D42

N79-15630

A DECISION MODEL APPLIED TO ALCOHOL EFFECTS ON DRIVER SIGNAL LIGHT BEHAVIOR

Stephen H. Schwartz and R. Wade Allen

Systems Technology, Inc.
Hawthorne, California

ABSTRACT

A decision model including perceptual noise or inconsistency is developed from expected value theory to explain driver stop and go decisions at signaled intersections. The model is applied to behavior in a car simulation and instrumented vehicle. Objective and subjective changes in driver decision making were measured with changes in blood alcohol concentration (BAC). Treatment levels averaged 0.00, 0.10 and 0.14 BAC for a total of 26 male subjects. Data were taken for drivers approaching signal lights at three timing configurations. The correlation between model predictions and behavior was highly significant. In contrast to previous research, analysis indicates that increased BAC results in increased perceptual inconsistency, which is the primary cause of increased risk taking at low probability of success signal lights.

INTRODUCTION

One of the motivations for developing the driver decision model described here was to measure and analyze the behavior of alcohol-impaired drivers. We desired to separate risk taking into components of risk perception and acceptance. If a driver takes increased risks, is it because he perceived the risk and decided to accept it or because he does not perceive the increased risk? Expected value theory provides a simple construct for making this distinction and has been applied in the past to describe impaired driver behavior, (References 1, 2, and 5).

Here we apply a Subjective Expected Value (SEV) model to explain driver stopping and going behavior at signaled intersections. Perceptual noise is included to reflect one type of driver inconsistency in the decision-making process (Reference 3). The model is applied to data collected as part of an automobile simulator study involving a typical drive-home scenario. Although measures were taken throughout the scenario on several tasks, we concentrate here on signal light behavior. We briefly present the decision model, the experimental results, and our analysis and interpretation in view of previous studies.

630

PAGE INTENTIONALLY BLANK

DECISION-MAKING MODEL

The model was derived to guide experimental design and measurement. The expected value approach is not new; however, the inclusion of perceptual noise as applied to signal light behavior is original. The basic scenario is a signal light at an intersection which has changed from green to amber and will change to red in 3 seconds. Based on his perception of speed and distance the driver must then decide whether to stop or go. The kinematics for this task have been described previously, Reference 4. Here we briefly derive an appropriate decision model subject to several assunptions.

We begin by simplifying what is actually a complex decicion task, Reference 11, in a simple two-alternative situation. Conceptually we are assuming this decision process takes place in parallel with the driver's continuous speed control behavior as illustrated in Figure 1. Perceptions of vehicle

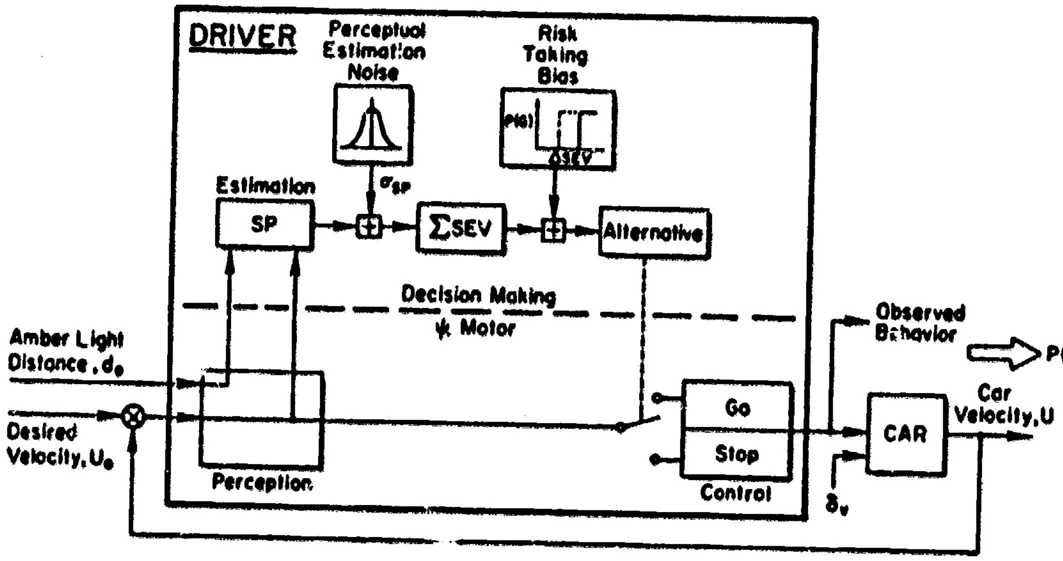

Figure 1. Signal Light Risk Acceptance Model

velocity and distance to the signal at the time the light changes to amber are used to form a subjective estimate of the probabilities of success and failure for the various alternatives. As indicated in the figure and discussed further below, these subjective probabilities are stochastic in nature. They are weighted with appropriate utilities or values and the driver selects the alternative with the highest expocted value. We define Subjective Expected Values (SEVs) for the two alternatives, go or stop, respectively:

$$\mathrm{SEV(Stop)} = \mathrm{SP(Pass/Stop)V(Pass/Stop)} + \mathrm{SP(Fail/Stop)V(Fail/Stop)} \quad (1)$$

$$\mathrm{SEV(Go)} = \mathrm{SP(Pass/Go)V(Pass/Go)} + \mathrm{SP(Fail/Go)V(Fail/Go)} \quad (2)$$

where SP(·) and V(·) are conditional subjective probabilities and values, respectively. From these equations and the several other simplifying assumptions, we can express the probability that a driver will attempt to go through the signal light. Further simplifying notation so that F = Fail and G = Go, the probability of Going is:

$$P(G) = \iint_{\text{Region}} f[SP(F/G), SP(F/S]\, dSP(F/G)\, dSP(F/S) \tag{3}$$

where the region is defined by:

$$P(G) = P[SEV(G) \geq SEV(S)] \tag{4}$$

With the assumptions listed in Table 1, it can be shown (see Reference 6 for derivation) that the P(G) is the Gaussian integral:

$$P(G) = \frac{1}{\sigma_{SP(F/G)}\sqrt{2\pi}} \int_{0}^{SP_c(F/G)} \exp\left\{\frac{-[SP(F/G) - \overline{SP}(F/G)]^2}{2\sigma^2_{SP(F/G)}}\right\} dSP(F/G) \tag{5}$$

TABLE 1. SOME MODEL ASSUMPTIONS

1. Operator selects decision alternative with largest subjective expected value. Values reflect utilities and are constant.
2. Subjective probabilities are mutually exclusive and exhaustive.
3. Subjective probabilities are Gaussian random variables in the region of interest.
4. Increased SP(F/G) decreases P(G), i.e., the values discourage go-failures.
5. The verbal estimates of SP(F/G) linearly reflect subjective perception.
6. The threshold value of SP(F/G), below which the operator selects the go alternative is $SP_c(F/G)$:
   - $\triangleq \overline{SP}(F/G)$ where P(G) = 0.5
   - is a constant as compared with being a random variable
7. SP(F/S) = 0.

A typical example of these concepts is illustrated in Figure 2. Repeated observations for a given situation, e.g., signals with the same time to the intersection, result in a distribution of subjective estimates illustrated by the top probability density curve. Assuming a cutoff subjective probability, $SP_c(F/G)$, as illustrated, the area under the density curve and to the left of the criterion is P(G). This is illustrated in the bottom of Figure 2, where the relationship of P(G) as a function of the average subjective estimate, $\overline{SP}(F/G)$, is illustrated. The slope of this relationship is determined by the variability of the subjective estimates, σ_{SP}. Note that the effect of increasing the variance of the subjective estimates is to increase P(G) for the case illustrated. Also shown is the consequence of a change in the driver's risk acceptance, $SP_c(F/G)$.

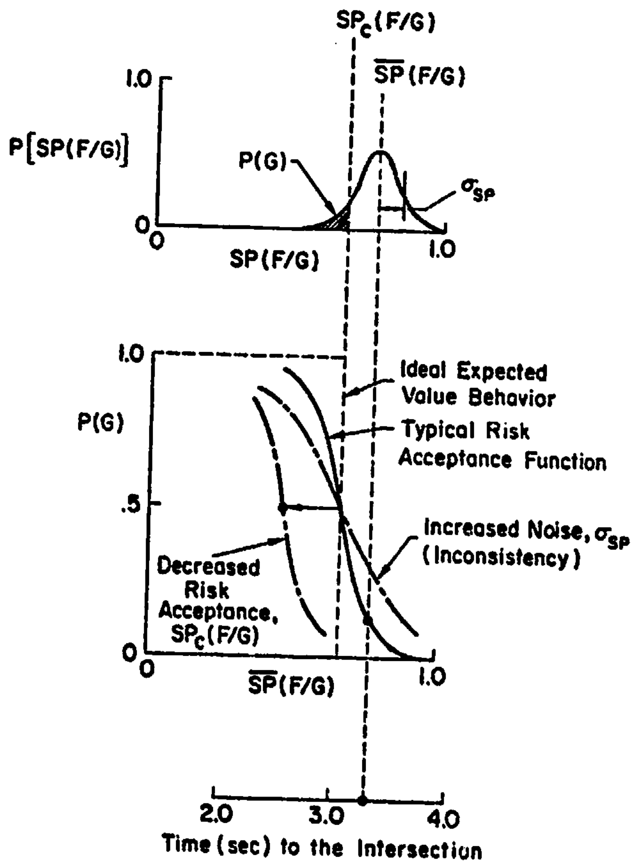

Figure 2. Typical Relationship Between Probability of Going, P(G), Subjective Probabilities of Fail Given a Go, SP(F/G), and Signal Timing

A useful empirical relationship is also apparent in Figure 2. Evaluation of Eq. 5 for the condition $SP_c(F/G) = \overline{SP}(F/G)$ results in $P(G) = 0.5$. Thus, the subjective cutoff $SP_c(F/G)$ can be determined empirically from objective behavior probabilities by selecting the value of $\overline{SP}(F/G)$ at $P(G) = 0.5$.

THE EXPERIMENTS

The signal light task was simulated in both a fixed-base simulator and instrumented vehicle on a closed course as described in the companion paper (see Reference 14). The signal light timing was controlled similarly in both simulation and field studies. When the vehicle approached the intersection, the signal light initially turned green. At a random-appearing time later, the signal turned amber. This time was controlled by a circuit which compensated for car speed such that the time interval to the intersection was the same for a given intersection type, regardless of the approach speed, if the driver maintained that speed. The amber light interval was fixed at 3 seconds, following which the light turned red. Thus, the probability for successfully making a light was controlled without placing an artificial speed restriction on the subject. Five signal timings were automaticlly commanded. One was set to require a sure stop (early yellow) and another a sure go (long green). The remaining three timings ranged from a probable stop to a probable go. The times to the intersection from the amber light typically ranged from 2.0 to 3.5 seconds. (The kinematics of stopping or going for these timings are discussed more fully in Reference 4.)

The subjects were instructed to behave as they normally would in a driving situation with a reasonable motivation for timely progress and a desire to avoid tickets and accidents. Also, a monetary incentive structure was provided as a tangible and quantifiable motivation for performance (see Reference 14).

Subjects were trained until objective performance and subjective estimates were consistent in the view of the experimenter. Subjective estimate training began with a short tutorial written exam used as a basis for discussion of the concepts of probabilities. Following this, each subject received two to three hours of practice driving in half-hour sessions spread over two days. Feedback on performance and subjective estimates was given throughout these training trials.

Subjects completed trials on each of two days. During an alcohol day, the trials corresponded to an across-subject average blood alcohol concentration (BAC) of 0.00 (baseline), 0.10 (ascending — when measured), 0.14 (peak), and 0.10 (descending). During the placebo day, the trials were given at approximately the same time of the day as for the above trials. The day order was counterbalanced among subjects.

Objective and subjective measures were taken, and the number of stop and go decisions was recorded. The number of failures and successes for each decision was detected automatically and recorded irrespective of whether or not the driver received a ticket. Corresponding subjective estimates were recorded during the run. Subjects were asked to give their estimate of failure on a scale of 0 to 100 percent immediately following randomly selected intersections. Nominally, six of each type of intersection were selected. Intersections for which the driver received a ticket were ignored. (A tacit assumption in using subjective estimates received after the execution of the signal task is that the subjective probabilities were unbiased by performance outcomes as perceived by the subject. To test this assumption, a parallel simulation experiment used selected intersections where the visual scene was blanked out immediately following the driver's commitment to a decision and prior to going through the intersection. Thus the driver received no feedback on his performance for these selected intersections. These results were similar to the "after the fact" estimates.)

RESULTS

The data were examined for each intersection independently over the eight trial conditions (four trials per session for placebo and alcohol sessions). Both objective and subjective data were analyzed to differentiate between changes in risk acceptance vs. risk perception.

In Figure 3 the objective probabilities of going, $P(G)$, and failing given a go, $P(F/G)$, for both the simulation and field test are compared to determine driver risk-taking behavior. The probabilities were computed by dividing the total number of outcomes by the total number of opportunities (e.g., $P(F/G)$ = Number of go failures/Number of go's). For example, Intersection 2 in the simulation resulted in the subjects always going, $P(G) = 1$, and the timing was such as to preclude go failures, $P(F/G) = 0$. The timing was also adequate on Intersection 3 to allow safe go's; however, in this case the drivers did not always go, i.e., $P(G) \doteq 0.75$. This behavior was not sensitive to alcohol, and the subjects appear to have been behaving conservatively on Intersection 3. Subjects did not go very frequently on Intersection 4 and had a high failure rate when they did. There is an indication of increased go behavior under alcohol for Intersection 4. This is also apparent for all the intersections in the field test.

Part of the reason for this increased going behavior on some intersection timing in spite of increased failures is illustrated in Figure 4. Here we note that the variability of the subjective risk perception, σ_{SP}, increases although the average perception of risk, $\overline{SP}(F/G)$, remains relatively constant. Considering a typical switching criterion, as shown in Figure 4, we see that the increased variability of risk perception with increased alcohol leads to a greater percentage of subjective estimates below this criterion. The justification for this interpretation was validated via statistical analysis of parameters for the proposed model.

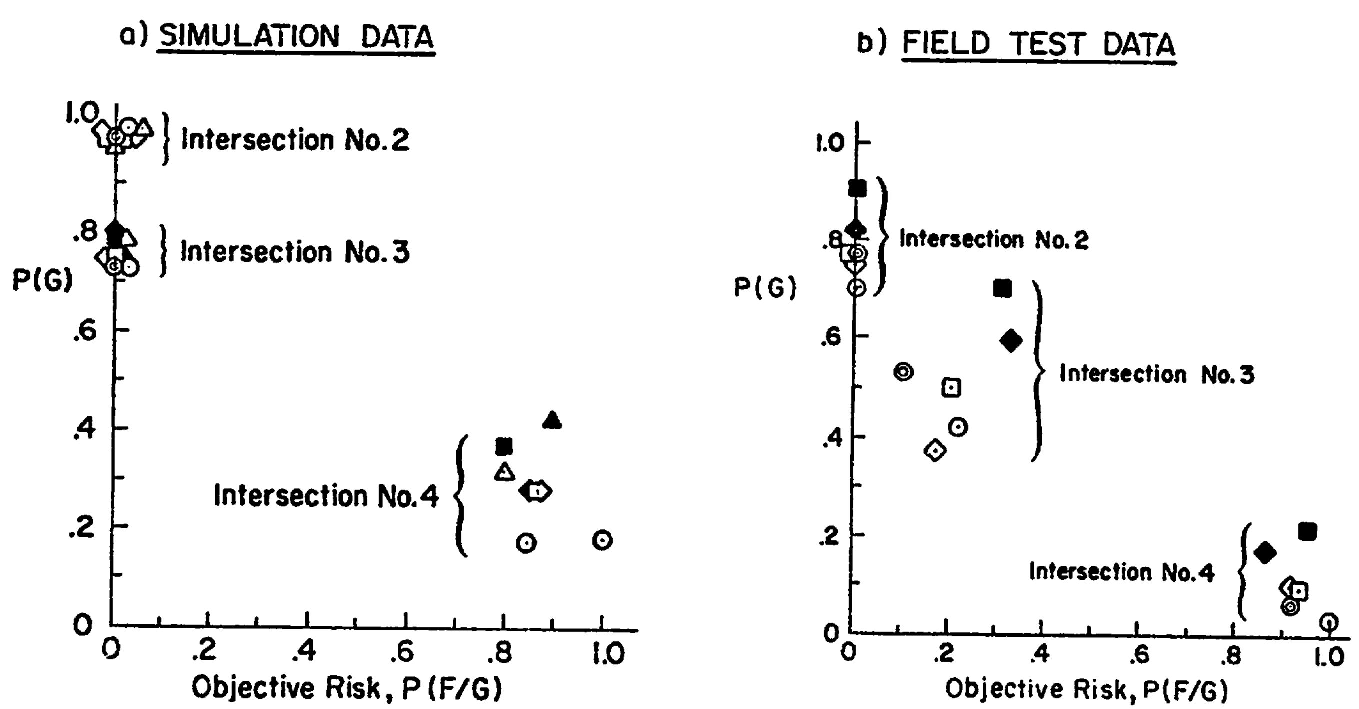

Figure 3. Alcohol Effects on Signal Light Risk-Taking Behavior

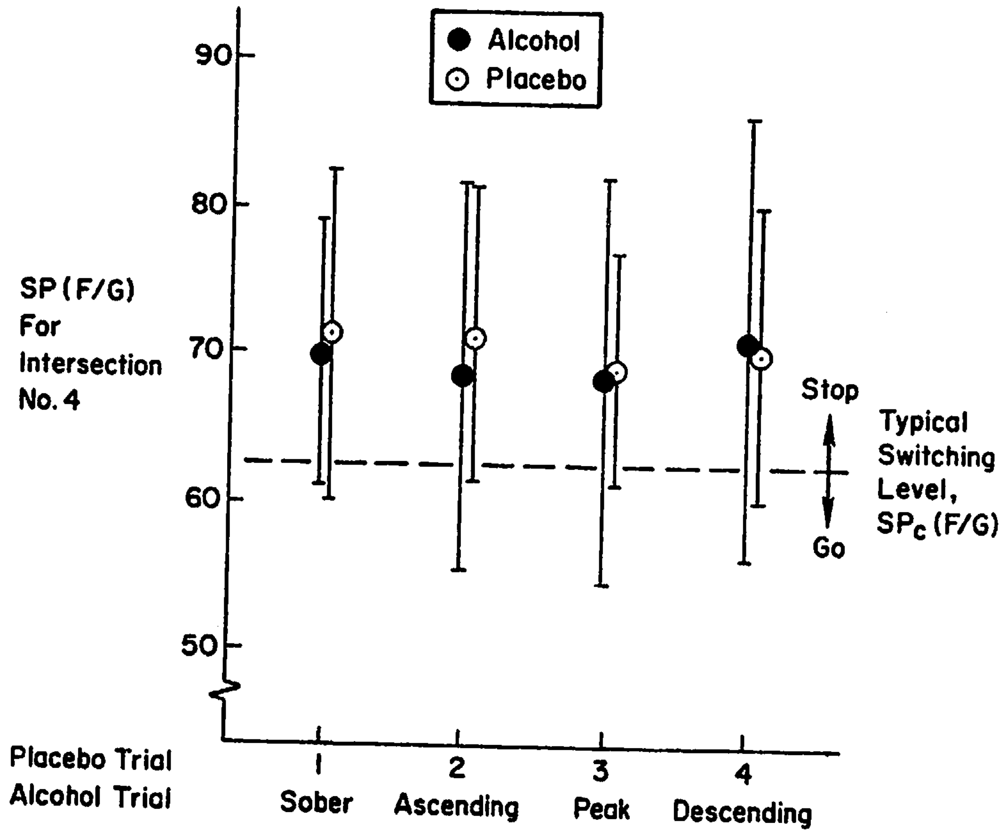

Figure 4. Changes in Subjective Estimates of the Probability of Failure Given a Go Attempt, SP(F/G) with BAC Condition

MODEL EVALUATION

The decision-making model discussed above was used to analyze driver risk acceptance behavior. This was accomplished in three steps. First, driver risk acceptance thresholds, $SP_c(F/G)$, were computed for each experimental treatment. Then the threshold data were analyzed to investigate changes under intoxication. Finally, the various risk perception data were combined according to Eq. 5 and resulting computed or estimated values of the probability of going, $\hat{P}(G)$, were compared with actual P(G) data to establish model validity.

Risk acceptance thresholds were computed for each subject and each run by curve fitting a risk acceptance function (Figure 5) to P(G) and $\overline{SP}(F/G)$ data for the three intersection timing conditions. A trigonometric function was used to describe the risk acceptance function:

$$P(G) = \frac{1}{2}\; 1 + \sin a\,[\overline{SP}(F/G) - SP_c(F/G)] \qquad (6)$$

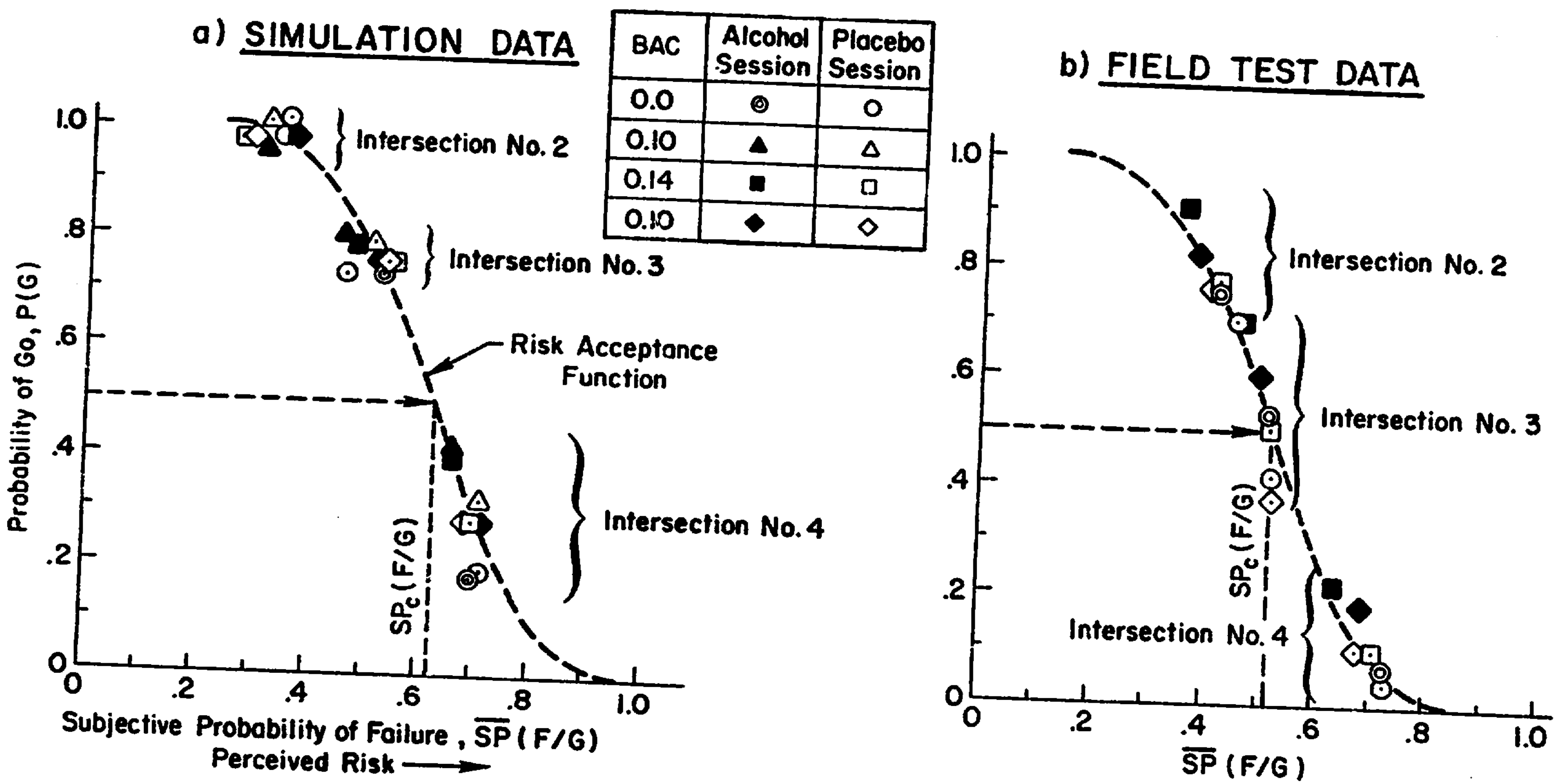

Figure 5. Alcohol Effects on Signal Light Decision Making Behavior

By rearranging this formula we obtain a relationship which can be used for a linear regression fit:

$$a\overline{SP}_i(F/G) - aSP_c(F/G) = \sin^{-1}[2P_i(G) - 1] \tag{7}$$

The data input for this regression fit is the mean subjective probability of failure and probability of going for each intersection. The derived values are then a and the risk acceptance threshold $SP_c(F/G)$. The parameter a describes the slope at the midpoint of the risk acceptance and is inversely proportional to the risk perception variability σ_{SP}.

The $SP_c(F/G)$ were computed and analyzed with no indication of alcohol effects on driver risk acceptance. The SP_c and $\dot{S}P(F/G)$ data were then used to compute probability of go estimates, $\hat{P}(G)$, according to Eq. 5. These compare favorably as shown in Figure 6. Analysis of covariance procedures were employed to compare the actual and estimated values of P(G). The F ratios indicated that P(G) was highly correlated with the computed estimate $\hat{P}(G)$, Reference 6.

These results suggest that the alcohol effects on the drivers' subjective risk perception, both $\overline{SP}(F/G)$ and σ_{SP}, are responsible for drivers increased going behavior while intoxicated. They also validate the usefulness of the model in analyzing that behavior.

There are other possible interpretations of these results. An intuitive one is that the variations in subjective estimates are due to variations in the time of the decision and not to variations in perception for a given time and distance relation. However, a preliminary analysis of the time histories for several of the subjects indicated that the response times did not change significantly under alcohol, Reference 7. In addition, there are other models which could be applied to the observed signal light behavior. A potentially fruitful approach is the signal detection model as developed by Green and Swets, Reference 8, expanded for application to man/vehicle problems by Curry, et al., Reference 9, and applied to the lane change maneuver by Cohen and Ferrell, Reference 10. Other types of criteria suggested in this work, such as likelihood ratio threshold and Newman-Pearson strategy, may be applicable. However, it is apparent from Figure 6 that the additional refining assumptions used in these models may not be necessary for interpreting the major effects of alcohol on decision behavior.

PREVIOUS RESEARCH

While increasing frequency of driving decision errors with increased BAC has been found by other researchers, the interpretation of which behavior component is primarily responsible for this increase has been inconsistent. Comparison between studies is confounded because of differences in tasks, reward and penalty conditions, alcohol treatment methods, and analytical approaches. However, the results can be interpreted and compared as follows.

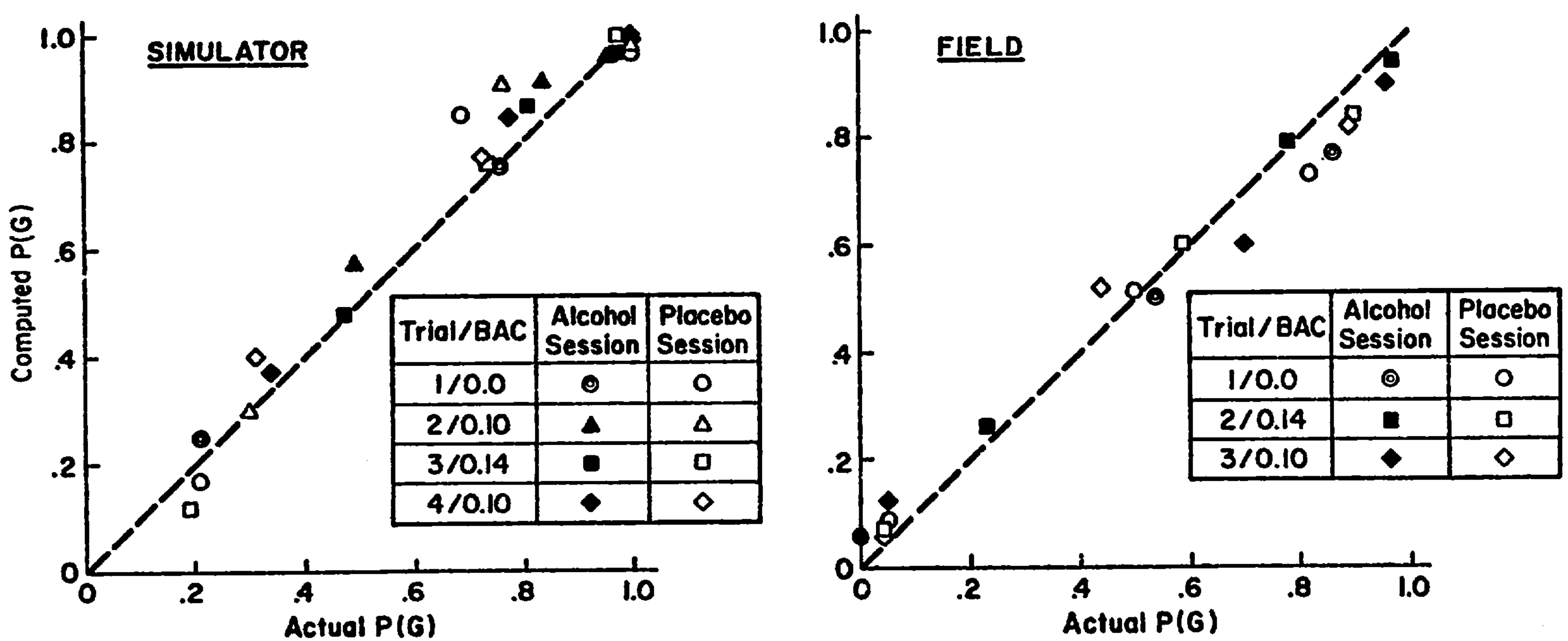

Figure 6. Comparison of Measured Versus Computed Probability of Going. $\hat{P}(G)$ Estimates Computed Using Measured Values of SP(F/G), σ_{SP}, and $SP_c(F/G)$

In agreement with our results, four of the five other studies commented on here found increased risk taking with increased alcohol intake. Cohen, Dearnaley, and Hansel, Reference 1, in evaluating bus drivers' willingness to drive through a cone-delineated gap found the number of attempts increased with alcohol intake. Lewis and Sarlanis, Reference 11, using a simulated traffic signal, found the number of go responses significantly increased under alcohol. Light and Keiper, Reference 12, also found an increased number of attempted passes in a simulated overtaking and passing task. Finally, Ellingstad, McFarling, and Struckman, Reference 13, in evaluating performance on laboratory analogs of automotive passing tasks with multiple discriminant analysis, found the discriminant "riskiness/indecisiveness" increased with alcohol. This discriminant included a positive loading on passing attempts. The only exception to this trend was presented by Snapper and Edwards, Reference 2, who found no significant change with BAC in the number of attempted lane changes through a given gap size on their closed course.

The interpretation of these data as resulting from changes in psychomotor skill, perceptual ability, or cognitive risk acceptance varies between authors. Re-analysis is difficult because only two of these studies took sufficient measures to delineate changes in decision strategies. Cohen, et al., Reference 1, asked the bus drivers to indicate levels of confidence expressed as the number of times out of five the driver thought he could succeed in driving through the different size gaps. The estimates did not change significantly on the average for the narrowest accepted gap; however, the accepted gap size decreased with increased alcohol intake. Therefore, he assumed "If the difficulty of the task remained unchanged, they became more optimistic and attached a higher subjective probability to the task." The variances in the estimates were not reported. Cohen concluded that the primary effects of alcohol were to decrease psychomotor skill and deteriorate "judgment," where we interpret judgment to include mean perception. Snapper and Edwards, on the other hand, asked their subjects for subjective probabilities and found no significant change in the mean for a given gap size. As they found no change in the mean subjective estimates and no increased risk taking, but with increased failures in execution, they concluded that the primary effect of increasing BAC was degraded psychomotor skill. Again, no data on the effects of BAC on the consistency or variability of the subjective probabilities were presented.

By comparison, our findings agree with most of these results but not with the authors' interpretations. As in most of these studies, we found increased risk taking and no change in risk acceptance, i.e., no change in the mean subjective estimate for a given intersection. However, our data suggest that increased risk taking is primarily due to increased variance or inconsistency in perceptual estimates. This interpretation could also explain the results found by the first four authors mentioned above if data on mean and variances of subjective estimates were available. The disparity between this conclusion and Snapper and Edwards' conclusion may be due to at least two factors. Their lane change task placed more emphasis on psychomotor execution than does the current signal light task; hence their results may have been more sensitive to this type of degradation. In fact, we found considerable degradation in the consistency of psychomotor performance in the other tasks in our driving scenario (Reference 7). In addition, a fundamental difference between our simulated driving tasks and those of both of the previous studies using subjective estimates is addition of temporal pressure. Our subjects were required to form their estimates in "real time" as opposed to the "stop action" type of judgments and driving scenarios used in previous studies.

Thus, the behavior skills required for the decision-making tasks of the other researchers are somewhat different from those studied here. Allowing for these differences, the other studies may have had the same cause for the increased risk taking as measured here, namely, distorted perception, but they did not present sufficient data to determine it.

In summary of previous decision-making studies, those aspects of our results which are directly comparable with previous research largely agree with those findings. Risk taking generally increased with increasing BAC. Interpretation of previous work beyond this point is difficult because of insufficient measures. However, that work does not disagree with the current conclusion that there is no change in risk acceptance. Our interpretation of these results, that perceptual distortion is a primary cause of alcohol-induced increased risk taking observed for simple tasks, is new.

CONCLUSIONS

An expected value model accounted for the effects of perceptual noise on decisions for drivers in a simulated signal light task. With this model, analysis of the significant changes in behavior for increasing BAC indicated no changes in risk acceptance; that is, subjects did not change their subjective criterion level. The primary cause of the increased risk taking found for intersections timed with a low probability of success was increased inconsistency or variance in their subjective perceptual estimates.

These results have ramifications both for researchers in this field and those attempting to apply the results. In future human decision-making work, measures of inconsistency in perception should be given as much attention as measures of central tendency. Also suggested by these results is that one method of reducing drinking driver errors may be to improve the driver's perceptual environment to decrease his inconsistency. We could expect these results to generalize the effects of alcohol on other such real-time decision tasks as aircraft and spacecraft control. In addition, the analytical framework used here may be useful in evaluating the effects of other drugs and stressors on human decision behavior.

ACKNOWLEDGMENT

This work was supported by the Department of Transportation, National Highway Traffic Safety Administration, under Contract No. DOT-HS-4-00999. The views expressed in this paper are those of the authors and do not necessarily represent those of the National Highway Traffic Safety Administration.

REFERENCES

1. Cohen, J.; Dearnaley, E. J.; and Hansel, C. E. M. The Risk Taken in Driving Under the Influence on Alcohol. Brit. Med. J., 21 June 1958, pp. 1438-1442.

2. Snapper, K.; and Edwards, W. Effects of Alcohol on Psychomotor Skill and Decision-Making in a Driving Task. Univ. of Michigan, Department of Psychology, NIAAA Grant No. MN22063-01, 1973.

3. Hurst, P. M. Consistency in Driver Risk Taking. Behavioral Res. in Driving Safety, combined issues, vol. 2, nos. 1-2, Spring-Fall 1971, pp. 73-82.

4. Allen, R. W.; Schwartz, S. H.; and Jex, H. R. Driver Decision-Making Research in a Laboratory Simulation. NATO Symposium on Monitoring Behavior and Supervisory Control, Berchtesgaden, 8-12 Mar. 1976.

5. Rapoport, A.; and Wallsten, T. S. Individual Decision Behavior. Ann. Review of Psych., vol. 23, 1972, pp. 131-176.

6. Allen, R. W.; Schwartz, S. H.; Hogge, J. R.; and Stein, A. C. The Effects of Alcohol on the Driver's Decision-Making Behavior. Systems Technology, Inc., TR-1053-1, Feb. 1978.

7. Allen, R. W.; Schwartz, S. H.; Stein, A. C.; and Hogge, J. R. The Effects of Alcohol on Driver Performance in a Decision-Making Situation. Presented at the 14th Annual Conference on Manual Control; published in this volume.

8. Green, D. M.; and Swets, J. A. Signal Detection Theory and Psychophysics. New York: Wiley, 1966.

9. Curry, R. E.; Gai, E. G.; and Nagel, D. C. Decision Behavior with Changing Signal Strength. In Proc. 10th Annual Conf. on Manual Control, Wright-Patterson AFB, OH, 9-11 Apr. 1974.

10. Cohen, H. S.; and Ferrell, W. R. Human Operator Decision-Making in Manual Control. IEEE Trans., vol. MMS-10, no. 2, June 1969, pp. 41-47.

11. Lewis, E. M., Jr.; and Sarlanis, K. The Effects of Alcohol on Decision Making with Respect to Traffic Signals. Dept. of Health, Education, and Welfare, Rept. No. ICRL-RR-68-4, 1969.

12. Light, W. O.; and Keiper, C. G. Effects of Moderate Blood Alcohol Levels on Automobile Passing Behavior. Dept. of Health, Education, and Welfare Report No. ICRL-RR-69-4, 1971.

13. Ellingstad, V. S.; McFarling, L. H.; and Struckman, L. L. Alcohol, Marijuana and Risk Taking. Dept. of Transportation, Rept. DOT HS-801 028, Apr. 1973.

14. Stein, A. C.; Schwartz, S. H.; and Allen, R. W. Use of Reward-Penalty Structures in Human Experimentation, published elsewhere this volume.