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# Side Impact Rib Fracture Injury Analysis

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## ABSTRACT

*A statistical analysis of injury outcome and biomechanical response was performed using data from 28 left side impact tests employing Heidelberg-type sleds and post-mortem human subjects, with the objective of advancing the development of thoracic injury criteria for lateral impact. Injuries were scored by the test centers according to AIS 90. Rib fractures accounted for the maximum AIS score in each case. Curvature data from chest band gauges were used for calculation of contours depicting the shape of the thorax at 1 ms time intervals following impact. Thoracic deformations were deduced from the contours. Risk factors studied included maxima of curvature, deflection, rib and spinal accelerations, the Thoracic Trauma Index (TTI), and Average Spinal Acceleration (ASA). Subject age at death was found to have a significant effect on injury outcome. Consequently, age was used as a confounder variable in logistic regressions for the prediction of dichotomous outcomes P(AIS³3) and P(AIS³4). Stepwise backward logistic regression indicated that subject age and maximum normalized curvature relative to initial curvature are the only surviving independent variables among all considered. Separate logistic regressions employing age and a single risk factor confirmed that age combined with maximum curvature difference yields the greatest statistical significance, and the highest-ranking goodness of fit. Results also showed that by employing the logarithm of curvature difference in the logit, goodness-of-fit can be improved, and the usual problem of a poor fit at low values of risk factor is eliminated. Thoracic deflection was found to be the second highest-ranking injury correlate for side impact, ranked above TTI and ASA in its ability to predict accurately and reliably the extent of side impact thoracic injury.*

## INTRODUCTION

Human fatalities due to side impact account for approximately one-third of all traffic fatalities (Cavanaugh, et al., 1993). The majority of side impact accidents occur in cross-traffic converging at intersections at relatively low speeds (e.g., 40-60 kph). The side of a vehicle is second only to the front as the most frequent impact location. The goal of minimizing side impact injuries will become increasingly important as the use of air bags reduces fatalities in vehicle collisions. A great deal of attention is now being given to the effective design and implementation of side air bags.

An automobile safety standard for side impact was established in October 1970, as the addition of Federal Motor Vehicle Safety Standard (FMVSS) 214, *Side Impact Strength – Passenger Cars*. This standard focused on increasing side door strength to minimize intrusion into the passenger compartment, and incorporated a quasi-static load test using a rigid cylinder placed against the side of a vehicle. FMVSS 214 resulted in the introduction of side door beams in all passenger cars by auto manufacturers. By the late 1970's, it was realized that while side door beams were effective in reducing accidental death in side impact collisions with fixed objects, they proved inadequate alone in impeding intrusion into the passenger compartment in a severe impact with another vehicle.

In October 1990, a new rule was appended to the Code of Federal Regulations, imposing an additional dynamic requirement, FMVSS 214: Side Impact Protection. This new rule set forth specific requirements for a dynamic test procedure simulating a 90° impact on a moving vehicle, to include measurements of acceleration at various locations on instrumented crash test dummies. The simulation of an automobile traveling at 48 kph (30 mph) impacting the left side of a target vehicle at 90° with speed 24 kph (15 mph) is accomplished by means of a "moving deformable barrier" (MDB), a 4-wheeled assembly of standard design, impacting a stationary test vehicle. Specially designed Side Impact Dummies (SID) are positioned in front and rear occupant positions on the side of the vehicle being impacted. The test data measured from SID instrumentation include the rib, spine and pelvic accelerations, which must not exceed certain threshold values for compliance with FMVSS 214. The rib and spinal accelerations are combined into a single measure denoted as the Thoracic Trauma Index, *TTI(d)*. Specifically, *TTI(d)* is given by

$$TTI(d) = \frac{1}{2}(G_R + G_{LS})$$

where $G_R$ is the maximum of peak accelerations of the lower and upper rib, and $G_{LS}$ is the lower spinal (T12 vertebra) peak acceleration. The value of *TTI(d)* cannot exceed 85g for 4-door vehicles and 90g for 2-door vehicles. The pelvic acceleration is assigned an upper limit of 130g. *TTI* was developed in the 1980's, as a result of analyses by Eppinger (1984) and Morgan (1986) of dynamic, kinematic and injury data from 84 sled tests employing post-mortem human subjects.

The present U.S. safety standard for side impact does not include a reference to either lateral or frontal thoracic deflection. In the late 1970's, Stalnaker et al. (1979) and Terriere et al. (1979) analyzed force-deflection data in a series of lateral drop tests onto unpadded and padded force plates, using post-mortem human subjects. Their conclusion was that chest compression correlated better with injury than thoracic acceleration. The European standard for side impact, EU Directive 96/27/EC, is different from FMVSS in several ways. The EU standard makes no attempt to simulate movement of the target vehicle, and employs the EUROSID dummy as a test subject. Furthermore, the European standard includes upper limits for the head injury criterion (HIC), the viscous criterion (VC), abdominal and pelvic forces, and rib deflection.

An alternate thoracic injury criterion was proposed by Cavanaugh et al. (1993), as the result of a study of 17 Heidelberg-type sled tests using unembalmed cadavers. Cavanaugh found that chest compression and ASA gave better agreement with observed injury data than acceleration and force-based criteria. ASA is the average slope of the velocity vs. time signature, taken over a specified time interval, where velocity is obtained by integrating the measured T12 lower spinal lateral acceleration.

In a study by Pintar et al. (1997), utilizing data from 26 Heidelberg-type side impact sled tests performed with post-mortem human subjects, it was found that TTI was a better predictor of thoracic injury than ASA or chest deflection. However, in a recent evaluation by Kuppa, et al. (2000) of 34 side impact sled tests, an extension of the study by Pintar, it was concluded that maximum normalized chest deflection and upper spinal resultant acceleration gave a better fit to injury data than TTI or ASA.

It is apparent that there are conflicting findings with regard to what constitutes a suitable injury correlate for thoracic injury due to frontal or side impact. The acceleration-based criteria referenced in FMVSS 208 and FMVSS 214 are deemed by many to not have a firm biomechanical basis. The overwhelming majority of injuries sustained by the thorax in automobile accidents are rib fractures. Variables that can be related in some way to the fracture stress of bone can be considered to be biomechanically-based, such as chest deflection and curvature. These variables are the focus of the present study, which utilizes the same data employed by Kuppa, et al. (2000), but explores a wider range of biomechanically-based risk factors. Of particular interest is the curvature (or more precisely, the change in curvature relative to the initial value) of horizontal cross-sections of the thorax, a quantity that can be measured directly by means of utilizing existing chest band instrumentation.

## TEST DATA DESCRIPTION

Side impact sled tests using post-mortem human subjects were performed at the Medical College of Wisconsin (MCW) and also at NHTSA's Vehicle Research Test Center at Ohio State University (OSU). The sled apparatus at both test centers is of the Heidelberg design (Kallieris, et al. 1981), configured for left side impacts against rigid and padded walls. The post-mortem subjects in the MCW tests were unembalmed fresh and frozen human cadavers, while those at OSU were fresh cadavers. Cardiovascular systems of the subjects were pressurized to approximate in-vivo conditions. Pulmonary systems were pressurized prior to impact, but left open to atmospheric pressure subsequent to the impact event. Additional details may be found in Kuppa et al. (2000) and Pintar (1996).

Both test centers utilized chest band instrumentation on test subjects, consisting of two 40-channel chest bands at levels of rib 4 and rib 7, for measurement of curvature at approximately every 2.5 cm around the chest perimeter. The local measurement of curvature allows the time dependent shape of a transverse cross-section of the thorax to be determined. Other thoracic-based instrumentation included: (1) triaxial accelerometers affixed to T1 or T2 vertebra, T12 vertebra, and the sacrum, and (2) uniaxial accelerometers affixed to left region of ribs 4 and 8 to measure lateral acceleration, and to the pelvis for determination of anterior-posterior acceleration.

Test subjects were examined and radiographed before and after testing, and necropsied subsequent to testing to identify both hard and soft tissue injury. The injury severity was quantified in accordance with the AIS 90 standard (Abbreviated Injury Scale, 1990). Most of the trauma to the thorax consisted of multiple rib fractures with occasional hemopneumothorax (pleural tears caused by fractured ribs). According to AIS 90, AIS=1 is characterized by only one rib fracture, AIS=2 results from 2-3 fractures, and AIS=3 is assigned when there are more than 3 fractures on only one side of the ribcage. A score of AIS=4 is assigned when there are more than 3 fractures on each side. The presence of a hemopneumothorax or a flail chest increases the AIS score by 1.

Side impact tests were performed with two impact velocities, 24 kph and 32 kph, and with several target configurations: flat rigid wall, flat wall with 10 cm of Ethafoam LC200 padding, rigid or padded wall with pelvic load plate offset by 12 cm to simulate an armrest. The test matrix employed in the present study is shown in Table 1. There are 4 female subjects among a total of 28 sled tests. Approximately two-thirds of the tests were performed at MCW. An earlier study by Kuppa et al. (2000) considered a slightly larger set of this same test group, 34 tests from MCW and OSU. The present work is an extension of that study. A detailed examination of injury records in the NHTSA Biomechanics database indicated that for 5 of the 34 tests, pre-existing rib fractures were indicated in pretest examinations of post-mortem subjects. Those tests have been excluded from the present analysis. In addition, a sixth test was identified by NHTSA as having questionable data, and was also excluded.

The average age at death among the 28 test subjects in Table 1 is 67.5 ± 13.6 years, with the youngest subject age 27, and the oldest age 84. The average age at death of subjects sustaining AIS ≥ 3 injury is 70.9 ± 9.2, while the average for those with AIS < 3 is only 56.5 ± 16.4. This implies that age is a confounder (an independent variable that is associated with both the dependent variable and a risk factor under consideration) among risk factors influencing thoracic injury due to side impact, a result also arrived at by Kuppa et al. (2000).

Table 1. Side Impact Sled Tests with Post-Mortem Human Subjects

| Test | Sex | Age | Mass (kg) | Test center | Test config. | AIS | rbfx |
|---|---|---|---|---|---|---|---|
| 3120 | M | 73 | 89 | MCW | RLF | 4 | 15 |
| 3122 | M | 27 | 72 | MCW | RLF | 0 | 0 |
| 3155 | M | 55 | 76 | MCW | RLF | 3 | 11 |
| 3276 | M | 70 | 71 | MCW | PLF | 0 | 0 |
| 3277 | M | 56 | 64 | MCW | PLF | 2 | 2 |
| 3278 | M | 50 | 93 | MCW | PHF | 2 | 3 |
| 3320 | F | 82 | 74 | OSU | PHF | 4 | 33 |
| 3321 | F | 75 | 42 | OSU | PHF | 4 | 25 |
| 3322 | M | 73 | 72 | OSU | RHF | 4 | 12 |
| 3323 | F | 59 | 81 | OSU | PHF | 4 | 21 |
| 3324 | M | 77 | 75 | OSU | RHF | 4 | 34 |
| 3325 | M | 63 | 61 | OSU | RHF | 4 | 16 |
| 3422 | M | 44 | 83 | MCW | RHF | 2 | 3 |
| 3423 | M | 49 | 62 | MCW | RHF | 4 | 5 |
| 3535 | M | 78 | 88 | MCW | RLO | 4 | 13 |
| 3536 | M | 84 | 76 | MCW | RLO | 4 | 15 |
| 3537 | M | 79 | 93 | MCW | RHO | 3 | 12 |
| 3538 | M | 74 | 77 | MCW | RHF | 5 | 22 |
| 3580 | M | 75 | 56 | OSU | PHF | 3 | 16 |
| 3586 | M | 79 | 146 | OSU | PHF | 4 | 20 |
| 3587 | M | 63 | 100 | MCW | PHF | 4 | 17 |
| 3588 | M | 72 | 66 | MCW | PLF | 4 | 10 |
| 3589 | M | 67 | 76 | MCW | PHF | 3 | 11 |
| 3661 | M | 74 | 51 | MCW | PLO | 3 | 4 |
| 3662 | M | 59 | 73 | MCW | PLO | 2 | 2 |
| 3664 | F | 67 | 74 | MCW | RLF | 0 | 0 |
| 3700 | M | 86 | 67 | MCW | RLF | 3 | 9 |
| 3719 | M | 79 | 53 | MCW | PLF | 0 | 0 |

**Test center**: MCW=Medical College of Wisconsin, OSU= Ohio State University (Vehicle Research Test Center); **Test configuration**: R=rigid wall, P=padded wall, L=24kph impact, H=32kph impact, F=flat wall, O=offset wall; **AIS**=Abbreviated Injury Scale (1990); **rbfx**=number of rib fractures

Table 1 indicates that about two-thirds (20) of the subjects sustained AIS ≥ 3 injury, while one-half (14) sustained an even higher level of AIS ≥ 4 injury. Hence, half of the subjects had 3 or more rib fractures on each side of the ribcage. Multiple fractures on the same rib were a common occurrence, with one subject incurring 34 rib fractures. It should be noted here that AIS does not distinguish between minor (hairline) rib fractures and displaced (disconnected) fractures. The AIS score for all of the 28 tests is attributable to rib fracture, and is the same as the maximum AIS (among all body regions) for a subject, which is denoted as MAIS.

## METHODS

The selection of risk factors, independent variables that might have an effect on the probabilistic outcome variable (thoracic injury), is limited by the available measured data, or quantities that can be derived from them. The measured data consist of local curvature of the thoracic cross-section, impact load forces, and acceleration measured at the sternum, ribs, spine, sacrum and pelvis. The curvature data can be used to calculate deflection, a biomechanically-based risk factor of major interest. Deflection can be calculated in a relatively straightforward manner from chest band contours.

The RBANDPC software module developed by NHTSA and included in NHTSA's SIMon (Simulated Injury Monitor) computer program (Bandak, et al., 2001) was used to calculate chest band contours from the curvature data measured for each band. Contours were calculated at 1 ms intervals starting at 2 ms prior to the time of impact, over a total interval of 200 ms for each chest band. The time of impact was deduced from direct observation of raw curvature data, and from sample contours obtained for each test. A visual inspection of curvature and of each contour generated served as a useful check on the integrity of the data. Chest bands consist of 40 curvature gauges placed approximately 2.5 cm apart, along the entire length of a band. The bands are made with a fixed length to accommodate all possible test subjects, so some overlap is always present. Curvature gauges in the overlapped region were ignored in this analysis. Data from faulty gauges were omitted from the chest band calculations, an acceptable practice which merely decreases spatial resolution. The curvature data were not filtered by the post-processing software.

Sample chest band contours for a typical left side impact are illustrated in Figure 1, where contours are shown at 6 ms intervals. The spine ("o" symbol) is located near the bottom center of the figure, and the sternum ("x" symbol) near the top center. The origin of each contour (X=0, Y=0) is chosen arbitrarily as the point at which the band crosses the spine, where X is the lateral direction and Y is the anterior-to-posterior direction.

A lateral deflection deemed to be representative of side impact is defined as the maximum of the change in distance between three pairs of points located at specified fractional distances along the band length, proceeding in a clockwise direction and starting at the location of the spine. The three point pairs are defined at 20%-80%, 25%-75% and 30%-70% of the circumferential distance along the band, as shown in Figure 2. This definition of "lateral" deflection, which will be denoted as variable *dmaxn*, is consistent with that employed by Kuppa et al. (2000), and will also be referred to here as a "6-point" deflection. A value of *dmaxn* is calculated for each chest band contour, and is taken as the larger of the two values over all time for the upper and lower chest bands. Hence, *dmaxn* is the maximum of 6 distances, each representative of a local lateral deflection of the full thoracic cross-section.

The complete set of risk factors evaluated for possible use as thoracic injury correlates is given in Table 2. In addition to *dmaxn*, three alternate representations for deflection are listed in Table 2: (1) maximum "single-point" deflection at the anterior-posterior left side mid-point (*latdefln*), (2) maximum "point-by-point" deflection along all points on all contours (*crdefln*), and (3) spatial average of maximum deflection over time at each point on contours (*avdefmxn*). The maximum "point-by-point" deflection is taken as the maximum of the largest distance between a point on a contour at time t and its initial position at $t = 0$, among all points on all contours over all time. Variable *avdefmxn* is a spatial average taken over the length of contours, of the maximum distance traversed by each point on a contour. This maximum distance will generally be nonzero for each point along a contour. Since *avdefmxn* is the average over all such points of this maximum, it accounts for deflection in all directions.

Due to the arbitrary position in space of each contour relative to the preceding contour, a lateral shift in Y-coordinates is performed prior to the calculation of variables *crdefln* and *avdefmxn*, such that the anterior-to-posterior “mid-point” on the left side aligns on each successive contour. This mid-point is computed at the initial time and is tracked with each contour at later times. The mid-point is defined simply as the leftmost point on the contour just prior to the initial time of impact. It is acknowledged that the shift in Y is chosen arbitrarily, and that the actual shift is unknown. Current chest band technology allows determination of the cross-sectional shape of the thorax, but not the position of the contour in space.

Table 2 also shows that the complete set of risk factors investigated includes spinal, rib and pelvic accelerations. However, it should be noted that acceleration is not considered to be a biomechanically-based risk factor for thoracic injury, since it alone cannot lead to the determination of the maximum stress experienced by the ribcage and internal organs of the thorax. Acceleration was included here for the sake of completeness and for comparison with results of similar studies.

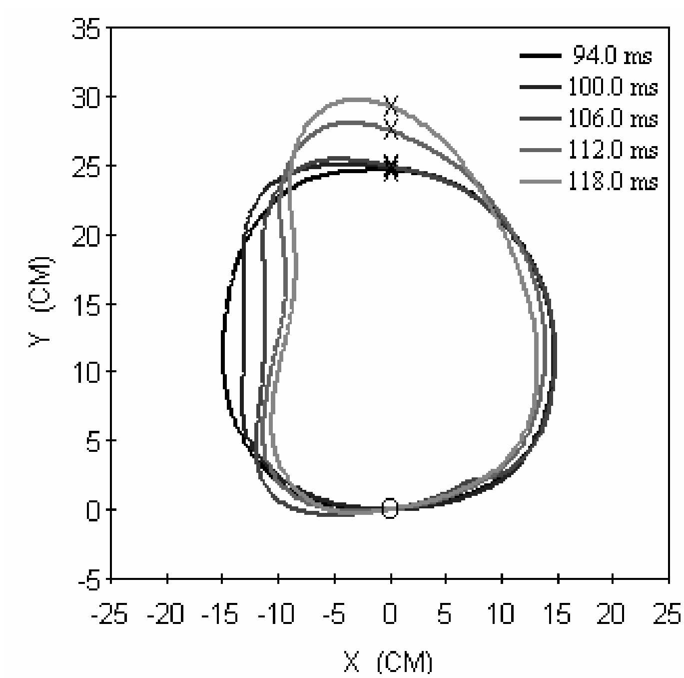


Figure 1: Chest band contours for lateral impact.

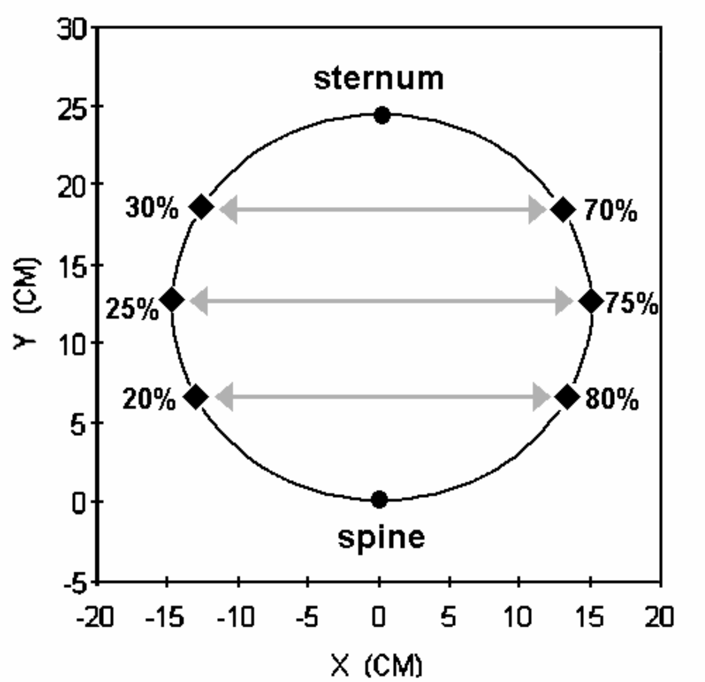


Figure 2: Locations along chest band for lateral deflection computation.

Table 2. Risk Factors Evaluated as Injury Correlates in Side Impact Analysis

| Symbol | Description |
|---|---|
| latdefln | Maximum normalized lateral single-point deflection |
| crdefln | Maximum normalized point-by-point deflection along chest band contours |
| avdefmxn | Spatial average of maximum normalized deflection at each point along a contour |
| dmaxn | Maximum normalized deflection between points at 20% and 80%, 25% and 75%, and 30% -70% along band, measured in a clockwise direction from spine |
| crvmaxn | Maximum normalized curvature along chest band contours |
| crvdiffn | Maximum normalized curvature difference along chest band contours |
| spnlrsn | Maximum normalized resultant lower spinal (T12) acceleration |
| spnursn | Maximum normalized resultant upper spinal (T2) acceleration |
| spl100 | Maximum normalized lower spinal lateral acceleration (FIR100 filter) |
| spl180 | Maximum normalized lower spinal lateral acceleration (SAE180 filter) |
| rll100 | Maximum normalized lower left rib lateral acceleration (FIR100 filter) |
| rlu100 | Maximum normalized upper left rib lateral acceleration (FIR100 filter) |
| pvsax,y,z,r | Maximum normalized pelvic acceleration, all directions and resultant (FIR100 filter) |
| asa10 | Average Spinal Acceleration (ASA) over 10-90% peak velocity interval |
| asa15 | Average Spinal Acceleration (ASA) over 15-85% peak velocity interval |
| asa20 | Average Spinal Acceleration (ASA) over 20-80% peak velocity interval |
| TTI | Thoracic Trauma Index (TTI) |

Note: Maxima for variables latdefln, crdefln, dmaxn, crvmaxn and crvdiffn apply to maximum of respective quantities for lower and upper chest bands. The value of avdefmxn is the maximum of spatial average for lower and upper bands.

Lower (T12) and upper (T2) spinal accelerations (*spnlrsn* and *spnursn* are the resultant components, respectively) are filtered in accordance with the SAE Class 180 (SAE180) digital filter. The lower spinal lateral acceleration (*spl180, spl100*) is filtered with an SAE180 filter, and also with a finite impulse response (FIR100) digital filter having a passband frequency of 100 Hz. An FIR100 filter is also applied to the lower and upper rib accelerations (*rll100, rlu100)* in the lateral direction.

Average Spinal Acceleration, proposed as a risk factor for thoracic injury by Cavanaugh et al. (1993), is determined by first integrating the lower spinal lateral acceleration *spl180* over time to obtain a velocity signature. The variables *asa10*, *asa15* and *asa20* are then calculated as averages of the slope of the velocity profile over time intervals corresponding to 10%-90%, 15%-85% and 20%-80% of peak velocity.

The Thoracic Trauma Index TTI (Eppinger et al., 1984) is computed as

$$TTI = 1.4 * age + \frac{1}{2}(rib100 + spl100) * \frac{mass}{75g} \tag{1}$$

where

$$rib100 = \max(1.3 * rlu100 - 2.02,\ rll100) \tag{2}$$

## Scaling of Risk Factors

All risk factors with the exception of *ASA* and *TTI* are normalized so that they are nondimensional. Chest deflections are divided by the initial chest width at the elevation of a chest band. In the case of the 6-point deflection *dmaxn*, the deflection at each of the three lines of a given contour is divided by the initial chest width at the location of each individual line. Curvature data, having units of reciprocal length, are normalized by multiplying by the initial chest depth (spine-to-sternum distance) at the chest band elevation.

Accelerations are scaled using the equal velocity-equal stress formulation described by Eppinger et al. (1984),

$$acc = acc_{nom}\left(\frac{mass}{75kg}\right)^{0.333} \tag{3}$$

where $acc_{nom}$ is the unscaled acceleration and *mass* is the mass of the subject in kg.

The Average Spinal Acceleration *ASA* is normalized to account for variation in subject age and mass according to the equation

$$ASA = ASA_{nom} * \frac{age}{45} * \frac{mass}{75kg} \tag{4}$$

The Thoracic Trauma Index *TTI* is calculated using Eq. (1), which includes the influence of subject age and mass. The variables *ASA* and *TTI* have units of g's.

## Statistical Methods

The probabilistic outcome for a specified level of injury can be cast as a dichotomous dependent variable *y*, which is 0 for no injury and 1 for an observed injury. A commonly used method of fitting dichotomous data to an analytic function is the *logistic regression*, where the assumed form for the probability P for given values of independent variables $x_1, x_2, x_3, ...., x_n$ is

$$P = \frac{e^{b_0 + b_1 x_1 + b_2 x_2 + .... + b_n x_n}}{1 + e^{b_0 + b_1 x_1 + b_2 x_2 + .... + b_n x_n}} \tag{5}$$

The independent variables $\mathbf{x} = (x_1, x_2, x_3, ...., x_n)$ constitute a set of risk factors and possible confounders (variables that are associated with both the dependent variable and one or more risk factors).

The *logit* is defined as

$$L(\boldsymbol{x}) = b_0 + b_1 x_1 + b_2 x_2 + ..... + b_n x_n \tag{6}$$

and is a linear function of the independent variables $x_i$, where the coefficients $b_i$ are constants to be determined by regression. The probability of injury is then given by

$$P = \frac{e^{L(\boldsymbol{x})}}{1 + e^{L(\boldsymbol{x})}} \tag{7}$$

Backward stepwise logistic regression is used to determine the set of $x_i$ that are statistically significant. In backward stepwise regression, the full set of risk factors for consideration is specified initially, and the regression process eliminates variables deemed to be statistically insignificant. Forward stepwise regression, where variables are added consecutively to the set **x** from an initial null set, is used to confirm the results of backwards regression. Statistical significance is evaluated by examining likelihood ratios and related statistics. Goodness of fit is assessed by consideration of several statistical measures such as the Hosmer and Lemeshow (1989) goodness of fit $\chi^2$ and the Goodman-Kruskal (1954) gamma.

Linear regression is used to construct a model for prediction of the number of rib fractures. Commercial grade statistical analysis tools STATISTICA (Statsoft, Inc., 1997) and STATA (Stata Corp., 1999) were employed for the logistic and linear regressions performed in this study.

## RESULTS

A statistical analysis of the effects on thoracic injury of side impact test subject characteristics such as age, mass and gender, and of test conditions and test center has already been performed by Kuppa et al. (2000). Kuppa found that while gender and mass made little difference, subject age has a significant influence on injury outcome, and should be included in the set of independent variables $x_i$ as a confounder variable. The effect of subject mass is already accounted for in part by scaling individual risk factors to account for dimensional effects.

An analysis of 28 of the original 34 tests with post-mortem human subjects (5 of the 34 were excluded from this study, as explained earlier) also showed that the subject age at death has a considerable influence on injury outcome, and should be a confounder variable. Logistic regressions using the subject age and one or more risk factors showed consistently greater statistical significance compared with those not having age as a confounder variable (e.g.- for *dmaxn*, p-level = 0.0006 with age included vs. p-level = 0.0465 without age). Hence, age was always included as a member of the set $x_i$ in this study.

Separate logistic regressions were performed for each risk factor in Table 2 using age as a confounder variable. Regressions for P(AIS ≥ 3) for deflection-based and curvature-based risk factors, and for ASA and TTI, are given in Table 3. The form of the logit, standard measures of statistical significance, and commonly used benchmarks for analysis of goodness of fit are included in Table 3. Statistical significance is assessed by examining the magnitude of the term $-2\ln(lr)$, where *lr* denotes the likelihood ratio, a measure of the ratio of the likelihood that the complete model captures the data to that for a model not including the $x_i$ in the logit *L* (a "constant only" model). The larger the value of $-2\ln(lr)$, the higher is the statistical significance of the logistic model. According to the "null hypothesis", where dependent variables would have no association with independent variables, the term $-2\ln(lr)$ has a Chi-squared distribution from which the probability of incorrectly rejecting the null hypothesis can be determined. The value of p in Table 3 is the probability associated with the value of $-2\ln(lr)$ given a Chi-squared distribution, and should be small (e.g., $p < 0.05$) for statistical significance. Table 3 also contains values of Pseudo $R^2$ given by

$$Pseudo\ R^2 = 1 - \frac{L_1}{L_0} \tag{8}$$

where $L_1$ is the log likelihood of the full model and $L_0$ is log likelihood of the "constant-only" model.

Table 3. Logistic Regressions for P(AIS ≥ 3)

| **Logit of model for P(AIS≥3)** | **-2ln(lr)** | **p** | **Pseudo $R^2$** | $c^2_{H-L}$ | $P_{H-L}$ | **Kruskal Gamma** |
|---|---|---|---|---|---|---|
| -16.48 + 0.151 age + 24.07 dmaxn | 14.92 | 0.0006 | 0.4453 | 10.59 | 0.2260 | 0.7875 |
| -9.94 + 0.111 age + 18.67 latdefln | 11.61 | 0.0030 | 0.3467 | 5.76 | 0.6737 | 0.7625 |
| -14.46 + 0.119 age + 33.70 crdefln | 14.96 | 0.0006 | 0.4465 | 11.36 | 0.1819 | 0.7750 |
| -12.66 + 0.124 age + 44.75 avdefmxn | 12.92 | 0.0016 | 0.3856 | 12.74 | 0.1211 | 0.7375 |
| -38.11 + 0.285 age + 2.710 crvmaxn | 24.73 | 0.0000 | 0.7382 | 1.89 | 0.9842 | 0.9500 |
| -15.38 + 0.128 age + 1.221 crvdiffn | 16.85 | 0.0002 | 0.5031 | 4.88 | 0.7698 | 0.8500 |
| -1.643 + 0.074 asa10 | 6.61 | 0.0101 | 0.1973 | 10.41 | 0.2371 | 0.5625 |
| -1.834 + 0.068 asa15 | 6.49 | 0.0109 | 0.1936 | 5.10 | 0.7464 | 0.5500 |
| -1.111 + 0.043 asa20 | 4.36 | 0.0367 | 0.1303 | 8.39 | 0.3959 | 0.4500 |
| -8.434 + 0.052 TTI | 11.50 | 0.0007 | 0.3432 | 5.29 | 0.7265 | 0.7500 |

lr = Likelihood ratio; H-L = Hosmer and Lemeshow (1989) goodness of fit measures

The form for Pseudo $R^2$ is due to Judge et al. (1985), and serves as a convenient measure of relative statistical significance. Pseudo $R^2$ ranges from 0 for a model with no significance to a maximum value of 1. The values of Pseudo $R^2$ in Table 3 indicate that maximum normalized curvature has the highest statistical significance, and ASA-based variables have the lowest. This observation is also consistent with values shown for $-2\ln(lr)$ and for p-level.

Table 3 includes results for two statistical measures of goodness-of-fit: (1) the Hosmer-Lemeshow (1989) Chi-squared statistic $c^2_{H-L}$, and (2) the Goodman-Kruskal (1954) Gamma (Γ). The Hosmer-Lemeshow $c^2_{H-L}$ is generally more effective than the Pearson residual in cases where the number of distinct covariate patterns J (number of distinct value combinations of the independent variables) is close to the number of observations N, which is indeed the case for the side impact data. The Hosmer-Lemeshow $c^2_{H-L}$ is defined by

$$X^2_{H-L} = \sum_{k=1}^{10} \frac{(o_k - n_k \bar{\pi}_k)^2}{n_k \bar{\pi}_k (1 - \bar{\pi}_k)} \tag{9}$$

where $n_k$ is the total number of subjects for the $k^{th}$ group. The number of positive responses among covariant patterns in the $k^{th}$ decile, $o_k$, is given by

$$o_k = \sum_{j=1}^{c_k} y_j \tag{10}$$

where $y_j$ is the observed number of positive responses in group k for covariate pattern j, and $c_k$ is the number of covariate patterns in the group. The average estimated probability for group k, $\bar{\pi}_k$, is given by

$$\bar{\pi}_k = \sum_{j=1}^{c_k} \frac{m_j \hat{\pi}_j}{n_k} \tag{11}$$

where $\hat{p}_j$ is the predicted probability of occurrence of covariate pattern j.

The Hosmer-Lemeshow $c^2_{H-L}$ statistic is essentially the application of the Pearson residual to data grouped into a relatively small number of consecutive bins, with 10 bins (the upper limit in Eq. 9) recommended for most data sets. A good fit of the model to the observed probabilistic outcomes is indicated by a small value of the $c^2_{H-L}$ residual. Generally, a value of $c^2_{H-L} < 5$ indicates that the fit is quite good, although there are exceptions. Small but finite probabilities predicted by the model that ideally should yield a zero probability can sometimes result in larger than expected values of $c^2_{H-L}$. The value of probability associated with $c^2_{H-L}$ is also given in Table 3. The larger the value of $P_{H-L}$ the better is the fit of the logistic regression model.

Results for the $c^2_{H-L}$ and $P_{H-L}$ goodness of fit measures obtained by the STATA (Stata Corp., 1999) computer code are given in Table 3, and indicate that the best fits are associated with the curvature-based risk factors *crvmaxn* and *crvdiffn*. These results are consistent with the high measures of statistical significance for these variables.

A goodness of fit statistic, which is a measure of the association of predicted probabilities for unlike pairs of dichotomous outcomes, referred to as "Kruskal Gamma", is also provided in Table 3. The Kruskal $\Gamma$ is due to Goodman and Kruskal (1954), and is defined by

$$\Gamma = \frac{nc - nd}{nc + nd} \tag{12}$$

where *nc* is the number of concordant pairs and *nd* is the number of discordant pairs. All possible pairs of events having unequal dichotomous outcomes are considered among the observed data. All other event pairs are ignored in the calculation of $\Gamma$. An event pair is considered to be concordant if the positive outcome (injury=1) of the pair is associated with a higher predicted probability than that for the event with the negative outcome (injury=0). Conversely, a pair is considered to be discordant if the positive outcome of the pair is associated with a lower predicted probability than that for the negative outcome. The minimum value of $\Gamma$ is -1 for the case in which *nc* = 0, and the maximum is +1 which occurs when *nd* = 0. The higher the value of Kruskal $\Gamma$, the better is the fit to the observed data, in terms of the proper association of unlike pairs of outcomes.

Table 3 shows that the largest values of Kruskal $\Gamma$ are obtained for the curvature-based variables *crvmaxn* and *crvdiffn*, a result consistent with the goodness of fit assessment based on the Hosmer-Lemeshow measure $c^2_{H-L}$. Large values of Kruskal Gamma ($\Gamma \geq 0.75$) also result for logits employing the deflection-based risk factors *dmaxn*, *latdefln*, *crdefln*, as well as the Thoracic Trauma Index *TTI*. However, Table 3 shows that in terms of both statistical significance and goodness of fit, the curvature-based risk factors *crvmaxn* and *crvdiffn* are the best predictors of thoracic side impact injury.

The logistic regression for P(AIS ≥ 3) with *crvdiffn* as a risk factor and *age* as a confounder is illustrated in Figure 3, where the logit is given by

$$L = -15.38 + 0.1278\,age + 1.221\,crvdiffn \tag{13}$$

Dichotomous outcomes for AIS ≥ 3 are also shown in Figure 3, in addition to a five point moving average of the binary outcome. The moving average of dichotomous outcome is seen to approximate the regression curve, and lies within the 95% confidence bands for the logistic regression. Goodness of fit for logistic regressions can be evaluated graphically by comparing observed and predicted cumulative counts of positive outcomes. The observed cumulative count for event *j* is given by $\sum_{i=1}^{j} D_i$ , and the predicted cumulative count by $\sum_{i=1}^{j} P_i$ , where

$D_i$ = dichotomous event variable (0 or 1) for event $i$

$P_i$ = predicted probability at $L_i$ , $P_i = e^{L_i}/(1+e^{L_i})$

$L_i$ = logit for event $i$, $L_i = b_0 + b_1 x_{1_i} + b_2 x_{2_i} + .... + b_m x_{m_i}$

$m$ = number of risk factors in logit

In Figure 4 the summations $\sum_{i=1}^{j} D_i$ and $\sum_{i=1}^{j} P_i$ are plotted against $L_j$ and compared for the logistic regression P(AIS ≥ 3) given by the logit in Eq. (13). The small differences between the two curves for $\sum_{i=1}^{j} D_i$ and $\sum_{i=1}^{j} P_i$ , the observed and predicted injury counts, serve as confirmation of a good fit for the logistic regression based on *age* and *crvdiffn*.

The statistical significance of maximum curvature difference can be verified using stepwise backward regression, where all independent variables are included as an initial set, with the less significant variables eliminated successively by the stepwise procedure. Prior to performing a stepwise regression, a determination should be made of risk factors that are strongly correlated. Variable groups that are strongly correlated should have only one member present in the initial set specified. Cross-correlation coefficients are given in Table 4, where each result applies typically to 28 samples. In cases where data do not exist for all 28 tests for both variables of a variable pair, the number of samples was reduced to a number as low as 21. Only variable pairs including accelerations *spnlrsn*, *spl100*, *spl180*, *rll100*, *rlu100* and *pvsay* (pelvic-sacrum resultant acceleration in the lateral direction) fall into that category. The correlation coefficients in Table 4 generally show a relatively weak dependence among risk factors (typically, r < 0.6). The exceptions are variables of the same type: (1) deflections *latdefln* (single-point lateral deflection) and *crdefln* (maximum distance traversed among all points on contours), (2) curvature-based parameters *crvmaxn* (maximum curvature) and *crvdiffn* (maximum curvature difference), (3) lower spinal acceleration with different digital filters, *spl100* and *spl180*, and (4) Average Spinal Acceleration *asa10*, *asa15*, *asa20*. Maximum curvature *crvmaxn* was excluded in favor of maximum curvature difference *crvdiffn*, which has the proper limit of zero prior to impact. The lower spinal acceleration *spl180* with SAE180 filter was excluded in favor of *spl100*, which employs a finite impulse response filter (FIR100) usually applied to thoracic and pelvic acceleration data in side impact crash dummy testing. Since ASA variables *asa10*, *asa15*, *asa20* are strongly correlated, only *asa15* was selected in the initial set of $x_i$ for stepwise logistic regression.

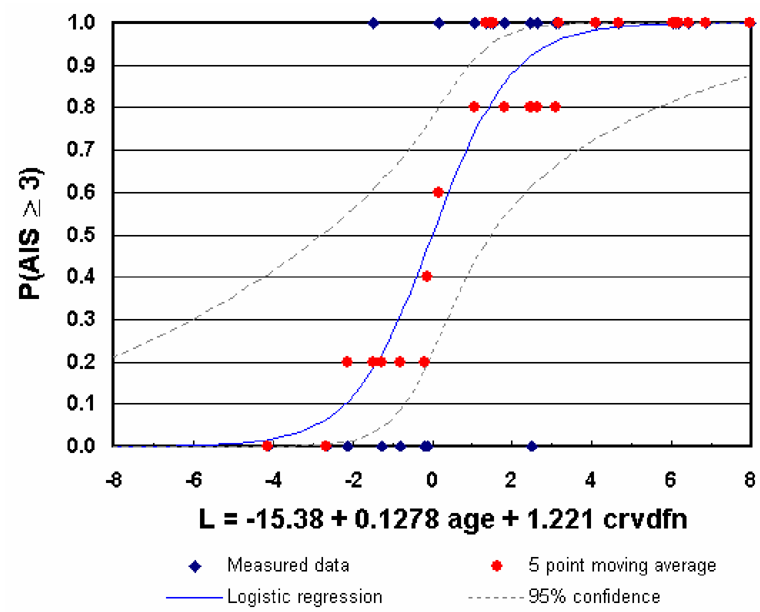


Figure 3: Logistic regression of P(AIS≥3) as a function of age and maximum normalized curvature difference.

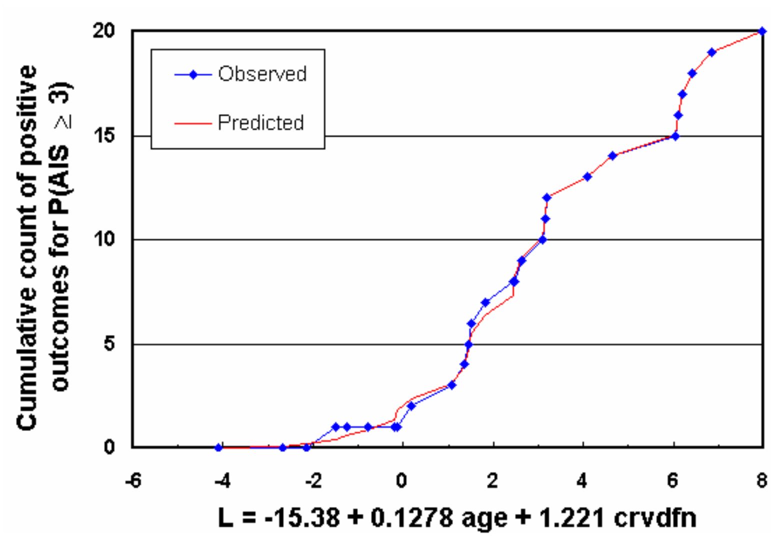


Figure 4: Comparison of cumulative count of positive outcomes for logistic regression of P(AIS ≥ 3).

Table 4. Cross-Correlation Coefficients Among Risk Factors

| | latdefln | crdefln | avdefmxn | dmaxn | crvmaxn | crvdiffn | spnlrsn | spnursn | spl100 | spl180 | rll100 | rlu100 | pvsay | asa10 | asa15 | asa20 | TTI |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| latdefln | 1.00 | 0.80 | 0.44 | 0.76 | 0.30 | 0.15 | -0.07 | 0.57 | 0.03 | -0.02 | 0.18 | 0.22 | 0.02 | 0.40 | 0.40 | 0.39 | 0.45 |
| crdefln | 0.80 | 1.00 | 0.71 | 0.79 | 0.59 | 0.47 | 0.21 | 0.73 | 0.32 | 0.26 | 0.27 | 0.34 | 0.13 | 0.57 | 0.54 | 0.48 | 0.47 |
| avdefmxn | 0.44 | 0.71 | 1.00 | 0.68 | 0.43 | 0.27 | 0.38 | 0.67 | 0.45 | 0.41 | 0.35 | 0.46 | -0.03 | 0.42 | 0.44 | 0.39 | 0.40 |
| dmaxn | 0.76 | 0.79 | 0.68 | 1.00 | 0.45 | 0.35 | 0.30 | 0.69 | 0.40 | 0.37 | 0.24 | 0.31 | 0.02 | 0.55 | 0.53 | 0.50 | 0.40 |
| crvmaxn | 0.30 | 0.59 | 0.43 | 0.45 | 1.00 | 0.84 | 0.08 | 0.55 | 0.35 | 0.30 | 0.10 | 0.28 | 0.16 | 0.36 | 0.36 | 0.35 | 0.33 |
| crvdiffn | 0.15 | 0.47 | 0.27 | 0.35 | 0.84 | 1.00 | 0.16 | 0.45 | 0.39 | 0.37 | 0.01 | 0.02 | 0.15 | 0.49 | 0.50 | 0.49 | 0.25 |
| spnlrsn | -0.07 | 0.21 | 0.38 | 0.30 | 0.08 | 0.16 | 1.00 | 0.28 | 0.93 | 0.67 | 0.31 | -0.04 | -0.04 | 0.09 | 0.10 | 0.09 | 0.04 |
| spnursn | 0.57 | 0.73 | 0.67 | 0.69 | 0.55 | 0.45 | 0.28 | 1.00 | 0.48 | 0.41 | 0.43 | 0.48 | 0.15 | 0.46 | 0.50 | 0.51 | 0.50 |
| spl100 | 0.03 | 0.32 | 0.45 | 0.40 | 0.35 | 0.39 | 0.93 | 0.48 | 1.00 | 0.99 | 0.29 | 0.05 | 0.04 | 0.32 | 0.31 | 0.38 | 0.26 |
| spl180 | -0.02 | 0.26 | 0.41 | 0.37 | 0.30 | 0.37 | 0.67 | 0.41 | 0.99 | 1.00 | 0.26 | 0.05 | 0.01 | 0.29 | 0.29 | 0.35 | 0.21 |
| rll100 | 0.18 | 0.27 | 0.35 | 0.24 | 0.10 | 0.01 | 0.31 | 0.43 | 0.29 | 0.26 | 1.00 | 0.48 | 0.52 | 0.01 | 0.09 | 0.10 | 0.25 |
| rlu100 | 0.22 | 0.34 | 0.46 | 0.31 | 0.28 | 0.02 | -0.04 | 0.48 | 0.05 | 0.05 | 0.40 | 1.00 | 0.13 | 0.08 | 0.11 | 0.09 | 0.61 |
| pvsay | 0.02 | 0.13 | -0.03 | 0.02 | 0.16 | 0.15 | -0.04 | 0.15 | 0.04 | 0.01 | 0.52 | 0.13 | 1.00 | 0.15 | 0.13 | 0.09 | 0.16 |
| asa10 | 0.40 | 0.57 | 0.42 | 0.55 | 0.36 | 0.49 | 0.09 | 0.46 | 0.32 | 0.29 | 0.01 | 0.08 | 0.15 | 1.00 | 0.97 | 0.89 | 0.60 |
| asa15 | 0.40 | 0.54 | 0.44 | 0.53 | 0.36 | 0.50 | 0.10 | 0.50 | 0.31 | 0.29 | 0.09 | 0.11 | 0.13 | 0.97 | 1.00 | 0.94 | 0.64 |
| asa20 | 0.39 | 0.48 | 0.39 | 0.50 | 0.35 | 0.49 | 0.09 | 0.51 | 0.38 | 0.35 | 0.10 | 0.09 | 0.09 | 0.89 | 0.94 | 1.00 | 0.63 |
| TTI | 0.45 | 0.47 | 0.40 | 0.40 | 0.35 | 0.25 | 0.04 | 0.50 | 0.26 | 0.21 | 0.25 | 0.61 | 0.16 | 0.60 | 0.64 | 0.63 | 1.00 |

Note: Risk factors are defined in Table 2.

Table 5 shows the results of stepwise backward logistic regression for the dichotomous outcome P(AIS ≥ 3), obtained using the STATA (Stata Corporation, 1999) computer code. When the initial set of independent variables $x_i$ included *age* as a confounder variable and all risk factors not having strong cross-correlation, only *age* and *crvdiffn* survived. This implies that maximum normalized curvature difference *crvdiffn* is the most statistically significant variable, and no other risk factors are required in combination with *crvdiffn* for a suitable description of P(AIS ≥ 3) using logistic regression. Variations in the order of specification of the initial set of variables $x_i$ did not alter the results of stepwise backward regression, nor did reducing the number of risk factors in the set. Results of forward stepwise regression, where variables are added successively based on statistical significance, gave results identical to those for backward regression.

Table 5. Results of Stepwise Backward Logistic Regression for P(AIS ≥ 3)

| **Initial Set of Risk Factors** | **Surviving Risk Factors** |
|---|---|
| age latdefln crdefln avdefmxn dmaxn crvdiffn spnursn spl100 rlu100 pvsay asa15 TTI | age crvdiffn |
| age crvdiffn spnursn | age crvdiffn |
| age dmaxn crvdiffn | age crvdiffn |

Note: Risk factors are defined in Table 2.

Logistic regressions for P(AIS ≥ 4) are given in Table 6. Results for measures of both statistical significance and goodness of fit indicate that curvature-based risk factors *crvmaxn* and *crvdiffn* also lead to the best fits for the dichotomous outcome variable P(AIS ≥ 4). Results for maximum normalized 6-point deflection *dmaxn* also indicate good statistical significance and a good fit to the data. The value of goodness of fit measure $P_{H-L}$ is surprisingly high at 0.9459 for *TTI*, although the statistical significance is not ranked high $(-2\ln(lr)=7.15)$ among data for the risk factors considered.

Table 6. Logistic Regressions for P(AIS ≥ 4)

| **Logit of model for P(AIS≥4)** | **-2ln(lr)** | **p** | **Pseudo $R^2$** | $C^2_{H-L}$ | $P_{H-L}$ | **Kruskal Gamma** |
|---|---|---|---|---|---|---|
| -10.61 + 0.062 age + 18.98 dmaxn | 10.95 | 0.0042 | 0.2821 | 9.39 | 0.3102 | 0.6877 |
| -6.94 + 0.045 age + 18.24 latdefln | 8.13 | 0.0172 | 0.2095 | 5.61 | 0.6908 | 0.6020 |
| -12.65 + 0.056 age + 36.71 crdefln | 13.23 | 0.0013 | 0.3408 | 8.26 | 0.4086 | 0.7143 |
| -10.06 + 0.064 age + 44.50 avdefmxn | 9.45 | 0.0089 | 0.2435 | 9.78 | 0.2806 | 0.6327 |
| -9.37 + 0.069 age + 0.531 crvmaxn | 9.81 | 0.0074 | 0.2527 | 6.35 | 0.6078 | 0.6122 |
| -9.30 + 0.059 age + 0.740 crvdiffn | 11.68 | 0.0029 | 0.3008 | 4.66 | 0.7937 | 0.6531 |
| -2.39 + 0.061 asa10 | 7.36 | 0.0067 | 0.1896 | 7.37 | 0.4976 | 0.5204 |
| -2.27 + 0.049 asa15 | 6.64 | 0.0100 | 0.1711 | 4.89 | 0.7694 | 0.5306 |
| -1.99 + 0.038 asa20 | 5.82 | 0.0158 | 0.1500 | 7.50 | 0.4835 | 0.4694 |
| -6.02 + 0.031 TTI | 7.15 | 0.0075 | 0.1842 | 2.81 | 0.9459 | 0.5204 |

lr = Likelihood ratio; H-L = Hosmer and Lemeshow (1989) goodness of fit measures

The logistic regression for P(AIS ≥ 4) with independent variables *age* and *crvdiffn* is illustrated in Figure 5, with the logit having the form

$$L = -9.304 + 0.0589\,age + 0.7403\ crvdiffn \tag{14}$$

A comparison of cumulative counts of positive injury outcomes for the logistic model of P(AIS ≥ 4) is shown in Figure 6. Both figures indicate that a logistic regression using maximum normalized curvature difference fits the data for P(AIS ≥ 4) quite well.

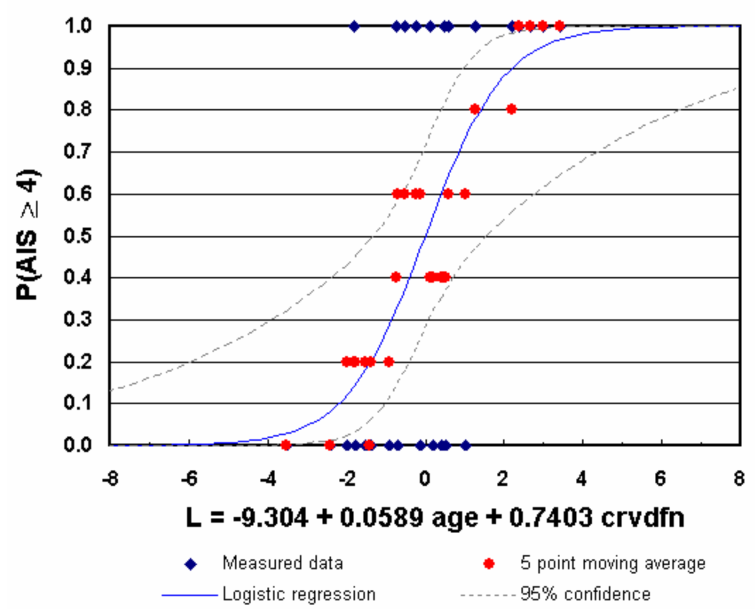


Figure 5: Logistic regression of P(AIS≥4) as a function of age and maximum normalized curvature difference.

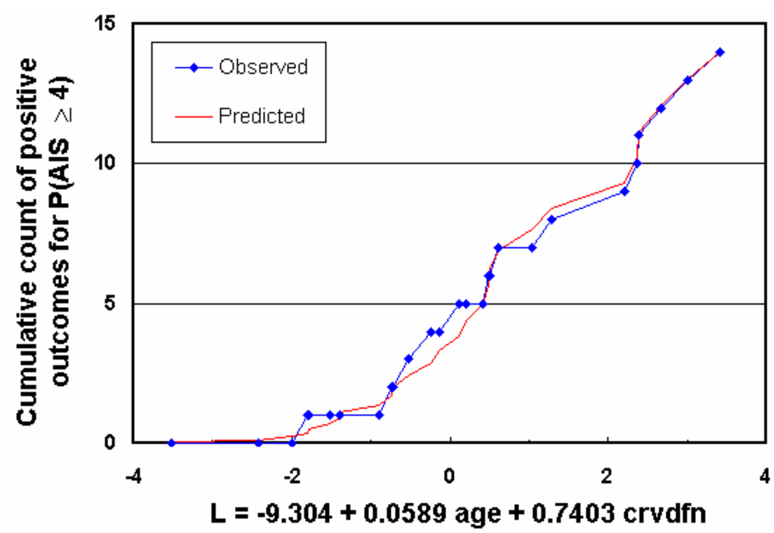


Figure 6: Comparison of cumulative count of positive outcomes for logistic regression of P(AIS ≥ 4).

## Logistic Model Improvement

The independent variables $\mathbf{x} = (x_1, x_2, x_3, ...., x_n)$ considered here as risk factors for thoracic injury are all quantities that assume either zero or positive values. As a consequence of the form for the logistic regression, Eq. (5), a nonzero probability of injury will result when the risk factors are all zero. Specifically, this probability is given by

$$P(\mathbf{x} = 0) = \frac{e^{b_0}}{1 + e^{b_0}} > 0 \qquad (15)$$

Hence, a finite probability of injury will be obtained for zero risk factor, e.g., the undisturbed state. If the constant $b_0$ is negative with a large magnitude, the predicted value of $P(\mathbf{x} = 0)$ can become extremely small. However, there is no guarantee that this will be the case, since $b_0$ is the result of the logistic regression procedure, and is unalterable for a given set of data. A technique that can be used to improve the fit of the model at low values of risk factor is to apply logarithms to the independent variables in the logit form,

$$L(\boldsymbol{x}) = b_0 + b_1 \ln(x_1) + b_2 \ln(x_2) + ..... + b_n \ln(x_n) \tag{16}$$

In the rare event that an individual risk factor $x_i$ is identically zero, a small tolerance value (e.g., $10^{-6}$) can be used in place of $x_i = 0$ in Eq. (16). Normally, the $x_i$ always have positive values for crash test data, since they are maxima over all time of some measured quantity believed to be representative of thoracic injury.

Logistic regressions were performed for all risk factors using the logarithmic form given by Eq. 16. It was observed that the effect of employing logarithms of risk factors in logistic regressions is to slightly improve both the goodness of fit and statistical significance, as shown in Table 7 for logits comprised of age and maximum curvature difference. Figures 7-10 also show a slight improvement in the fit of the logistic models for P(AIS ≥ 3) and P(AIS ≥ 4) when logarithms are employed. When all other risk factors are zero, the effect of a large number for subject age (e.g., 90) is to increase the probability of injury for an undisturbed thorax to some value above zero. This effect is eliminated when logarithms are applied to the risk factors. For example, if the linear form of the logit, Eq. (6), is used with the logistic regression employing age and maximum curvature difference, the probability of thoracic injury for a 90 year old is 2.1% for the undisturbed state. However, when the logarithmic form of the logit is used, Eq. (16), the predicted probability is 0.0% for an undisturbed thorax. This benefit is realized despite the fact that the constant $b_0$ is a relatively large negative number for the regressions using maximum curvature difference. Model improvements were more significant for risk factors other than curvature difference, since the estimated probabilities of injury for an unimpacted thorax are generally higher for other risk factors (e.g., for *dmaxn*, P(AIS ≥ 3) is 5.3% for an undisturbed thorax of a 90 year old). Maximum normalized curvature *difference* is preferred over maximum curvature as a risk factor, since curvature itself has an undesirable lower limit of a finite value for its maximum in the undisturbed state. Although the 95% confidence bands of the logistic regressions are relatively wide for low values of the logit (as a consequence of the small number of samples), it is still reassuring that the model has the proper limit in this region.

Table 7. Logistic Regressions With and Without Logarithms Applied to the Independent Variables

| **Logit of model** | **-2ln(lr)** | **p** | **Pseudo $R^2$** | $C^2_{H-L}$ | $P_{H-L}$ | **Kruskal Gamma** |
|---|---|---|---|---|---|---|
| **P(AIS≥3)** | | | | | | |
| -46.63 + 7.866 ln(age) + 8.025 ln(crvdiffn) | 17.91 | 0.0001 | 0.5347 | 5.41 | 0.7124 | 0.8750 |
| -15.38 + 0.128 age + 1.221 crvdiffn | 16.85 | 0.0002 | 0.5031 | 4.88 | 0.7698 | 0.8500 |
| **P(AIS≥4)** | | | | | | |
| -25.32 + 3.620 ln(age) + 5.201ln(crvdiffn) | 11.89 | 0.0026 | 0.3063 | 5.28 | 0.7278 | 0.6735 |
| -9.30 + 0.059 age + 0.740 crvdiffn | 11.68 | 0.0029 | 0.3008 | 4.66 | 0.7937 | 0.6531 |

The results of stepwise backward logistic regression did not change when logarithms of risk factors $x_i$ were employed. Subject age and maximum curvature difference were still the only surviving independent variables. The results shown in Table 5 apply to both linear and logarithmic forms of the logit.

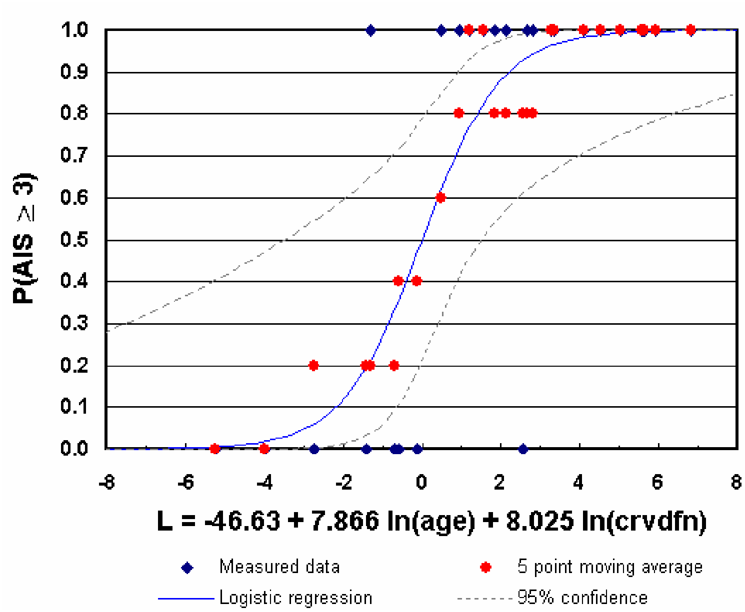


Figure 7: Logistic regression of P(AIS ≥ 3) using logarithms of age and maximum normalized curvature difference.

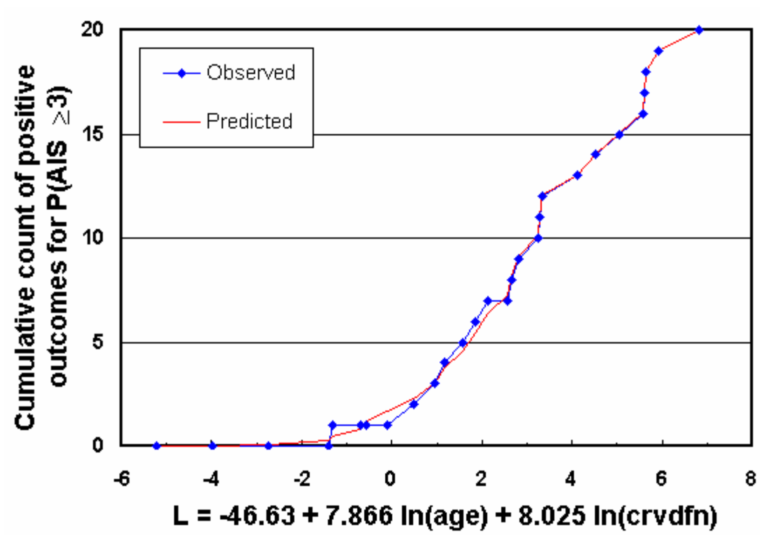


Figure 8: Comparison of cumulative count of positive outcomes for logistic regression of P(AIS ≥ 3) using logarithms of age and maximum curvature difference.

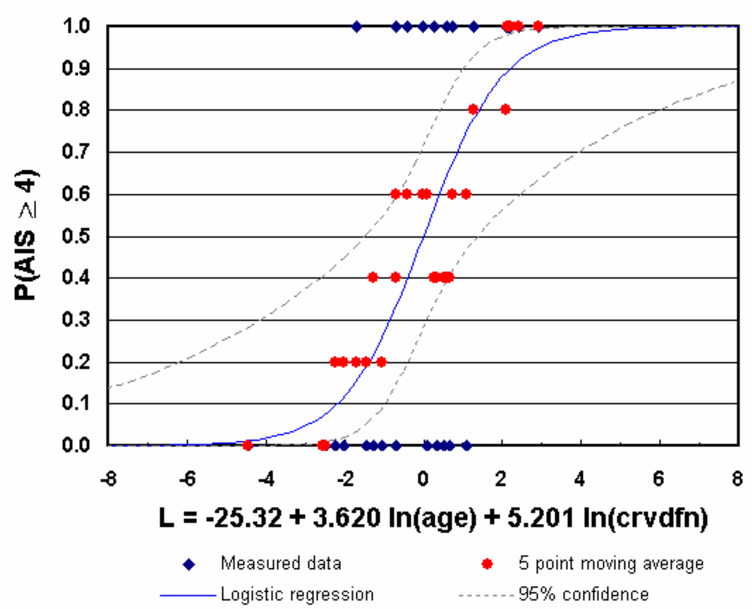


Figure 9: Logistic regression of P(AIS ≥ 4) using logarithms of age and maximum normalized curvature difference.

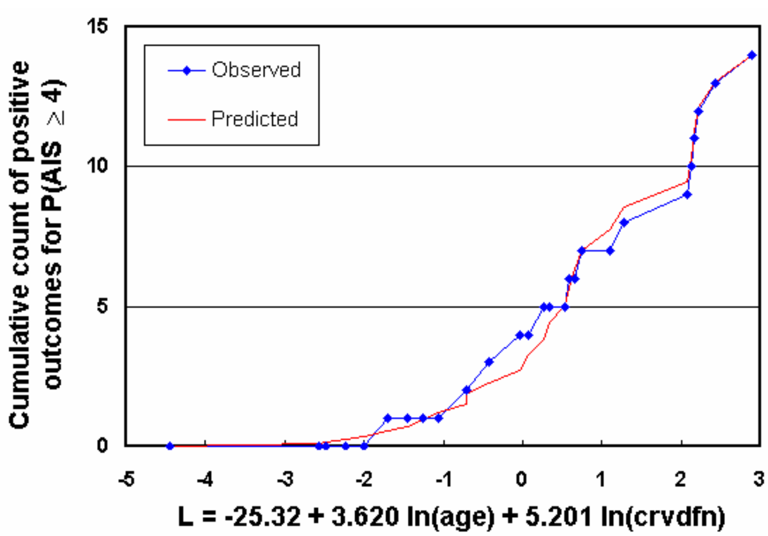


Figure 10: Comparison of cumulative count of positive outcomes for logistic regression of P(AIS ≥ 4) using logarithms of age and maximum curvature difference.

## Linear Regression for Number of Rib Fractures

Side impact injury data also includes the number of rib fractures sustained by the post-mortem human subjects. It is of interest to determine whether maximum normalized curvature difference can be used to estimate the number of rib fractures using a linear regression model. For simplicity, a single independent variable is employed, scaled linearly with age,

$$x_1 = crvdiffn * (age/45) \quad (17)$$

Scaling the risk factor linearly with age removes the troublesome effect of a zero value of risk factor leading to a positive number of rib fractures, resulting from the use of a linear combination including age. A linear regression for the number of rib fractures *rbfx* is sought, where

$$rbfx = b_0 + b_1\, crvdiffn\, (age/45) \quad (18)$$

The results of linear regression using independent variable $crvdiffn * (age/45)$ are shown in Table 8, where the constant coefficients were calculated as $b_0$ = -8.248 and $b_1$ = 1.835. The p-value for this regression is small at 4 x $10^{-6}$ , and the $R^2$ sufficiently large at 0.55, indicating good statistical significance. The linear regression for the number of rib fractures is shown in Figure 11, and is seen to exhibit a higher degree of scatter than logistic regressions for dichotomous injury outcomes. This is an expected result, since it is more difficult for a model to predict the exact number of fractures, especially in light of the fact that the severity of individual fractures (hairline vs. displaced) is not accounted for in the injury scoring.

Table 8. Linear Regression for Number of Rib Fractures

| Linear regression for number of rib fractures | n | P-value of F-stat | $R^2$ | Adj. $R^2$ | Std. Err. |
|---|---|---|---|---|---|
| rbfx = max ( -8.01 + 1.82 crvdiffn (age/45) , 0) | 28 | 3.60 x $10^{-6}$ | 0.5685 | 0.5519 | 6.347 |

The linear regression given by Eq. (18) yields a negative value of *rbfx* for sufficiently small values of maximum curvature difference,

$$crvdfn < -(b_0/b_1)(45/age) \quad (19)$$

This suggests that a threshold applies to *crvdiffn*, whereby it is necessary to exceed some finite level of curvature difference in order to reach the fracture stress of the ribcage. In light of such a threshold, a maximum of zero should be applied to the estimated number of fractures such that the value of *rbfx* cannot become negative if *crvdfn* falls below the threshold. Hence, the full description for *rbfx* becomes

$$rbfx = \max(-8.248 + 1.835\, crvdiffn\, (age/45),\ 0) \quad (20)$$

The values for linear regression coefficients $b_0$ and $b_1$ imply that the threshold value of *crvdfn* for the onset of rib fracture is given by

$$crvdfn_{threshold} = 202.3/age \quad (21)$$

Hence, an older subject has a lower threshold of maximum curvature difference.

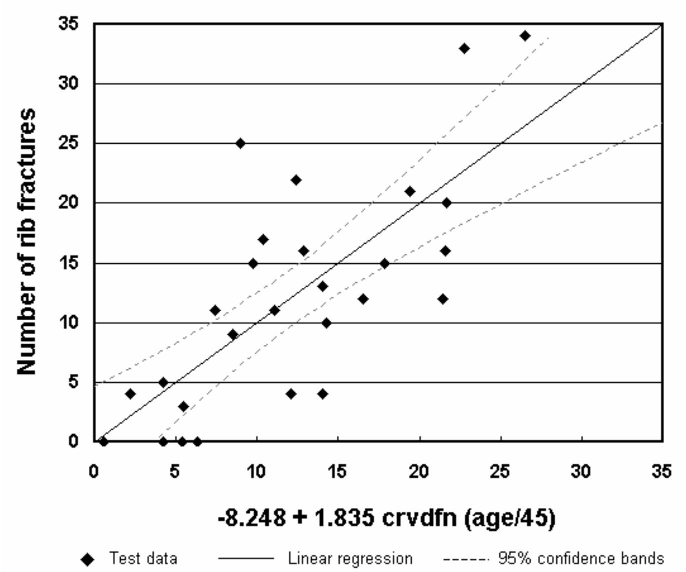


Figure 11: Linear regression for number of rib fractures using maximum curvature difference scaled by age.

## CONCLUSIONS

The most serious thoracic injuries are rib fractures, or soft tissue injury associated with hemopneumothorax, which is caused by rib fracture. Injury test scores for the maximum value of the Abbreviated Injury Scale (AIS) correspond to rib fracture for all 28 side impact crash tests analyzed in this study.

Results of statistical analysis showed that subject age at death has a significant influence on injury sustained in side impact. The effect of age can be attributed to the change with age in material properties of bone, with the fracture stress of human bone tissue decreasing with increasing age.

Logistic regressions serve as effective models for thoracic injury characterized by categorical outcomes for AIS, and lead to both statistical significance and good fits to the measured data. Among an extensive set of risk factors considered, including deflection-based and acceleration-based risk factors, only the age confounder and maximum normalized curvature difference (with respect to the curvature of the undisturbed thorax) survive as independent variables in stepwise backward and forward logistic regressions. Individual logistic regressions employing age as a confounder variable and a single risk factor have reaffirmed that models employing maximum curvature difference have the highest degrees of statistical significance and the best fits to observed data for dichotomous injury outcomes $P(AIS \geq 3)$ and $P(AIS \geq 4)$.

Probabilistic models based on logistic regression have the property of yielding finite probabilities when all of the independent variables are nonzero. A method that can be used to improve the behavior of logistic regressions for very low values of risk factor is to apply logarithms to all independent variables in the logit. Model predictions for zero risk factor (e.g., an undisturbed thorax) result in a zero probability of injury using this technique, with accompanying improvements in overall goodness of fit and statistical significance.

Maximum curvature can be envisioned as a function of the maximum stress reached within the thorax, and as such, curvature can be conceived of as a biomechanically-based risk factor for thoracic injury. The same cannot be said of acceleration-based risk factors.

The use of curvature as an injury criterion in crash dummy testing presumes that the compliance around the entire perimeter of a dummy torso can be related to that for a human subject. Ideally, relationships must be found between curvature as measured on a dummy and as determined from post-mortem human subjects, or models should be formulated for the calculation of curvature as a function of dummy-based measured quantities. It is suggested that both tasks be carried out in future research activities relating to the assessment of thoracic injury due to side impact.

## ACKNOWLEDGEMENTS

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# DISCUSSION

PAPER: **Side Impact Rib Fracture Injury Analysis**

PRESENTER: ***Paul Masiello, JAYCOR***

**Q**UESTION: *Richard Kent, UVA*

One comment, one question, maybe. The comment is: I'm surprised that you're able to get maximum curvature to emerge as an independent predictor separately from deflection given that you're not changing, really, the boundary condition too much at the side impact with a plate kind of a thing; and so, you would expect those things to be pretty co-linear. So, I'm surprised that they do provide unique information.

The second–The question I have is: We've done similar kinds of analyses on our frontal impact data, and we found extreme sensitivity to one or two subjects where you may have an excessive curvature or something, often can be a remnant of the chest band or other factors related to the test. Did you–given the fairly low n of 25 or 28 or something–Did you do a sensitivity analysis because we found sensitivities even to one or two subjects with our data set, which was, I think, maybe around 40. So, maybe a little higher numbers, and we still saw sensitivities just due to one or two subjects. And, I wonder if you have an effect like that in your data and if you looked for that?

**A**NSWER: Well, the first question–The first question: Deflection doesn't appear to be necessary with the use of maximum curvature. I've seen some correlations that seem to do well with both. But the fit's so good anyway; it appears that deflection's not needed in the presence of the curvature. That's the case where a simple beam–I know, of course, the thorax is a lot more complicated than that as a shape. But, it just might be that curvature alone can, can make the determination.

Second question: No, I haven't really been able to do any kind of sensitivity study on a number of samples. Could be that you could get some effects. I'm sure the results would be different. We just need more samples to, to evaluate.

**Q:** *Guy Nusholtz, Daimler/Chrysler*

Your plots–your logistic plots: You're merely plotting numbers against numbers, so every single curve is the same regardless of what your logistic functions.

**A:** If you plot it against the logic, that's true.

**Q:** So, it almost becomes–The only way a plot, then, can show anything meaningful is to break it into the multi-dimensional space and then plot several plots to show what the effect is. Then, you can get a better feel for where it is–

**A:** Yes.

**Q:** –As opposed the moving average. It's just a suggestion in terms of that. Did you check for any cross terms in your logistics?

**A:** No, we did not check for cross terms.

**Q:** (inaudible)

**A:** The Rolf Epigenger's study showed that that wasn't beneficial to do, and we had a limited time, so we didn't do that.

**Q:** Okay. And, the third question is: It looked like age is your dominant–It looked to me, at least–and I haven't done the analysis, but it looked like age is the dominant parameter and so your risk function might just be age.

**A:** Well, to a large extent.

**Q:** Just be young and you're safe.

**A:** To a large extent age is important, but age is probably not correlated to the other risk factors, which is a good thing. And, I'd like to downplay the stepwise logistic progression–stepwise regression because actually it could be misleading because if you have–Stepwise just looks at–The first variable it finds it appears to be the most statistically significant. Stays with it and adds other ones. But if that first variable is a linear, is a correlate of some linear combination of the other risk factors, it could leave a misleading result. So while the result of stepwise regression is gratifying because it's in agreement with everything else, it's not the final answer to making assessments.

**Q:** And with that in mind: Did you look at your variables without age to run correlated tests? Do you still get the same ring quarterly?

**A:** Without age: No, we just did a few cases, as was shown in the table and we saw that the, you know–

**Q:** Was degraded.

**A:** As statistically significant. So, we didn't deal with that. Just age alone.

**Q:** Thank you.

**Q:** *Jeff Crandall, University of Virginia*
Paul, I had a question for you. In terms of what Rich Kent mentioned earlier, in terms of a couple cadavers giving you, maybe, outliers: I was wondering whether you could determine whether curvature was sort of a cause or effect variable? In other words, if you had failure of the thorax, you might have large changes in the curvature subsequent to failure. And, have you given any thought to that?

**A:** No. Not really. The cause and effect is really hard to show in any case. All of this–All of these statistics just show associations relationships. They don't show cause and effect. That's something more you have to appeal on the physical grounds and have to look at a lot of different data to see if, you know, your results are consistent among different data sets to do cause and effect. We only have 28 samples right now.

**Q:** Good. Thank you.