Structural Attributes of the Striking Vehicle that Control Aggressivity toward the Struck-Vehicle in Frontal Collisions

Jeremy J. Blum[1], Paul Scullion[2], Richard M. Morgan[2], Kennerly Digges[2], and Cing-Dao Kan[2]
[1]: Penn State University [2]: The George Washington University

ABSTRACT

This study of vehicle aggressivity in head-on collisions analyzes the effect of vehicle-related factors in the bullet vehicle on injury outcome in the target vehicle. The variables that were considered and studied in the bullet vehicle included Average Height of Force (AHOF), crush-zone stiffness, vehicle type, and vehicle weight. As with previous research, a data-mining analysis of 107,000 collisions finds that an increase in the striking vehicle weight has the largest correlation with higher serious/fatal injuries. Unlike previous research which focused on crush-zone stiffness, this research finds that the second most important explanatory variable is AHOF, with a higher AHOF associated with higher injury risk.

Keywords: Frontal Impacts, Injury Severity, Compatibility, Statistics, Databases

STUDIES OF VEHICLE AGGRESSIVITY in head-on collisions have focused on a range of structural attributes of a bullet vehicle that increase the likelihood of serious injury to occupants of a struck vehicle. Multiple studies (e.g., Evans, 2004) have shown that the weight of the bullet vehicle has the largest influence on this injury risk. However, there is disagreement about the importance of various secondary structural characteristics, including Average Height of Force (Digges and Eigen, 2000), stiffness of the crush zone (Mohan and Smith, 2007), and vehicle body type.

This study investigates the influence of these secondary factors, by linking injury outcomes in real-world head-on collision data with the structural characteristics of vehicles derived from laboratory crash tests. The real-world, head-on collisions data included the injury outcomes to 107,000 drivers from NHTSA's State Crash data files. The structural attributes of the other (bullet) vehicle was derived from 567 frontal crash tests performed by the USA New Car Assessment Program (NCAP).

This large number of observations enabled a novel approach to the analysis of this data. Previous researchers have used regression models to analyze real-world vehicle aggressivity data. These models necessitate the researchers to make assumptions about the the relationship of a large range of potential independent variables on the dependent variable. The study, however, used a data-mining approach that automated the process of finding the most statisticallly significant linkage between injury outcome and range of possible explanatory variables. In this study of the likelihood of serious or fatal injury to a belted driver in the struck vehicle in a head-on collision, the range of possible explanatory, structural variables included the Average Height of Force (AHOF), initial stiffness, relative and absolute measures of total crush, crush in the engine compartment, and crush in the occupant compartment, the Crush-Work Stiffness Kw400 metric of "stiffness" (Mohan and Smith 2007), vehicle body type, and vehicle weight.

RELATED RESEARCH

Previous researchers have investigated the influence of the characteristics of the other vehicle on the injury outcome to the driver in head-on collisions. Often, the data in these studies has linked the results of laboratory crash tests with real-world accident databases. Regression models have then been used in an attempt to determine the relationship between the injury outcome to the driver and the structural characteristics of the other vehicle.

Data for studies of vehicle aggressivity often links real-world crash data with results from laboratory crash tests. Kahane, for example, compared NCAP test results with fatality risk in real-world crashes recorded in the FARS database (1994). FARS does not generally describe the physical characteristics of vehicles. Kahane linked crash records to fundamental impact responses from the NCAP frontal tests, including HIC, femur force, and chest acceleration of the dummy occupants. Similarly, Austin examined five years of police-reported crashes from seven states in the State Data

System (2005). The state files give information on both drivers in a head-on collision, including injury severity, age, and gender in their records. State data files have little engineering information, but they have a large number of crash observations. As in the earlier Kahane study, the Austin paper used the NCAP laboratory tests to obtain structural attributes of passenger vehicles.

Statistical analysis of real-world head-on collisions and finite element simulation of these collisions have looked at a range of structural characteristics that may affect vehicle aggressivity, including AHOF, stiffness of the crush zone, vehicle body type, and vehicle weight. Vehicle weight has universally been found to be the most important structural characteristic, because an increased weight of a bullet vehicle directly increases Δv for the struck vehicle. However, there has been significant debate over the importance of secondary explanatory variables.

The vehicle body type has been found to be pickups, SUVs and minivans associated with a higher risk to the driver of the other vehicle (Kahane 2003). The increased aggressivity of minivans could be explained by their heavier than average weight. However, increased vehicle weight could not explain the increased risk to the driver of the other vehicle posed by pickups and SUVs.

Kahane posits that an increased aggressivity in near-side collisions could be the result of a higher AHOF, while an increased aggressivity in head-on collisions could be the result of a higher stiffness (Kahane 2003). Other researchers have also focused on crush-zone stiffness and the stiffness distribution as possible explanatory variables in aggressivity in head-on collisions (Klanner *et al.* 1998). More recently, there has been an attempt to explain aggressivity in terms of mismatches in the stiffness of the striking and struck vehicles in a head-on collision (Takizawa *et al.* 2004) (Moustafa *et al.* 2005).

However, other studies report that it is unclear if crush-zone stiffness, and mismatches in this stiffness, are indeed associated with higher injury risk. For example, finite element simulations of head-on collisions vehicles with changes designed to reduce these mismatches have shown that the improvements in compatibility are limited to a certain impact speed range (Hirayama *et al.* 2007).

METHODOLOGY

The analysis of the real-world head-on collisions consisted of the following stages:

- Extraction of Structural Variables from NCAP Frontal Tests
- Association of State Accident Data with NCAP Frontal Test Data
- Execution of the Classification Tree Algorithm

DATA

The first set of data is derived from NCAP tests, which measure the dynamic crash performance of passenger vehicles in frontal collisions into a rigid wall (see Figure 1). The tests measure the forces transmitted into a rigid barrier, the longitudinal acceleration in the rear-seat area, and the static and dynamic crush of the vehicle (NHTSA 2001).

Figure 1: NCAP Crash Test into a Rigid Wall Barrier

Structural attributes, including stiffness, occupant compartment crush, and so on, can be calculated from the NCAP data files. For example, the initial stiffness is defined as the initial slope of the force-versus-crush curve of the barrier crash, shown as a dashed line in Figure 2.

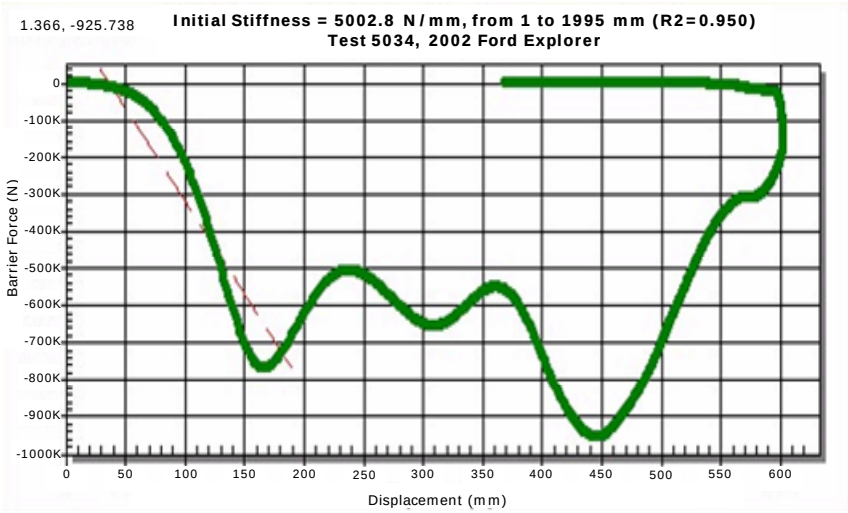

Figure 2: Initial Stiffness Derived from NCAP Crash Test

Another example is the Average Height of Force (AHOF), shown in Figure 3. The forces at a given height about the ground are multiplied by the height, and the products are summed. AHOF is defined as that sum divided by the sum of all the forces measured at the wall.

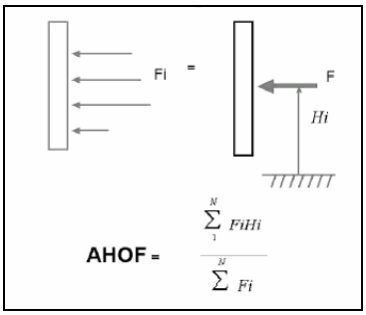

Figure 3: AHOF Derived from NCAP Data Set

The second data set was derived from real-world crash data, collected by a number of states within the USA to provide basic information for a large number of crashes. Each state maintains a database that contains broad information about people, vehicles, and conditions written down in Police Accident Reports (PAR's). Each state has different requirements for collection and reporting of crash data. Beginning in about 1980, NHTSA began collecting crash information based on information based on PAR's. Currently, the NHTSA obtains data from twenty-nine states and compiles it into the State Data System. Most states use the KABCO injury severity code (K is killed and A is incapacitating injury while other injury categories are not severe). A measure of crash severity, such as Δv, is not available in the State Data System.

This study uses state crash data from Florida for 1992 to 2004, Illinois for 1990 to 2003, Maryland for 1989-2001, Ohio for 1990 to 1999, and Pennsylvania for 1997 to 2001 and 2003 to 2004. In this analysis, driver injury was defined as K or A on the KABCO scale and driver non injury was considered as B, C, or O on the KABCO injury scale.

EXTRACTION OF STRUCTURAL VARIABLES FROM NCAP FRONTAL TESTS

A wide variety of structural attributes were extracted from the 1991-2006 NCAP frontal test data using NHTSA's *Load Cell Analysis* software package. NCAP tests results were excluded from this analysis if the *Load Cell Analysis* program reported suspicious or faulty sensor data, unless there were no valid test results available for a given vehicle model from a different year. Eliminating the tests with questionable data resulted in 567 tests that were included in the study.

These structural attributes include:

- Average Height of Force (AHOF)

- Initial Stiffness
- Vehicle body type (LTV versus passenger vehicle)
- Vehicle weight
- Relative and absolute measures of crush
- Crush-work stiffness 200, 300, and 400, measures of the work required to crush 200, 300, and 400 mm, respectively, of a vehicle's front end

The parameters generated from NCAP were generated based on a single test condition. Some of these parameters can vary under different, real-world crash conditions. Mohan and Smith (2007) used finite element simulations to evaluate the influence of impact speed and vehicle mass on crush-work stiffness 400 and AHOF. They found added mass—as in an increased number of occupants—had no influence on crush-work stiffness. However, crush-work stiffness varied with impact speed. Neither mass nor impact speed changed AHOF.

ASSOCIATION OF STATE ACCIDENT DATA WITH NCAP FRONTAL TEST DATA

The state accident data and NASS CDS data were linked to the NCAP test data using the vehicle VINs reported in each data set. While a number of USA State Crash Data files were available, this analysis was limited to ones for which the VIN was recorded. This data included Florida for 1992 to 2004, Illinois for 1990 to 2003, Maryland for 1989-2001, Ohio for 1990 to 1999, and Pennsylvania for 1997 to 2001 and 2003 to 2004.

Following a VIN-based matching algorithm (explained in Blum, 2008) the authors linked the laboratory-tested vehicles to the vehicles involved in the real-world collisions. In addition, the algorithm uses a list of vehicle sisters and clones based on the 2004 list from Neptune Engineering (Anderson 2007). Vehicle sisters and clones are vehicles that are based on the same platform, e.g. the Chevrolet Celebrity 4-door and the Buick Century 4-door. If we are unable to find a match based on the previous criteria, we then attempt to match a crash observation with a sister or clone vehicle in the NCAP data.

EXECUTION OF THE CLASSIFICATION TREE ALGORITHM

The analysis of the linked data set was done using a decision tree classification algorithm developed by the SAS Institute (SAS Institute 1995). Given the large set of accident observations that were gathered, this classification algorithm enables an automated search for the most important structural attributes. The approach includes the following useful attributes:

- It uses an automated process to select the most statistically important structural variables,
- It automates the search for the value ranges for these structural variables that produce the best outcome for the driver, and
- It does not assume that all structural variables are equally important for all vehicle types.

The decision tree algorithm used in this analysis is the TreeDisc algorithm, a data mining macro created by the SAS Institute. This decision tree algorithm takes as input a set of data, a dependent binary variable, and a large number of possible independent variables. The algorithm recursively runs through the following steps:

1. The algorithm uses statistical tests (chi-squared tests of contingency tables) to select the most important independent variable
2. Then, the algorithm automatically searches for the most significant discretization of this independent variable.
3. The records are then split into subgroups based on this discretization, and the algorithm is run on the subgroups.

The recursion in the algorithm terminates under one of two conditions. It will terminate if the minimum number of observations in a leaf node falls below a predetermined threshold (which is set based on the sample size between 1,000 and 2,500) or if the optimally merged predictor for the next level falls below a p-value of 0.1.

For this analysis, the following selection criteria were used to select observations from the merged data file:

- Head-on collisions, involving 2 vehicles;
- Where the driver was belted,

- Where the structural parameters were known for the other vehicle (i.e. the state accident record could be linked to a valid NCAP frontal test);
- Where one of the vehicles was towed or disabled, or one of the drivers was seriously/fatally injured (in order to eliminate minor crashes from the dataset).

The effects of using a tow away threshold for crash analysis have been studied (FHWA, 1998). It turns out that, to combat reduction in funding, many state agencies no longer report property-damage-only (PDO) crashes. If some state agencies report PDO and some state agencies do not, researchers can not analyze the state data in the aggregate without removing the PDO cases. A benefit of increasing the analysis threshold to tow-away crashes is a much greater consistency of crash rates among individual states, i.e., if the states have the same crash rates at the tow away threshold, then it may be possible to analyze all the combined state data set.

Value ranges for each of the value independent structural variables were established. These ranges grouped vehicles into five equal groups, i.e. vehicles with values for a given variable less than or equal to the 20th percentile in the accident records, vehicles with values for a given variable that were greater than the 20th percentile but less than or equal to the 40th percentile, etc. In addition to these structural variables, the classification algorithm input included the vehicle body type (LTV versus car) and whether or not an airbag deployed. If adjacent subgroups were very similar, the software combined these similar groups into an aggregate group.

LIMITATIONS OF THE ANALYSIS

The data sets used in this analysis presents limitations that should be kept in mind when interpreting results. The data derived under laboratory conditions in the NCAP frontal tests may not correlate well with real-world crash conditions. The State Data files do not contain an engineering measure of accident severity, but do contain large numbers of accident observations.

The structural attributes from the NCAP data may not correlate with real-world attributes because of their generation under laboratory conditions. For example, in these frontal tests, vehicles collide with a planar barrier. Consequently, the amount of intrusion due to bumper mismatches would not be captured in the NCAP tests.

In addition, recent studies found that the small (10% - 15%) frontal offset crashes on the deriver's side are associated with higher risks of severe trauma (Lindquist et al., 2004). Analyzing the forces distributed across the entire front of the rigid barrier—as done in this paper—most likely will lack the meticulous focus on the side of the vehicle where the small offset occurs.

Similarly, the State Data Files report a driver's vehicle as having a frontal crash, but do not report the degree of frontal overlap going from full engagement to small overlay. Recently, Sullivan et al. (2008) defined taxonomy of seven separate classes of frontal crashes (using NASS/CDS data). The frontal crashes in the State Data Systems can not be subdivided into these seven classes.

The State Accident Databases contain no engineering measure of accident severity (e.g. ΔV). To mitigate this limitation, this study considers attempts to limit consideration to the most severe in which one of the vehicles required towing or the driver experienced a serious or fatal injury. Moreover, the significant number of cases used in this study mitigates this limitation through the law of large numbers.

VEHICLE AGGRESSIVITY RESULTS

A study of vehicle aggressivity was made on a dataset comprised of accident observations in which the structural parameters of the striking vehicle and the injury outcome for the driver of the other/ struck vehicle. The classification tree algorithm was applied to 107,000 observations fitting this requirement and in which the driver was fatally/seriously injured, or one or both of the vehicles was towed. The minimum number of observations in a node was set to 2,000, and the maximum number of levels in the tree was set to four.

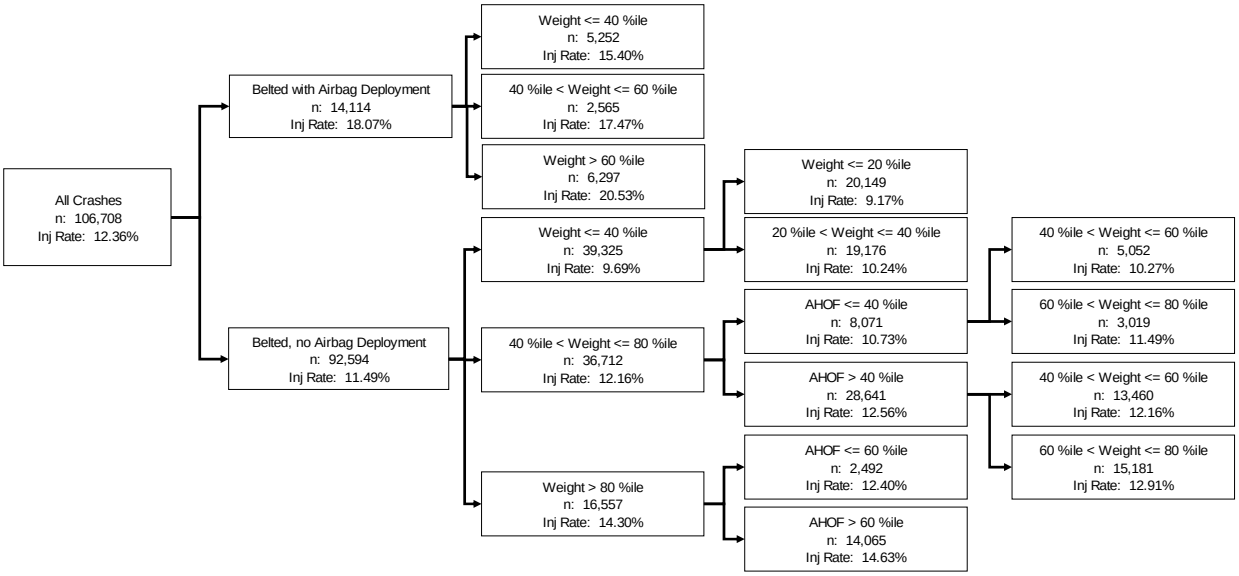

Figure 4: Classification Tree for Vehicle Aggressivity

The classification tree, shown in Figure 4, found that airbag deployment in the struck (target) vehicle had the most significant correlation with the injury outcome to the driver. In other words, data mining first divided the 106,708 cases by whether an air bag was present and deployed in the target vehicle, or not. The importance of the airbag deployment variable is due to its likely correlation with accident severity. In other words, when the air bag variable has the value, deployed, it is considered a surrogate for the higher-severity crashes, 14,114 in number. In terms of the structural variables, the striking vehicle's weight was found to have the most significant correlation to injury risk, and the striking vehicle's AHOF was also found to be correlated with injury risk. Other variables yielded insignificant or inconsistent results, and were excluded from this analysis. These variables included the relative and absolute measures of crush, the stiffness metrics, and the vehicle body type.

The relationship between vehicle weight and AHOF and injury risk conforms to results from previous literature. As the striking vehicle's weight increases, the risk of injury to the driver of the other vehicle increases. Similarly, as the striking vehicle's AHOF increases, the risk of injury to the driver of the other (target) vehicle also increases. For these data, data mining found neither AHOF nor any other secondary structural variable were linked to injury risk in the higher-severity crashes.

Striking Vehicle Weight and Aggressivity

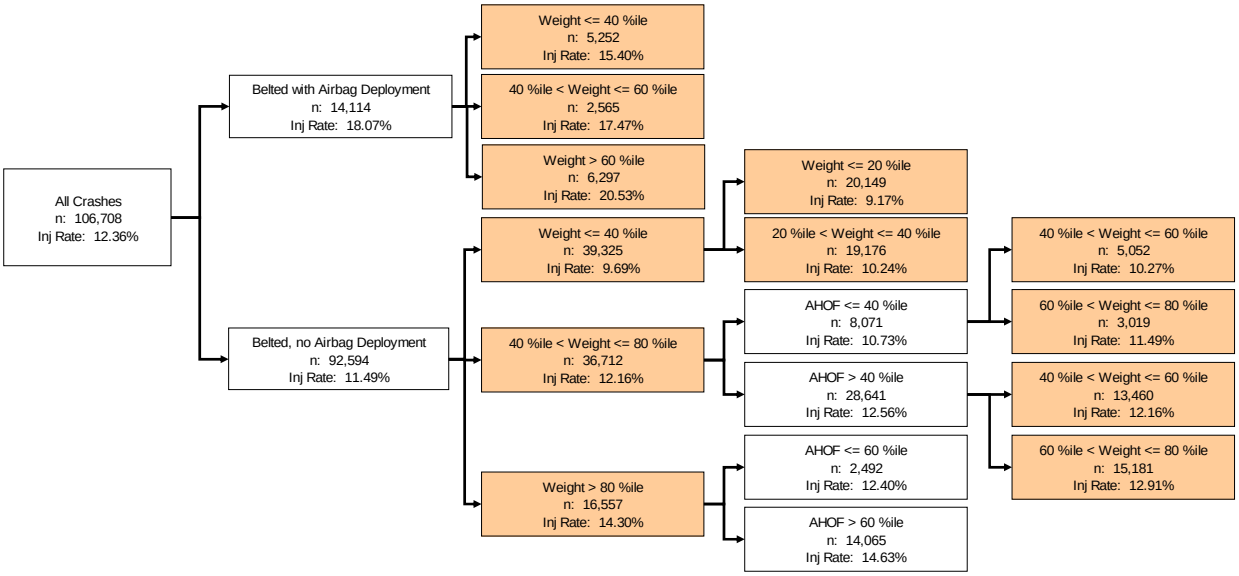

Figure 5: Striking Vehicle Weight in the Vehicle Aggressivity Classification Tree

As shown in Figure 5, the striking vehicle weight is the dominant structural parameter in the vehicle aggressivity classification tree. There is a strong association between the striking vehicle weight and injury risk regardless of whether an airbag deployed in the struck vehicle. Moreover, after splitting the cases by vehicle weight in the second level of the tree, the correlation between injury risk and the weight is strong enough that the tree is subdivided again by vehicle weight at the third and fourth levels of the tree.

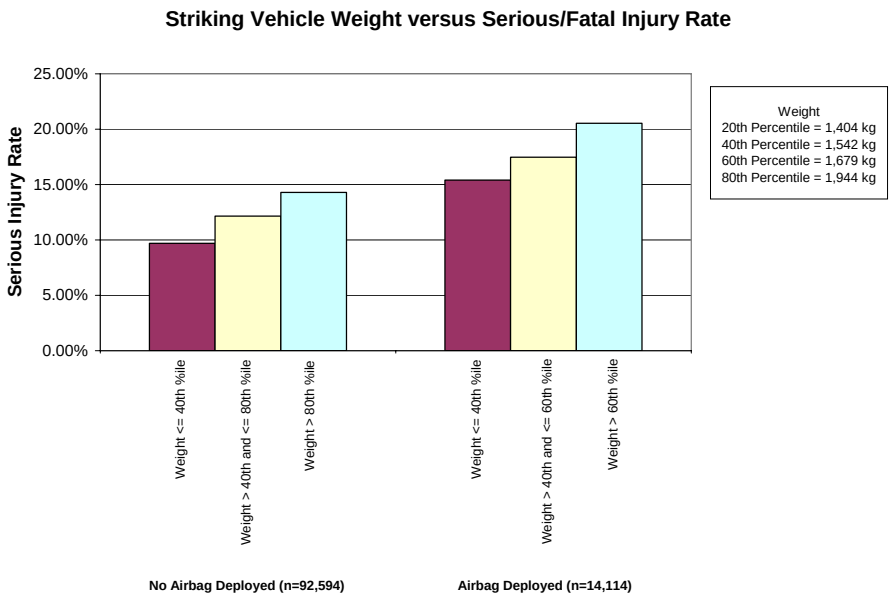

Figure 6: Injury Rates by Striking Vehicle Weight at Second Level of the Classification Tree

Figure 6 depicts the relationship between the striking vehicle weight and injury risk for the second level of the classification tree shown in Figure 5. The kilogram equivalents for the different percentile weights are shown in the legend of the figure. In the second level of the tree, as the striking vehicle

weight increases, the injury risk to the driver of the other vehicle increases. Moreover, this relationship holds when striking vehicle weight appears in the third and fourth levels of the aggressivity classification tree.

At the second level, the classification tree divides the vehicles into three groups. The threshold for striking vehicle weight in the safest group is the 40th percentile, while the threshold for the most dangerous group varies between the 60th and 80th percentiles.

The increase in risk to the driver of the other vehicle between the lightest and heaviest groups of vehicles was significant, at 33.3% (when an airbag deployed) and 47.6% (when no airbag deployed).

Striking Vehicle AHOF and Aggressivity

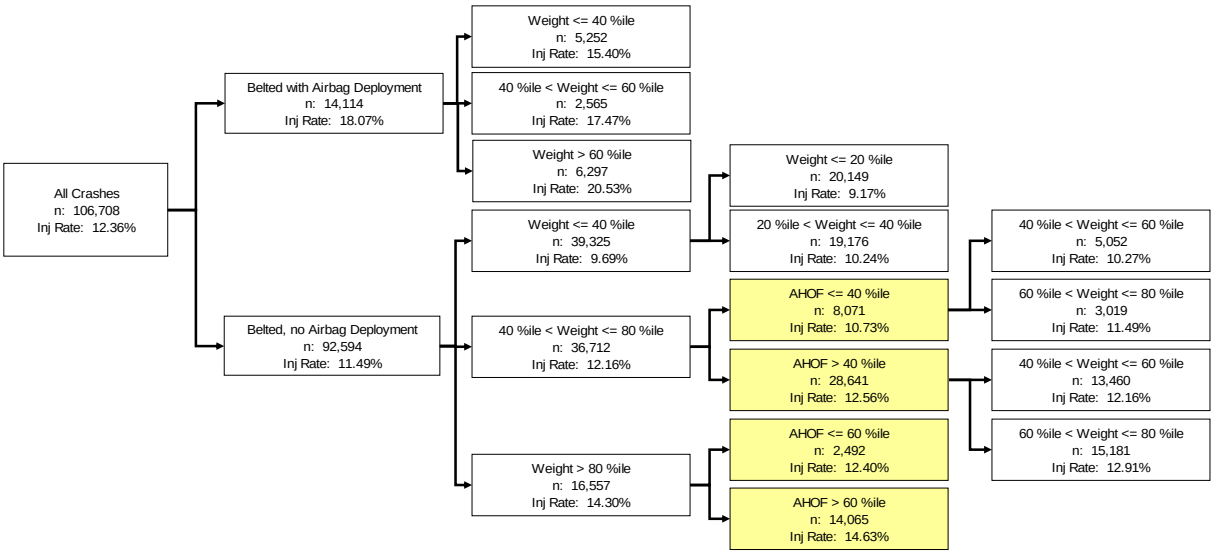

Figure 7: Striking Vehicle AHOF in the Aggressivity Classification Tree

As shown in Figure 7, the AHOF had a strong correlation with injury for heavy vehicles when no airbag deployed, i.e., in the lower-severity collisions. A bane of the safety analyst is that there is almost always a lack of large numbers at a critical point in the investigation. At the higher-severity crash branch of the tree, the leaves have 5,252, 2,565, and 6,297 data remaining. As the data mining cut offs at 1,000 to 2,500 samples, the data mining may have stopped because no suitable secondary structural variable was available. On the other hand, it is possible that the data mining ceased because of small numbers, and the smaller sample size prevented the classification tree analysis from identifying further structural variables. Having worked out the methodology of (1) linking a data set of no injury with a data set of no engineering information and (2) applying the classification tree analysis in a meaningful way to automotive safety, the authors wish to continue their study with much larger data collections from the State Data Files.

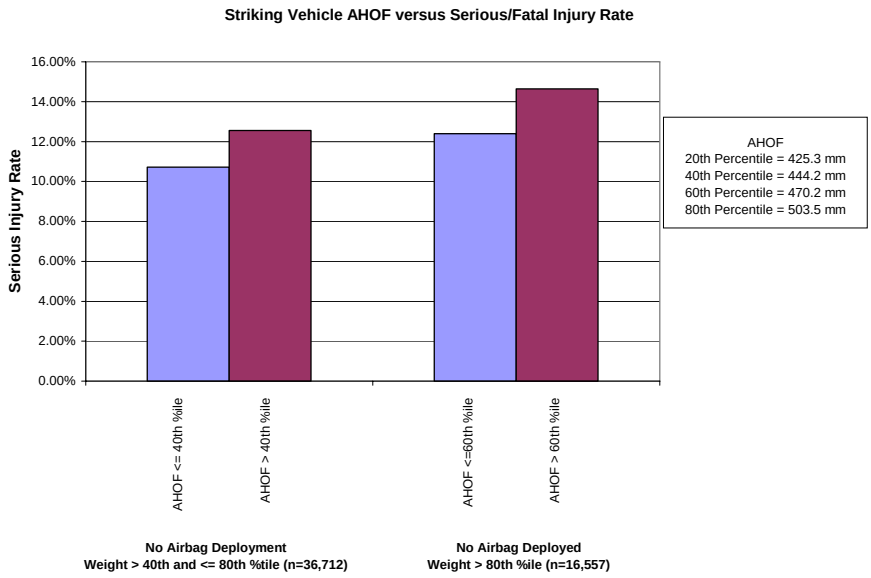

Figure 8: Injury Rates by Striking Vehicle AHOF

For both mid-weight and heavy striking vehicles, a higher AHOF was associated with an increased risk of serious/fatal injury to the driver of the other vehicle. The threshold for striking vehicle AHOF was either the 40th percentile or 60th percentiles. As shown in the legend for Figure 8, these thresholds correspond to 442.2 mm and 470.2 mm, respectively.

The increase in risk to the driver of the other vehicle between the lower AHOF and higher AHOF groups of vehicles was less significant than in the case of striking vehicle weight, at 17.1% (when no airbag deployed and striking vehicle weight was between the 40th and 80th percentiles) and 18.0% (when no airbag deployed and striking vehicle weight was above the 80th percentiles).

It is notable that for mid-weight vehicles (vehicles in the 40th to 80th percentile weight), differences in AHOF were more highly correlated with a risk of serious or fatal injury than vehicle weight. In Figure 7, we see for these vehicles that at the third level of the tree the observations are divided based on AHOF, with vehicles with the higher AHOF correlated with a 17.1% higher risk of serious or fatal injury. On the other hand, a vehicle weight in the 60th-80th percentile had only an 8.85% higher risk of serious or fatal injury than a vehicle in the 40th-60th percentile

DISCUSSION

This data mining approach confirmed that the weight of the bullet vehicle had the largest correlation with the injury outcome to the driver in the struck vehicle. Heavier bullet vehicles are associated with a higher level of serious or fatal injury to the driver of the other vehicle. However, for mid-weight and heavy striking vehicles, a decrease in a striking vehicle's AHOF is correlated with a 17.1% lower risk for serious injury to the driver of the struck vehicle. On the other hand, none of the stiffness metrics were found to have a statistically significant correlation to increased injury risk to the driver of the other vehicle.

The authors associated airbag deployment or non deployment as a substitute variable for crash severity. AHOF might be a substitute variable for some form of vehicle geometry such as bumper mismatch.

In a previous data-mining study of vehicle self-protection, the authors found that an increased stiffness of the struck vehicle is correlated with a lower the risk of injury to the driver (Blum *et al.*, 2008). The same study did not find reveal a statistically significant correlation between AHOF and vehicle self-protection. Taken together, these studies suggest that an increase in the stiffness of vehicles is likely to improve self-protection in head-on collisions without a negative effect on vehicle aggressivity. At the same time, a decrease in the AHOF of mid-weight to heavy vehicles could lower the vehicle aggressivity in head-on collisions without a significant adverse effect on vehicle self-protection.

The authors observed that the classification tree analysis adds to and enhances well-established techniques such as logistic regression analysis. Classification models tend to use categorical responses while regression models use continuous and binary responses as targets (dependent variables). In logistic regression analysis, the analyst wants to approximate the regression function. In data mining with a classification tree approach, the analyst wants to approximate the probability of class membership among selected input (independent) variables. A decision tree clearly and graphically displays the interrelationships among the multiple factors that form the decision tree model. This data-tree insight can stand alone, or this data-tree insight can aid the analyst in his or her logistic regression analysis.

CONCLUSIONS AND FUTURE STEPS

The analysis used data from NHTSA's State Data System, which is limited by having no variable (like ΔV) assessing crash severity. In addition, the State Data System does not describe the varying amount of overlap between two vehicles in a head-on collision. The analysis linked the crash vehicles in the State Data System to vehicles crashed in the USA NCAP, which is limited in that each test is done at a single impact velocity.

A data mining analysis of vehicle aggressivity in real-world head on collisions found statistically significant relationships between the risk of serious or fatal injury to a driver in a head-on collision and a number of vehicle structural parameters measured in the NCAP tests. The analysis of these real-world collisions produced the following three major conclusions:

- The most important determinant of the risk of serious or fatal injury to a driver in the target vehicle is the weight of the striking vehicle.
- At lower severity collisions, increases in the AHOF of medium and heavy vehicles tend to increase the injury risk for drivers of other vehicles.
- None of the metrics for crush-zone stiffness of the striking vehicle were found to be correlated with a higher risk of serious or fatal injury to the driver of the struck vehicle.

Previous results have found that increased crush-zone stiffness offer improved self-protection (Blum *et al.* 2008). This analysis, therefore, suggests that vehicle manufacturers should focus on reducing the AHOF of mid to heavy vehicles while increasing the stiffness of their vehicles in order to improve injury outcomes in head-on collisions.

Future work is planned to expand this analysis to include additional perspectives and collision types. The correlation between the structural parameters in vehicle protection and aggressivity for side impact collisions will also be examined. The analysis will also be expanded through the examination of additional data sources to further substantiate the relationships discovered in the current analysis.

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