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Relationships Between Crash Casualties and Crash Attributes

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ABSTRACT

This work addresses and evaluates the likelihood of human casualty in highway crashes, projected on the basis of field crash data that may become available electronically by sensors at crash time, and/or observed at the crash scene by emergency attendants. Termed collectively as a "crash signature", such data are treated as predictors and are selected from: crash severity, general area of damage, direction of force, occurrence of rollover, intrusion, vehicle crush and its specific horizontal location, collision partner, vehicle class and size, occupant age, gender, restraint use and type, seating position, and other. Crash signatures are converted into responses such as: (a) the likelihood of the most severe outcome, fatality or survived injury, by severity AIS per occupant; and (b) the same per vehicle. Cars are the vehicles selected for this investigation. A likelihood is quantified by a probability of occurrence, as a function of a string of predictors selected for maximum resolution and sensitivity, and minimum contribution to error. Likelihood determinations are performed via maximum likelihood based logistic regressions, best suited for treating dichotomous responses: "yes or no" such and such a response or outcome. Each likelihood is accompanied by a standard error or by upper and lower confidence bounds, and each procedure is evaluated by pertinent scores. All cited procedures and findings are based on the data of the National Accident Sampling System (NASS) files 1988-1995, compiled by the National Highway Traffic Safety Administration (NHTSA). This provides a nationally representative sample of about 95,000 crash involved car occupants, and 190,000 incurred injuries, all with attributes that collectively encompass as a minimum the predictors and responses cited earlier. The paper provides pertinent predictive relations which, notwithstanding complexity, are fully programmable. Probabilities of specific outcomes may vary from nearly zero to virtually 100%, depending on circumstances. Detailed and illustrative findings are presented in tabular and graphic forms.

INTRODUCTION

The advent of high volume highway accident records, many of them nationally representative and of a research caliber, addressing a broad spectrum of crash, vehicle, occupant, and casualty attributes, makes it easier now to address and evaluate several important issues in highway safety.

At the same time, the wide scope and the complexities of the available data point to the need for developing ways and means in order to capture the essential aspects of the highway crash environment in a succinct and insightful fashion. The purpose of this paper is to take a first cut in responding to the cited need.

BASIC DATA

The data compiled in the eight years, 1988-1995, of NASS/CDS are the basic data used. The NASS weights, necessary for national projections, are used as weighing factors in any data processing procedure.

Many outcomes and their severity may be considered individually or in combinations for the purpose of human casualty prediction. Also many crash, car, occupant, and injury attributes are in principle available in the accident experience to assist, as predictors, in the derivation of said algorithms on the basis of a crash signature. The number and type of predictors are often limited by practical considerations imposed by the type of contemplated applications, the strength of probability --predictor correlation, and by the amount and quality of available data for the derivation of the algorithms.

NOMINAL PROCEDURE FOR TREATING THE RAW DATA

In view of the dichotomous nature of the outcomes at issue (e.g. "Yes" or "No" Fatality or MAIS 3+) a maximum likelihood procedure, specifically a logistic regression with weighing factors, is used to fit various algorithms to the raw data. Essentially, the probability of casualty is projected as:

P = 1 / [1 + exp(-w)]   (1)

w = A0 + A1*PRED1 + A2*PRED2 + ... (2)

where PRED1, PRED2, etc are the selected predictors; and A0, A1, A2, etc are coefficients estimated by the logistic regression.

When dealing with analyses of data from the NASS, it must be taken into account that this file contains a sample as opposed to a census of national data. In order to deal with this, the applicable statistical procedures are those prescribed in "Survey Data Analysis" (SUDAAN) software, Research Triangle Institute, Research Triangle Park, North Carolina, 1992. Such procedures are applicable in the analysis of data from multi-stage sample designs, like that of the NASS.

ESTIMATION OF STANDARD ERRORS AND CONFIDENCE BOUNDS

The SUDAAN logistic procedure yields values for coefficients: A0, A1, A2, etc appearing in (2). The same procedure provides also the covariance matrix: COV(Ai, Aj). This helps in the calculation of the variance of the argument w of the probability appearing in (1). Specifically, the variance of w is given by:

var(w) = Sum[Cov(Ai, Aj)*xi*xj]   (3)
over all i and j

Note that i or j assume the values: 0, 1, 2, etc, corresponding to the intercept and the predictors appearing in relation (2). When an analyst assigns desirable values to xi and xj, an application of (3) yields the variance: var(w).

Moreover, to a first approximation, the variance of the probability (1) is given by:

var(P)={exp(-2w)/[1+exp(-w)]**4}*var(w)   (4)

and the standard error of P is:

seP = square root [var(P)]   (5)

Also to a first approximation, the 95% confidence bounds of P are given by: P +/- (1.96 * seP)

ADDRESSED PREDICTORS

In this paper the basic data, i.e. data concerning car occupants involved in towaway crashes, are used for the derivation of algorithms that estimate: (a) the probability of a crash involved occupant being a fatality; (b) the probability of a crash involved occupant with at least one injury of maximum severity MAIS 3+; and (c) the probability of a crash involved occupant with at least one injury of MAIS 2+. Extension to other outcome populations is readily evident. Short notation for the predictors addressed in developing algorithms is given below:

ONEVEH Single Car Crash
BIGTRK Collision with Large Vehicle
ROLL Planar Crash with Rollover Occurrence
DELTAV Total Delta V, mph
GADSP Side Damage, Passenger Compart.
GADSNP Side Damage, Excluding Passenger Compartment
GADB Rear Damage
DOFS Direction of Force: 8-10 & 2-4 O'Clock
DOFB Direction of Force: 5-7 O'Clock
MAXC Maximum Crush, inches
INTRU Intrusion, 6 inches or more, in Front
CURBWT Car Curb Weight, in 100 lbs
FRPAX Right Front Seat Pasenger
RRPAX Rear Seat Pasenger
BELT Safety Belt Use
BEBA Air Bag Deployment & Belt Use
AGE Car Occupant's Age
FEMALE Occuppant's Gender
OCCWT Occuppant's Weight, lbs
OCCHT Occuppant's Height, inches
ENTRP Entrapment
EJC Complete Ejection
EJP Partial Ejection

These predictors are alternatives and operate in conjunction with a baseline that addresses unrestrained male car drivers, in primarily planar and frontal crashes with other cars. Thus, given the cited baseline, the only two alternatives addressed above for a collision partner are: ONEVEH and BIGTRK. Similarly GADSP, GADNSP, and GADB are the alternatives to frontal damage included in the baseline. Top damage is not addressed because of a relatively low incidence.

In fact it is important to note that rollover in general is not included in the development of the algorithms at issue. This is necessitated by the desire to include Delta V as a most influential parameter. This parameter is not defined in general rollover. Thus, predictor ROLL appearing in the above list covers the crashes which are initially planar, with a possible subsequent rollover.

Other implicitly understood alternatives not named in the above list are: direction of force 11 to 1 O'Clock, driver's seat, no restraint use, male occupant, and no ejection. These are baseline attributes. Most other attributes are either binary (yes or no), or continuous.

PROGRAMMABLE ALGORITHMS

Optimal algorithms are presented below in order of increasing complexity. Relation (1) is always the basic platform. The simplest way of formulating the exponent "w" is in terms of DELTA V, the most influential parameter, as shown below:

$$w = A0 + A1 \cdot DELTAV \quad (6)$$

where DELTAV=Total Delta V in mph continuously.

The logistic regression (1) and (6) applied on the basic data, seeking the probability for fatality or MAIS 3+ or MAIs 2+, yields the coefficients A0 and A1 and the associated standard errors, with numerical values shown in the first cluster of Table I. Next we address the more complex, but still relatively simple, fit shown in (7) below:

$$w = A0 + A1 \cdot DELTAV + A2 \cdot DOFS + A3 \cdot DOFB \quad (7)$$

where in addition to DELTAV we include:
DOFS = 1 if the direction of force is 8-10 or 2-4 O'Clock, else DOFS=0;
DOFB = 1 if the direction of force is 5-7 O'Clock, else DOFB=0; and if DOFS=DOFB=0 then the direction of force is 11 to 1 O'Clock.

Numerical values for the coefficients A0, A1, A2, and A3 appear in the second cluster of Table I.

In a similar fashion we augment the resolution of the algorithms by including additional predictors as shown in the following three progressively complex cases:

$$w = A0 + A1 \cdot DELTAV + A2 \cdot DOFS + A3 \cdot DOFB + A4 \cdot AGE + A5 \cdot BELT + A6 \cdot BEBA \quad (8)$$

$$w = A0 + A1 \cdot DELTAV + A2 \cdot DOFS + A3 \cdot DOFB + A4 \cdot ROLL + A5 \cdot FRPAX + A6 \cdot RRPAX + A7 \cdot AGE + A8 \cdot BELT + A9 \cdot BEBA \quad (9)$$

$$w = A0 + A1 \cdot ONEVEH + A2 \cdot BIGTRK + A3 \cdot ROLL + A4 \cdot DELTAV + A5 \cdot GADSP + A6 \cdot GADSNP + A7 \cdot GADB + A8 \cdot MAXC + A9 \cdot INTRU + A10 \cdot CURBWT + A11 \cdot FRPAX + A12 \cdot RRPAX + A13 \cdot BELT + A14 \cdot BEBA + A15 \cdot AGE + A16 \cdot FEMALE + A17 \cdot OCCWT + A18 \cdot OCCHT + A19 \cdot ENTRP + A20 \cdot EJC + A21 \cdot EJP \quad (10)$$

where in addition to predictors defined earlier,
AGE = occupant's age in years continuously;
BELT = 1 if a safety belt is in use; else BELT=0;
BEBA = 1 if an air bag deploys in addition to a safety belt in use; else BEBA=0;

ROLL = 1 if car rollover occurs; else ROLL=0;
FRPAX = 1 if the occupant is in front seat right; else FRPAX=0;
RRPAX = 1 if the occupant is in rear seat; else RRPAX=0; if FRPAX=RRPAX=0 then we deal with the driver;
ONEVEH = 1 if this is a single car crash; else ONEVEH=0;
BIGTRK = 1 if the collision partner is a big truck; else BIGTRK=0; if ONEVEH=BIGTRK=0 then the collision partner is a car;
GADSP = 1 if the damage area is on the car's side and includes the passenger's compartment; else GADSP=0;
GADSNP = 1 if the damage area is on the car's side but excludes the passenger's compartment; else GADSNP=0;
GADB = 1 if the damage area is rear; else GADB=0;
MAXC = maximum crush, in inches continuously;
INTRU = 1 if 6 inches or more intrusion occurs in the front compartment; else INTRU=0;
FEMALE = 1 if the occupant is female; else FEMALE=0;
OCCWT = occupants weight in lbs continuously;
OCCHT = occupants height in inches
ENTRP = 1 if entrapment occurs; else ENTRP=0;
EJC= 1 if a complete ejection occurs; else EJC=0;
EJP=1 if a partial ejection occurs; else EJP=0; if EJC=EJP=0 then No Ejection Occurs.

Numerical values for the coefficients appearing in relations (8), (9), and (10) may be found in the third, fourth, and last cluster of Table I, respectively.

Note in the results shown in Table I that most predictors are binary, except for such predictors as Delta V, Age, etc which are continuous variables. The magnitude of coefficients for such continuous predictors must be interpreted in conjuction with the units of their measurement. Thus the coefficient value of 0.177 for Delta V in Table I (A) goes along with a Delta V in mph. It represents the increase per mph of the corresponding term in the algorithm. Similarly coefficients associated with: age, maxc, curbwt, occwt, and occht elsewhere in the cited Table must be interpreted on a basis of: per each year of age, per each inch of crush, per each 100 lbs of car curb weight, per each lb of an ocupant's weight, and per each inch of an occupant's height, respectively.

GOODNESS OF FIT AND PREDICTED V. OBSERVED OUTCOMES

A car's crash severity, Delta V, is such a strong determinant of occupant casualty outcome that it covers most of the variability observed in the field experience with relatively small errors. See for example Table I (A). Nevertheless, both the predictive resolution of an algorithm, and the goodness of the fit to the field data improve as further predictors are included, even if they are less influential than Delta V.

However beyond a certain point, diminishing returns become evident as may be seen in the progression of algorithm complexity, from (A) to (E) in Table I. As more predictors are included in the analysis, some prove to be quite marginal, given that the error of their coefficient assumes values comparable to the coefficient proper. Thus caution is recommended in order to avoid misleading results and conclusions.
Except for predictors with coefficient errors approaching the coefficient values, all predictors and all algorithms shown in Table I have been found statistically highly significant, on the basis of various statistical scores. Said algorithms account for most of the variability observed in the field experience. Discernible improvements are evident as one progresses from (A) to (C) in Table I, but beyond that point, further improvements are marginal and they may be misleading.

Quantitatively speaking, the bottom line for taking or not taking into account the influence of a predictor is the magnitute of the error relative to the coefficient of the predictor at stake.

In addressing the association of predicted probabilities of a certain outcome with actually observed outcomes we determined that the percentage of correct predictions varies from about 75% to 96%, depending on algorithm complexity and severity of predicted outcome. In addition, we used a score known as Somer's D that measures association on a 0 to 1 scale (no association to perfect association). For the algorithms that project probability of fatality (A to E in Table I) the cited indicator was found to have values: 0.686, 0.727, 0.801, 0.803, and 0.850, respectively. The corresponding values for MAIS 3+ outcome are: 0.587, 0.626, 0.686, 0.691, and 0.748, respectively.

NUMERICAL APPLICATIONS & ILLUSTRATIONS

The probability of fatality among towaway crash involved car occupants, without any further qualification, is about 0.6%. For injured occupants at MAIS 3+, or at MAIS 2+ the probability is: 6.8% and 14.7%, respectively. These may be considered as alternative statements for casualty rates per 100 occupants.

Each of these rates may be resolved by crash severity, Delta V, with the help of algorithm (6). The results of this resolution are shown in Fig. 1. Further resolution, i.e. by direction of force in addition to Delta V, is provided when algorithm (7) is applied. Figure 2 illustrates results relevant to MAIS 3+. A similar algorithm may provide resolution by Delta V and restraint use and type. Results concerning MAIS 3+ are illustrated in Fig. 3. Resolution by Delta V and occupant's age is illustrated in Fig. 4.

The results obtained via relatively simple algorithms, as illustrated in Figs 1 to 4, could equally well and perhaps more appropriately be obtained from more complex algorithms that encompass the predictors at stake in the cited figures, plus additional predictors that could be influential.

More complex algorithms can be applied for obtaining results concerning one or a few predictors of immediate interest, with stipulated values. In practice this method is applied to a multi-predictor algorithm by assigning to predictors, other than those of immediate interest, their mean values on the basis of the field experience. The advantage of using this more cumbersome method is that the additional predictors are frozen at values common to the entire population under consideration, something that helps minimize possible confounding effects. It is also understood that no additional predictors should be entertained unless they have statistically significant coefficients, i.e. small errors.

MULTI-PREDICTOR ALGORITHMS

Very long and cumbersome algorithms may result if one insists on including many interesting and available predictors, even if all are statistically significant. Applications and results may become intractable. For this reason we developed a good approximation to the projection of a casualty probability on the basis of a known coefficient, without having to make a full application of a cumbersome algorithm. As a first approximation, the following relation holds:

$$DeltaP = P*(1-P)*A \quad (11)$$

where DeltaP is the casualty probability increment resulting from the inclusion of a predictor with coefficient A, in any case where a probability P has been projected in the absence of said predictor. Note that in relation (11) the probability P and the increment DeltaP are on a 0 to 1 basis, as opposed to 0 to 100%. Also note that the increment becomes a reduction when coefficient A is negative.

It is evident that the increment or reduction varies from zero, at P=0, to a maximum at P=0.5, and back to zero at P=1. For convenience, relation (11) is graphically illustrated in Fig. 5, for four different values of regression coefficients: 0.25, 0.50, 1.0, and 2.0. Other values are readily obtained by interpolation.

The primary application of (11) is to assist in the quantification of effects described by the coefficients of multipredictor algorithms, such as those appearing in Table I (D) and (E). It is evident that (11) should be applied stepwise, especially when an one step application leads to the absurd result of (P+DeltaP) > 1. For the same reason (11) is applicable to individual evaluations, as opposed to an evaluation of several influences combined.

REVIEW OF THE RESULTS

It is informative to review the numerical results obtained by the algorithms in this paper, in comparison with results known from earlier and independent studies concerning factors that influence the rates, or probabilities, of casualty. Note, for example in Fig. 1, that the probability of MAIS 3+ is about 50%, consistent with a widely held benchmark.

Resolution by direction of force, see Fig. 2, shows the 8-10 and 2-4 O'Clock impacts to dominate the threat of serious casualty, with the 11-1 O'Clock impacts second, and the 5-7 O'Clock impacts in the familiar distant third rank.

As recognized in several restraint effectiveness studies, the effectiveness of restraints is about 50% from about 10 or 15 mph DeltaV to about 30 mph. Thereafter, the effectiveness starts declining and becomes negligibly small at high crash severities This is readily evident in the algorithm results shown in Fig. 3.

The small superiority seen for "belt & air bag" v. "belt only" in Fig.3 is actually substantially larger when the results are controlled for possible confounders beyond crash severity only. This is evident in the relevant coefficients appearing in multi-predictor algorithms such as those shown in Table I (C) to(E).

Furthermore, by comparing the relevant restraint coefficients as a function of casualty severity, it appears that the superiority of "belt & air bag" v. "belt only" is dominant at high casualty severities, e.g. fatalities or MAIS 3+, but declines at lower severities, e.g. MAIS 2+. This situation, although still confused by the accompanying statistical uncertainties, is consistent with the notion that the air bag is very effective in preventing high severity injuries although it may cause lower severity injuries.

The multipredictor algorithm (10), with coefficients shown in Table I (E), reveals quantitatively several factors of strong influence, fully consistent with qualitative notions held intuitively. Beyond Delta V, age, and restraint use or type discussed earlier, strong influences are seen here associated with rollover, ejection (whether complete or partial), with entrapment, intrusion, and maximum crush. Recall that positive coefficients are associated with an increase of casualty probability that may be approximately, and one at a time, estimated via (11).

Such an estimation is illustrated in Fig. 6 for the strong influences cited above. Most other influences, as implied by their coefficients in Table I(E), are either weak when considered in conjunction with strong influences, or are not significant in view of the accompanyig standard error.

CONCLUSIONS

Research reported in this paper, although still not fully mature, provides useful applications in succinct and insightful descriptions of the car crash environment. In adition, several further applications may be anticipated. For example, practitioners of post-crash emergency care for traffic accident casualties, from emergency vehicle dispatch centers to trauma centers and hospitals, could benefit from ways of projecting casualty severity on the basis of a crash signature.

Such adjunct information could supplement anatomical and physiological information, currently used, in order to enhance the timeliness and appropriateness of emergency care decisions. This is especially applicable if the additional information becomes available at crash time, well before the emergency care complex is fully activated. Essentially, the advent of high tech, low cost sensors and electronics that may soon be carried on cars and other vehicles, could allow the transmission, at crash time, of crucial information concerning crash circumstances, crashed vehicle(s), and crash involved occupants.

Irrespective of electronic acquisition of crash signatures at crash time, as discussed above, very similar information could be retrieved and transmitted by emergency attendants after they reach the crash scene. It becomes then a matter of translating this information into data useful to dispatch and emergency teams, either ready to attend the accident scene, or preparing for appropriate treatment(s) in emergency facilities. This paper has addressed and evaluated the state-of-the-art in translating advance notification data, either from vehicle mounted sensors at crash time, or from emergency attendants at the scene.

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Table I. Logistic Regression Coeficients and Standard Errors

(A) Rel (6) Predictor	Fatality Ai Coeffcnt	Fatality Std Error	MAIS 3+ Ai Coeffcnt	MAIS 3+ Std Error	MAIS 2+ Ai Coeffcnt	MAIS 2+ Std Error
Intercept	-8.252	0.326	-5.450	0.157	-3.761	0.148
DELTAV	0.177	0.011	0.178	0.010	0.136	0.011

(B) Rel (7) Predictor	Fatality Ai Coeffcnt	Fatality Std Error	MAIS 3+ Ai Coeffcnt	MAIS 3+ Std Error	MAIS 2+ Ai Coeffcnt	MAIS 2+ Std Error
Intercept	-9.032	0.259	-5.820	0.139	-4.029	0.115
DELTAV	0.198	0.010	0.202	0.006	0.155	0.006
DOFS	1.462	0.189	0.556	0.099	0.465	0.083
DOFB	-1.921	0.343	-2.170	0.307	-1.177	0.245

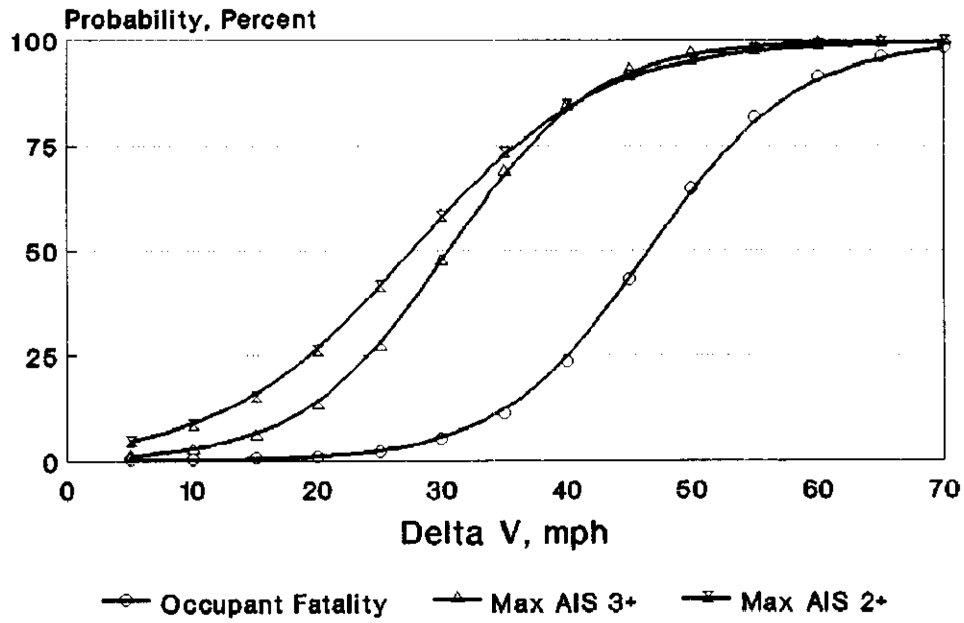
(C) Rel (8) Predictor	Fatality Ai Coeffcnt	Fatality Std Error	MAIS 3+ Ai Coeffcnt	MAIS 3+ Std Error	MAIS 2+ Ai Coeffcnt	MAIS 2+ Std Error
Intercept	-10.830	0.293	-6.538	0.213	-4.393	0.143
DELTAV	0.211	0.009	0.208	0.007	0.157	0.006
DOFS	1.301	0.196	0.457	0.101	0.403	0.087
DOFB	-1.716	0.303	-2.025	0.240	-1.060	0.194
AGE	0.051	0.004	0.033	0.002	0.026	0.002
BELT	-0.859	0.234	-0.826	0.098	-0.839	0.082
BEBA	-1.478	0.684	-1.564	0.325	-1.001	0.330

(D) Rel (9) Predictor	Fatality Ai Coeffcnt	Fatality Std Error	MAIS 3+ Ai Coeffcnt	MAIS 3+ Std Error	MAIS 2+ Ai Coeffcnt	MAIS 2+ Std Error
Intercept	-11.144	0.366	-6.710	0.211	-4.449	0.152
DELTAV	0.211	0.009	0.208	0.006	0.157	0.006
DOFS	1.298	0.203	0.432	0.102	0.397	0.087
DOFB	-1.781	0.317	-2.049	0.242	-1.068	0.195
ROLL	1.280	0.322	1.758	0.237	1.339	0.271
FRPAX	0.890	0.323	0.251	0.113	0.156	0.100
RRPAX	-0.186	0.350	0.263	0.231	0.016	0.149
AGE	0.053	0.005	0.035	0.002	0.026	0.002
BELT	-0.887	0.224	-0.811	0.095	-0.840	0.081
BEBA	-1.353	0.667	-1.518	0.327	-0.990	0.334

Table I Cont'd. Logistic Regression Coeficients and Standard Errors

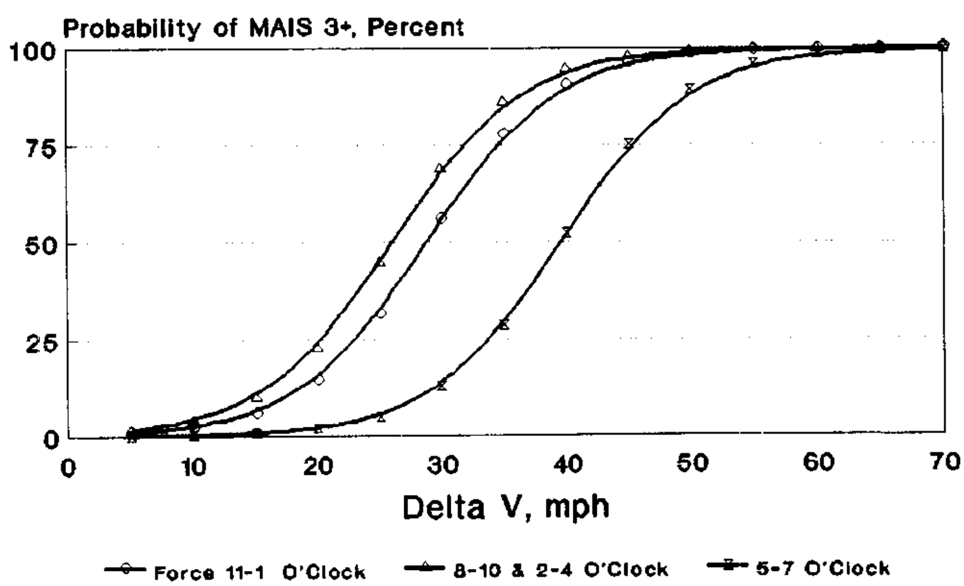
(E) Rel (10) Predictor	Fatality Ai Coeffcnt	Fatality Std Error	MAIS 3+ Ai Coeffcnt	MAIS 3+ Std Error	MAIS 2+ Ai Coeffcnt	MAIS 2+ Std Error
Intercept	-11.901	3.094	-6.118	0.703	-4.584	0.600
ONEVEH	0.259	0.230	0.322	0.152	0.155	0.134
BIGTRK	0.312	0.280	0.002	0.124	0.084	0.132
ROLL	0.764	0.357	1.157	0.284	1.086	0.316
DELTAV	0.135	0.014	0.164	0.010	0.126	0.010
GADSP	1.113	0.224	0.219	0.131	0.260	0.122
GADSNP	-0.076	0.496	0.057	0.241	0.256	0.183
GADB	-2.046	0.553	-1.793	0.254	-1.237	0.206
MAXC	0.056	0.011	0.037	0.007	0.039	0.007
INTRU	1.076	0.335	0.807	0.128	0.648	0.119
CURBWT	-0.012	0.031	-0.027	0.009	-0.031	0.008
FRPAX	1.034	0.341	0.232	0.138	0.017	0.118
RRPAX	0.348	0.347	0.103	0.203	-0.209	0.164
BELT	-0.512	0.275	-0.650	0.111	-0.691	0.093
BEBA	-1.341	0.405	-1.356	0.373	-0.698	0.400
AGE	0.060	0.005	0.042	0.003	0.030	0.003
FEMALE	0.334	0.268	0.464	0.115	0.396	0.102
OCCWT	0.002	0.004	0.003	0.002	0.001	0.002
OCCHT	-0.004	0.038	-0.014	0.011	-0.000	0.009
ENTRP	0.932	0.294	2.378	0.480	2.358	0.511
EJC	2.896	0.506	1.859	0.838	1.270	0.886
EJP	1.915	0.368	1.468	0.368	1.166	0.414

Fig. 1. Probability of Shown Outcome,
as a Function of Car Crash Severity



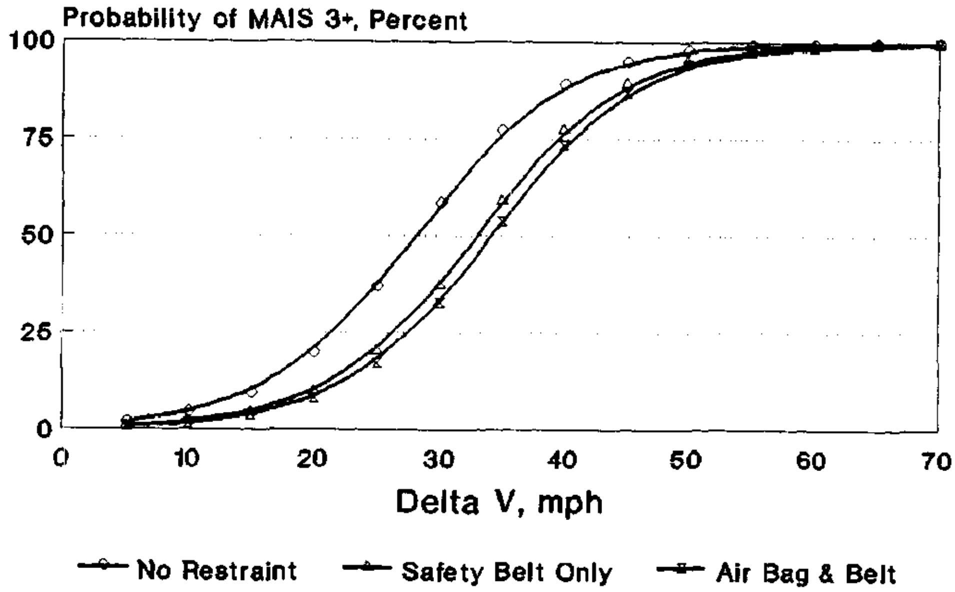
The NASS/CDS 1988-1995

Fig. 2. Sensitivity of Max AIS 3+
to the Direction of Force,
as a Function of Car Crash Severity



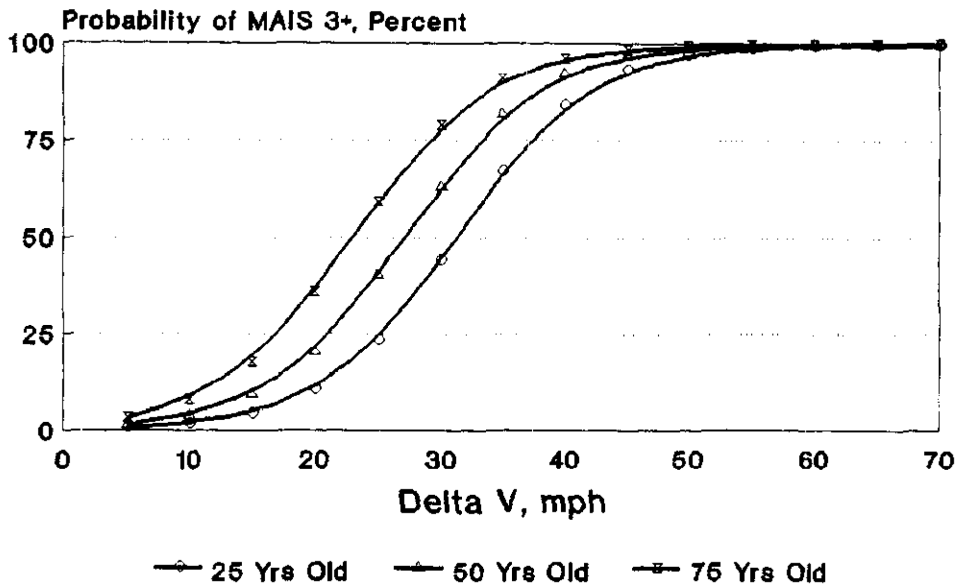
The NASS/CDS 1988-1995

Fig. 3. Sensitivity of Max AIS 3+
to an Occupant's Restraint Use and Type,
as a Function of Car Crash Severity



The NASS/CDS 1988-1995

Fig. 4. Sensitivity of Max AIS 3+
to an Occupant's Age,
as a Function of Car Crash Severity



The NASS/CDS 1988-1995

Fig. 5. Sensitivity of Casualty Probability to Shown Values of a Logistic Regression Coefficient

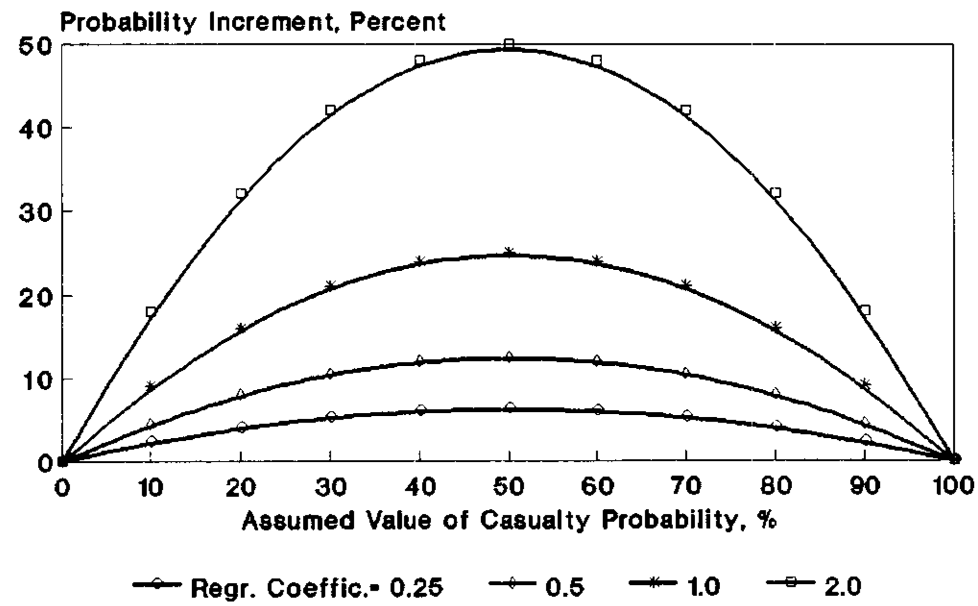


Fig. 6. Increase of MAIS 3+ Probability over Shown Base, Due to Shown Influences

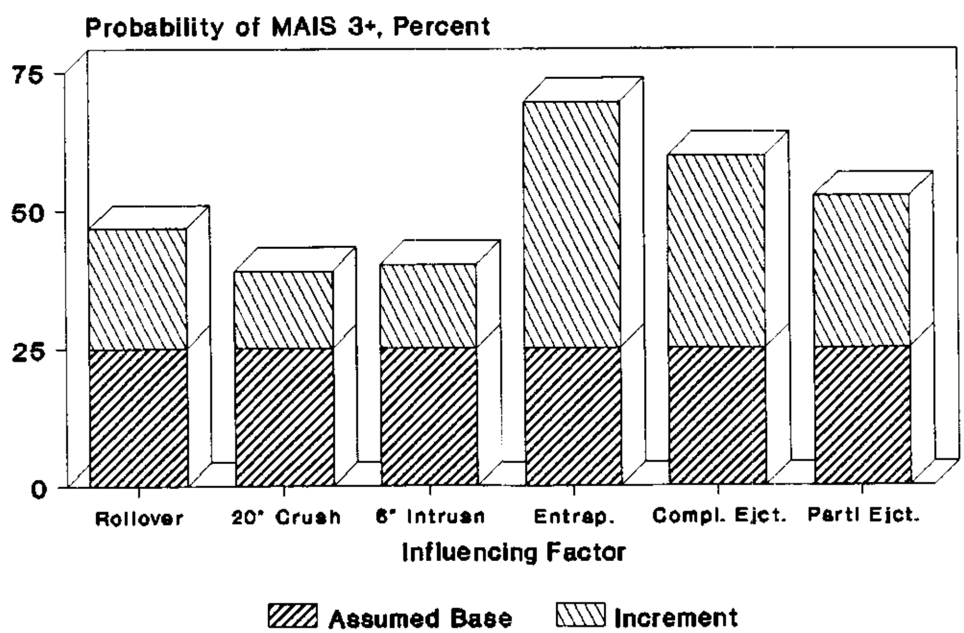


Table I(E), & Relation (11)