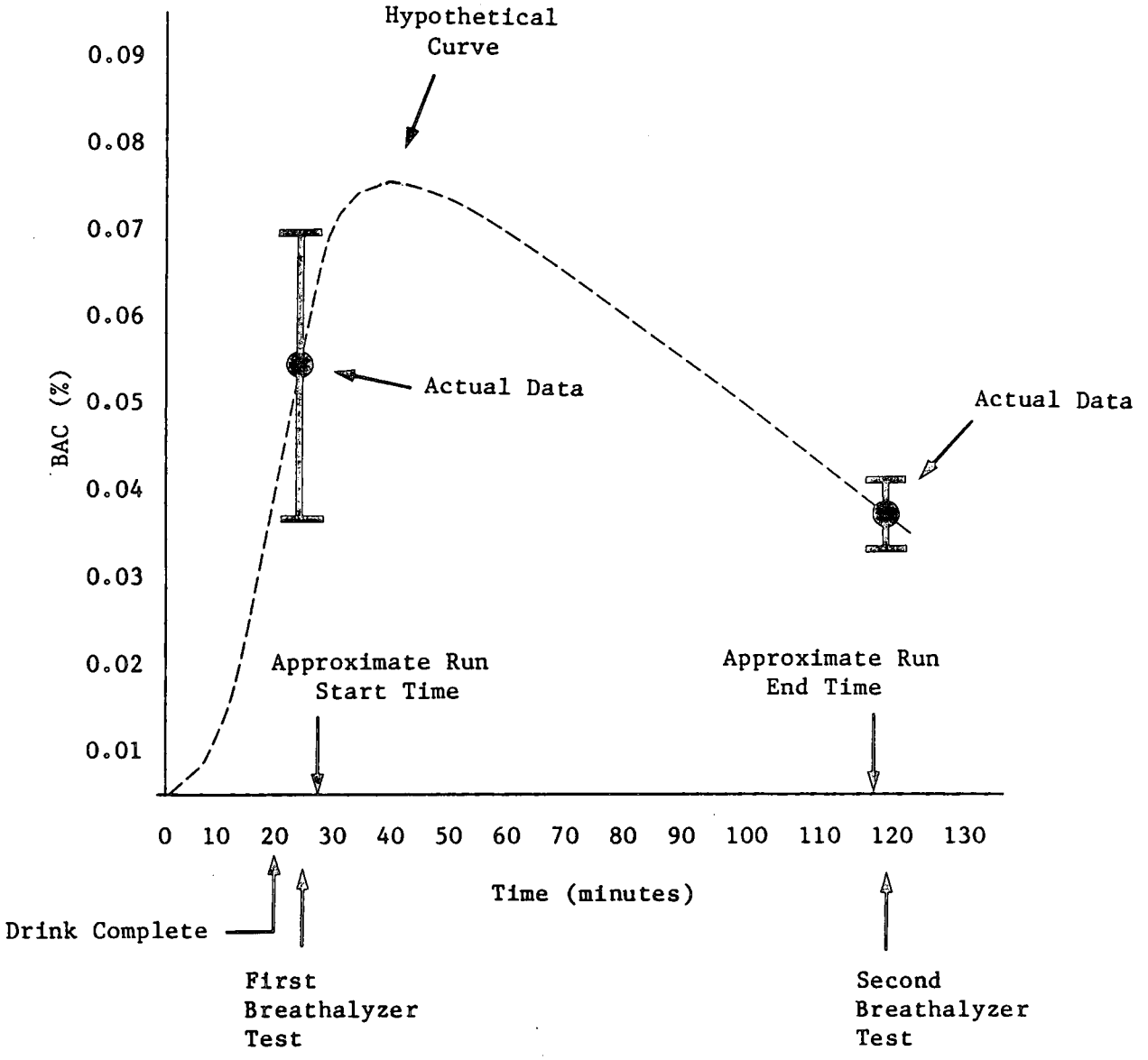

Figure 14. Interpolation of Breathalyzer Results to an Estimated Peak Value

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