20S-21

*Stapp Car Crash Journal,* Vol. 65 (November 2021), pp.


# Occupant-based Injury Severity Prediction

Susan H. Owen
Jeffrey W. Joyner
Global Product Safety & Systems, General Motors

Peng Zhang
Stewart C. Wang
University of Michigan International Center for Automotive Medicine

**ABSTRACT** – Road traffic injuries continue to be a leading cause of death around the world. Rapid emergency response is a key factor in improving occupant outcomes. Over the past ten years, Injury Severity Prediction (ISP) models have been developed and deployed to assist in effective dispatch of emergency medical services (EMS). Prior versions of ISP have relied on driver-based scenarios that are not relevant in many of the possible autonomous vehicle (AV) contexts. This paper describes the development and validation of occupant-based ISP models that predict injury severity for specific vehicle seat positions. Models show improved predictive performance, sensitivity 80% and specificity over 95%, for front row occupants. Second row occupant models have similar specificity, but sensitivity scores dropped due to occupant heterogeneity and small sample sizes of seriously injured occupants.

**KEYWORDS** – AACN, ISP, injury severity prediction, emergency response.

## INTRODUCTION

In its most recent Global Status Report on Road Safety, the World Health Organization (WHO) estimates that 1.35 million people were killed in 2016 road traffic deaths worldwide (WHO, 2018). This makes road traffic injuries the top cause of death for children aged 5-14 and adults aged 15-29, and the eighth leading cause of death overall. Recent initiatives from the World Bank (Marquez et al., 2017), the Bloomberg Global Road Safety Program (Bloomberg Philanthropies, 2014) and the Pulitzer Center (Hundley, 2013) also focus on the need for improved road safety, especially in low- and middle-income countries. In the US, the National Highway Traffic Safety Administration (NHTSA) reports that 36,560 people were killed in US automotive crashes in 2018 (NHTSA, 2019). One factor in reducing fatalities and improving injury outcomes is providing rapid and effective post-crash emergency response. Efforts aimed at improving survival after a crash is one of the six key strategies promoted by the WHO (WHO, 2016).

Since 2010, General Motors (GM) has been using an Injury Severity Prediction (ISP) model to estimate the likelihood of high-risk injuries to vehicle occupants whenever a vehicle is involved in a collision that triggers Advanced Automatic Collision Notification (AACN). When such a collision occurs, vehicle event data are sent via telemetry to OnStar's back office systems and fed through the ISP model. If the model predicts a 20% or greater probability that one or more vehicle occupants has an injury severity score (ISS) of greater than 15, a "high" injury risk is displayed to the OnStar Emergency Advisor responding to the AACN call. The Emergency Advisor can relay that information to 9-1-1 dispatchers and other on-scene crash responders. The ISS 15+ target corresponds with the need for a Level 1 or Level 2 trauma center, and thus is specifically relevant to supporting timely and appropriate EMS dispatching. The 20% threshold is based on guidelines set by a National Expert Panel for Field Triage convened in 2005 (Sasser et al., 2009).

While the ISP threshold for determining "high" injury risk has remained constant over the past decade, the underlying model has evolved to leverage improved vehicle sensor data. These changes have demonstrated increasing predictive performance. The original ISP algorithm gave a vehicle-level prediction of the probability that one or more occupants would have an ISS greater than 15. Inputs to the model included crash characteristics that were available via OnStar telemetry as well as occupant characteristics that could be collected from the OnStar Emergency Advisor. Specifically, the model used Principal Direction of Force (PDOF) in 90-degree quadrants, maximum delta-velocity, presence of multiple impacts, and front-row seat belt use from telemetry data and provided the option for Emergency Advisors to input data on the presence of older (age 55 or older) or female occupants. The model was fit using 1999-2008 National Automotive Sampling System—Crashworthiness Data System (NASS-CDS) crash and injury data (Kononen et al., 2011). The ISP model was later updated to version 2 (ISP-V2) using NASS-CDS data through 2013. ISP-V2 combined two models based on front row occupancy, one for the driver-only scenario and one for cases with a driver and right front passenger. ISP-V2 refined the use of Principal Direction of Force (PDOF) inputs, shifting from quadrant-based to PDOF specified in ten-degree increments. The driver plus right front passenger scenario incorporates an interaction term to account for injuries associated with same row occupant interactions (Wang et al., 2017). The model still produced a single, vehicle-level prediction of one or more occupants having an ISS greater than 15 but did so with better predictive performance than the original ISP model.

Other recent approaches to support improved emergency crash response have attempted to predict the presence of specific severe injuries that would require trauma care. Stitzel et al. (2015) develop a list of injuries likely to require level 1 or 2 trauma care and fit a multivariate logistic regression model to predict an occupant's risk of having an injury on the list. The model is fit using driver and right front passenger data from NASS-CDS, including crash type, delta-V (longitudinal or lateral, depending on crash type), belt use, multiple impacts, and air bag deployment (front or side, depending on crash type). Weaver et al. (2015) focused specifically on frontal, single impact crashes with front airbag deployment to predict severe injuries to adult drivers and right front passengers. Logistic regression models were used to develop injury risk curves for specific injuries and body regions, based on delta-v and belt use. While such models might one day be capable of providing early insights on specific injury risks, the pipeline for providing this information to medical service providers in the US has not yet evolved. To date, AACN communications have been focused on supporting fast and effective emergency dispatch through public service answering points (PSAPs), rather than on the delivery of medical care. Shifting the focus would require engagement and acceptance of medical providers across the country.

Outside the US, additional research in injury prediction has demonstrated several efforts to improve emergency response efficiency and effectiveness with country-specific models. Lubbe and Kiuchi (2013) leverage the German In-depth Accident Database (GIDAS) to explore the development of injury prediction algorithms for accidents in Germany. Buendia et al. (2015) use accident characteristics available on-scene to develop an injury severity prediction algorithm to support Sweden's long-term goal of eliminating loss of life due to road accidents. More recently, Nishimoto et al. (2018) explored the use of large-scale police report data from the Japan Traffic Accidents Database (J-TAD) to develop and validate an injury severity prediction model for Japan. A detailed comparison of these models is provided in the Discussion section below. Differences in fleets, emergency response system designs, and crash data timeliness and accuracy continue to drive variation in the development and validation of injury severity prediction models around the globe.

In 2018, two developments prompted further updates to the ISP model: 1) advances in Autonomous Vehicle (AV) technology, and 2) improvements in passenger presence detection. Progress toward AVs is significant because both ISP-V1 and ISP-V2 models relied on front row occupant data (predominantly driver information) to predict vehicle-level injury outcomes. AVs, especially those targeted for rideshare domains, present a new paradigm in which non-driver outcomes become a primary concern. To accommodate this change, the ISP model was refocused from vehicle-based assessments of driver or driver plus right front passenger scenarios to a set of seat-specific occupant risk models. The occupant-based models continue to leverage vehicle event data but assess the injury risk through the lens of a specific seat occupant. Expansion in passenger presence detection promises to enable better data on rear seat occupancy and seat belt usage, further supporting the change in ISP focus. The new occupant-based ISP models seek to provide an injury severity prediction for each occupied seat in the vehicle. "High" injury risk predictions are graphically displayed to OnStar Emergency Advisors who are then able to provide 9-1-1 dispatch and other crash responders with a more robust account of potential injury risks and resource needs. While AV technology helped motivate the move to an occupant-based ISP, the resulting models can be implemented immediately to improve response for all vehicles.

To date, few studies have been done to quantify the impact of AACN/ISP on improved injury outcomes. Plevin et al. (2017) leverage data on passenger vehicle fatalities and associated EMS response times to explore whether AACN data could improve mortality by increasing the effectiveness of EMS response. Lee et al. (2019) also examine the potential of AACN to save lives through improved emergency response times and appropriate delivery of seriously injured occupants to trauma centers (as opposed to local hospitals). While this early research suggests important benefits from AACN implementation, it is not sufficiently detailed to estimate effects from model improvements. Such measurement would require a more detailed accounting of crash characteristics, EMS response time and resources, hospital transport decisions, and occupant medical outcomes. Absent such data, researchers continue to improve ISP performance based on feedback from customers and the EMS community.

The remainder of the paper will describe the development of occupant-based ISP models, detail the resultant models, and discuss model validation.

## METHODS

Development of occupant-based models followed a similar approach to that used for ISP-V2 (Wang et al., 2017), except separate logistic regression models were attempted for each first and second row seat position. Based on OnStar's history with ISP-V2, implementation of occupant-based models required proven performance improvements. A validation step was planned in which ISP-V2 and occupant-based models predicted injury severities for a holdout sample of NASS-CDS crash data so that results could be compared to each other and to actual occupant ISS outcomes.

### Data Preparation

Table 1 identifies the NASS-CDS data elements used for occupant-based ISP model development. Data for crash years 2004-14 were used for model fitting, while 2015 data were withheld for use in validating the occupant-based models and output comparisons to ISP-V2. Additional cases from 2017 Crash Investigation Sampling System (CISS) data were added to the validation set to further explore second row model performance due to limited second row occupants with severe injury.

Table 1: NASS-CDS data elements used in ISP model development

| Variable Name | Variable Description |
|---|---|
| RATWGT | Ratio Inflation Factor: an adjusted weight provided by NASS-CDS to enable annual estimates of US crashes. |
| BODYTYPE | Vehicle body type: description of vehicle body style (e.g., 4-door sedan). |
| MODELYR | Vehicle model year. |
| DVTOTAL | Total Delta-V: Estimate of maximum total change in velocity experienced by a vehicle during a crash. |
| PDOF1 | Principal direction of force 1: Clock direction of highest severity impact in degrees. |
| PDOF2 | Principal direction of force 2: Clock direction of second highest severity impact in degrees. |
| ROLLOVER | Extent of vehicle rollover, in number of quarter turns. |
| SEATPOS | Occupant's seat position at time of crash. |
| MANUSE | Manual belt system use: Occupant seat belt use at time of crash as determined by NASS investigator. |
| AGE | Occupant age at time of crash. |
| SEX | Occupant sex. |

Including cases from older crash years would have increased the data set but may not have accurately represented the vehicle crash or occupant protection performance of vehicles in the field today. Since the occupant-based ISP models will be exercised on newer (even future) vehicles, crash years were limited and vehicles with model year prior to 2000 were removed from the data set. Vehicles flagged as having rolled over were also excluded, as the ISP does not attempt to account for non-planar crash and injury dynamics.

Small numbers of center seat and third row (or higher) occupants limited model development to first and second row outboard occupants (i.e., NASS-CDS SEATPOS = 11, 13, 21, and 23). The resulting data set had 422 vehicles and 588 occupants, distributed as illustrated in Figure 1. Second row occupant data were sparse, especially when considering crashes by PDOF. Since left- and right-side vehicle structures are similar in the rear seat, left rear occupants are assumed to have the same injury risk as right rear when PDOFs are mirrored. The second row occupant models for seat positions 21 (left rear) and 23 (right rear) were therefore combined using transformed input data.

Address correspondence to Susan Owen, susan.owen@gm.com

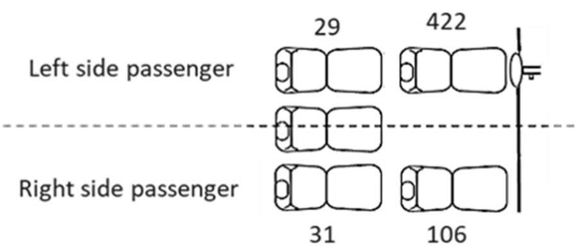


Figure 1: Distribution of 2015 NASS-CDS occupants used in ISP-OCC validation

**Model Fitting**

Models for seat positions 11 (left front / driver), 13 (right front), and 22/23 (second row outboard) were fit individually. First, two key methodological decisions needed to be addressed: whether NASS-CDS weights would be used to put more emphasis on certain cases, and whether automated variable selection techniques would be employed to determine the subset of predictor variables to include in the models. Four modelling options were considered, as described in Table 2.

Table 2: Framework to assess NASS-CDS weights and variable selection in ISP-OCC modeling

| | Automated variable selection | No automated variable selection |
|---|---|---|
| Weighted | Weighted, Variable selection | Weighted, No variable selection |
| Not weighted | Not weighted, Variable selection | Not weighted, No variable selection |

In the end, models built without NASS-CDS weights and without automated variable selection were chosen. NASS-CDS weights are determined based on the stratified multiphase sampling design used to select US towaway crashes to investigate each week (Zhang and Chen, 2013). Weights are assigned at a crash level based on geographic, crash-level injury (i.e., hospital transport and hospitalization) and vehicle age factors. They provide researchers a consistent way to estimate US national crash populations from a small annual sample. The population of OnStar AACN crashes for which the ISP is calculated must meet a higher severity threshold than the NASS-CDS towaway population. To trigger an AACN event, a vehicle must meet one or more thresholds identified by the vehicle's Sensing Diagnostic Module (SDM) including commanded air bag or seat belt pretensioner deployment, rollover prediction, and delta-V thresholds. While AACN-level crashes are consistent with a subset of the NASS-CDS sample, the prevalence of NASS-CDS cases within the larger context of national crashes is not relevant to the AACN population. Specifically, the largest CDS weights are typically applied to the most common, lowest severity crashes – those least relevant to AACN. To fit occupant-based ISP models, the filtered set of unweighted NASS-CDS occupant cases were thus treated as a convenience sample. Eliminating weights had little effect on model performance, other than to remove issues that occurred when extreme weights (i.e., values in excess of 5,000) were assigned in the NASS-CDS data. (See Appendix A for more detail on the effect of weighting on the driver (seat position 11) model.)

Automated variable selection was dropped due to the small data set available for the rear seat occupant model. When used in this case, variable selection might ignore potentially important factors. Therefore, all variables used in ISP-V2 were retained in developing models for each seating position.

A final consideration in developing occupant-based models was the potential for physical interaction between same row occupants. ISP-V2 incorporated an interaction effect by modeling distinct driver-only and driver plus right front passenger scenarios. A similar approach was taken for the occupant-based driver (seat position 11) model but could not be used for the right front passenger (seat position 12). In this case, the non-interaction scenario enables application in AV (non-driver) situations. Since NASS-CDS data does not contain AV cases, the interaction effect for the right front passenger was based on the driver model and then extrapolated for the non-interaction case.

The variables included in the resulting occupant-based ISP models are as follows:

- Logarithm of Delta-V
- Principal Direction of Force (PDOF), modeled using cyclic splines
- Principal Direction of Force (PDOF) and same row passenger interaction, modeled using cyclic splines
- Belt status (binary)
- Multiple event (binary) based on presence/absence of PDOF2
- Age ≥ 55 (binary)
- Gender (binary for Female)

The effect of PDOF was evaluated through periodic basis splines. The degrees of basis splines were treated as hyper-parameters, which were optimized by minimizing Akaike information criterion (AIC). In the final models, PDOF was modeled as periodic basis splines with 9 degrees of freedom and thus the model coefficient summaries listed in Appendix B include 9 PDOF coefficients. Similarly, PDOF with same row interaction was modeled with 6 degrees of freedom.

## RESULTS

Figure 2 illustrates the relative contributions of each variable to the final driver (seat position 11) model. Similar figures for right front passenger and second row occupant models are included in Appendix C. Delta-V, a common surrogate for crash severity, dominates all three models. Belt use and occupant age are consistently the second and third most important factors, though the order shifts between driver and non-driver models. Multiple events and PDOF-related spline factors comprise most of the remaining significant effects, with gender near the bottom in all three models.

Note that vehicle body type was initially considered for model inclusion, but later removed because it provided no measurable improvement in model performance. This is likely because delta-V is the result of the mass difference between the vehicles involved in the crash and thus captures much of the effect of body type on injury outcomes.

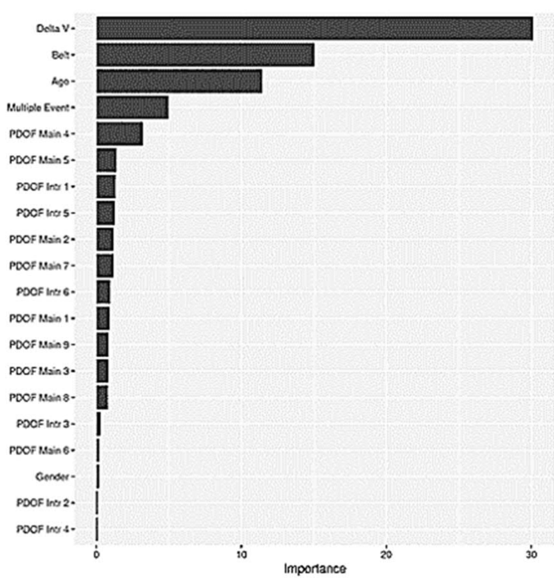


Figure 2: Plot of t-statistics for each variable in the occupant-based ISP model for Drivers, with PDOF contributions broken out by spline terms

The original ISP model was validated based on a large set of Michigan crashes (Wang et al., 2017). The validation assessment compared predicted injury severity to actual injury outcomes at a vehicle level. That is, the ISP predicted whether any vehicle occupant would have a 20% or higher probability of an ISS of greater than 15 and validation considered whether medical records for occupants reported an ISS > 15. Measures of sensitivity and specificity were used to evaluate algorithm accuracy. In this context, sensitivity gives the probability that the ISP will evaluate to "high" when the observed ISS is greater than 15 and specificity is the probability that the ISP will evaluate to "not high" when the observed ISS is less than or equal to 15. Analysis showed that when occupant age and gender were available, the algorithm had a sensitivity of 64% and a specificity of 96%. Without age and gender, sensitivity dropped to 45% while specificity increased to 98%. Validation of ISP-V2 leveraged the same set of MI-based crashes, showing sensitivity improved to 73% while specificity remained high at 93% (Wang et al, 2017).

Validation of the occupant-based ISP models similarly compared predicted vs. actual observed occupant outcomes, leveraging cases from the holdout 2015 NASS-CDS dataset with required data. The appropriate seat-specific model was applied to each vehicle occupant based on their reported seat position. Table 3 describes the number of occupants in each seat position, based on their predicted and actual injury outcomes. The new models showed improved performance in sensitivity for first row occupants with some degradation in specificity, as shown in Table 4.

Table 3: NASS-CDS 2015 case distribution for occupant-based ISP validation

| | | Occupant-based ISP prediction: probability (ISS > 15) > 0.2 | | | | | |
|---|---|---|---|---|---|---|---|
| | | Driver (11) | | RF Pass (13) | | Row 2 (21/23) | |
| | | T | F | T | F | T | F |
| Actual ISS>15 | T | 46 | 11 | 12 | 3 | 3 | 2 |
| | F | 66 | 299 | 19 | 72 | 6 | 49 |

Table 4: Performance of occupant-based ISP and ISP-V2 models on NASS-CDS 2015 cases

| | Driver (11) | RF Pass (13) | Row 2 (21/23) | ISP-V2 |
|---|---|---|---|---|
| Sensitivity (95% CI) | 81% (68, 90) | 80% (52, 96) | 60% (15, 95) | 61% (48, 72) |
| Specificity (95% CI) | 82% (78, 86) | 79% (69, 87) | 89% (78, 96) | 94% (91, 96) |

Since earlier models did not account for second row occupants, the occupant-based ISP model for seat positions 21 and 23 had no previous baseline for comparison. Table 4 shows second row model sensitivity and specificity were in line with ISP-V2 performance, but were based on few cases, as reported in Table 3 and seen in the broad confidence interval (CI) reported for second row sensitivity. To improve confidence in the second row model's performance, additional cases were pulled from the recently released NHTSA CISS data for crash year 2017. This provided 248 additional second row occupants, only 4 of which reported ISS of over 15. The occupant-based ISP continued to show high specificity (97%) but was unable to appropriately predict any of the high severity cases.

## DISCUSSION

Injury severity prediction models developed around the world share a common high-level goal of improving emergency crash response in order to improve occupant outcomes. Variation in available input data and operating contexts lead to differences in model formulation. Tables 5a and 5b summarize the output metrics and input data used in the final versions of several recently published models. Note that model framing varies, with one model predicting only driver outcomes, while another predicts front row outcomes, and others predict the likelihood of an ISS 15+ outcome for any occupant.

Table 5a: Summary of global ISP model inputs and output metrics ("n/a" designates not applicable to model)

| | ISP-V2 (US) | Lubbe and Kiuchi (Germany) |
|---|---|---|
| Output metric | Probability any occupant has ISS > 15 | Probability front row occupant has ISS > 15 |
| Speed or Delta-V | Delta-V (from NASS-CDS WinSMASH) | Delta-V |
| Crash type | PDOF (10-degree increments) | Front, near side, far side, rear |
| Location | n/a | n/a |
| Multiple events | (Y/N) | (Y/N) |
| Occupant location | Driver, driver + front passenger | Front row |
| Belt use | All belted (Y/N) | (Y/N) |
| Airbag deployment | n/a | n/a |
| Occupant age | At least one >= 55 (Y/N) | n/a |
| Occupant gender | At least one female (Y/N) | n/a |
| Vehicle type | n/a | n/a |

Table 5b: Summary of global ISP model inputs and output metrics ("n/a" designates not applicable to model)

| | Buendia (Sweden) | Nishimoto (Japan) |
|---|---|---|
| Output metric | Probability occupant has ISS > 15 | Probability of driver fatality or serious injury |
| Speed or Delta-V | Posted speed limit (20-120km/h in 10km/h increments) | Pseudo Delta-V derived from police travel speed estimates and involved vehicle masses |
| Crash type | Categories: single, intersection, longitudinal, rear, tram/train, animal, other | Front, driver near side, driver far side, rear |
| Location | Urban, rural | n/a |
| Multiple events | n/a | (Y/N) |
| Occupant location | Front, back | Driver only |
| Belt use | (Y/N) | Driver (Y/N) |
| Airbag deployment | Deployed, not deployed, no airbag | n/a |
| Occupant age | <55, 55+ | Drivers: <55, 55-64, and 65+ |
| Occupant gender | Male, female | n/a |
| Vehicle type | n/a | Passenger car, Kei-car |

Variation in available input factors drive additional model differences. For example, all models attempt to comprehend inputs related to delta-V (change in velocity as experienced by a vehicle and occupant in a crash). ISP-V2 and the Lubbe and Kiuchi model leverage either actual or crash investigation-based delta-V values in model fitting and prediction. Nishimoto et al. use police-estimated travel speed and vehicle mass to calculate a pseudo delta-V. Buendia et al. rely on posted speed limits to comprehend potential crash speed. Figure 2 and similar charts in the Appendix show that delta-V has the greatest influence on the occupant-based ISP models. This is not surprising, as delta-V is a surrogate for the severity of the crash. Models that must rely on speed limit or estimated travel speed, neither of which capture the vehicle crash dynamics as accurately as delta-V, are expected to have lower injury prediction performance.

The Lubbe and Kiuchi model is most like the front row occupant-based models described. Rather than incorporate PDOF directly, they categorize crash types into front, rear, near side, and far side. The Lubbe and Kiuchi model does not leverage occupant-specific inputs such as age and gender. They report model performance to have sensitivity of 90% and specificity of 76% against a GIDAS validation data set. It is important to note that the population of vehicles on the road in Germany (especially the number of large trucks and SUVs) may be significantly different than in the US. Increased homogeneity in vehicles should drive reductions in experienced delta-Vs. When combined with speed limit, road type, and other environmental differences, these factors make it difficult to assess the degree to which model performance should be expected to change with regional traffic characteristics.

Over time, injury severity prediction models should continue to evolve. Models will gain predictive power as data on crash dynamics and injury outcomes improve. Advances in vehicle telemetry promise to enable near real-time access to crash dynamics and airbag deployment data from a vehicle's SDM and occupancy data from seat sensors for connected vehicles. While improved vehicle data should drive greater consistency in model inputs, differences in emergency response around the globe may continue to drive different use cases and thus different model objectives. Further research is needed to understand how injury severity predictions are used by emergency responders in various environments and to quantify the impact of ISP on occupant outcomes. This is especially true for models that predict specific injuries such as those described by Weaver et al. or Stitzel et al. Such models could prove a valuable complement to ISP if mechanisms were in place for effectively transmitting detailed injury risks to appropriate medical care providers. Specific injury prediction models would need to be expanded to address a broader spectrum of crash dynamics (e.g., multiple crash events) and vehicle occupants (especially second row).

For occupant-based ISP models, Table 4 shows that the predictive performance of front row models continues to improve. Future enhancements may require a deeper level of insight to crash dynamics (e.g., data on time to maximum delta-V or more fidelity on lateral and longitudinal components of delta-V). Larger data sets of occupant outcomes for late model year vehicles will also be needed to enable ISP models to evolve in alignment with rapid changes in safety technology performance.

Table 4 shows that the second row occupant ISP model had similar specificity to front row models. Sensitivity was lower, but on par with prior vehicle-level models. Table 3 shows that the validation data set was small, including only 5 occupants with ISS greater than 15. Two cases have false negative results in which the occupant-based ISP predicts "not high" severity, but the actual ISS was above 15. The first involved a 4-month-old male infant in a rear facing child seat in the second row right position of a 2007 Toyota Highlander. The vehicle was struck in the rear, rotated counterclockwise and sideswiped a leading vehicle with its right side. The seat was deformed by passenger compartment intrusion and injuries were attributed to the car seat shell. The second case involved a 41-year-old unbelted Female second row left occupant of a 2010 Toyota Highlander. The vehicle was struck on the left side (PDOF 290), rotated counterclockwise, and then struck a concrete wall on the right. The occupant was fully ejected through the left rear and fatally injured. Note that both cases involve dynamics not specifically captured in the occupant-based ISP model (i.e., car seat deformation and occupant ejection).

To further validate second row model performance, additional occupant data from 2017 CISS data were evaluated. This provided four additional occupants with ISS of 15 or more. Summary case details are provided below:

1. CASEID 8890, PSU 32, Vehicle 1: A multiple impact single vehicle event involving a 2006 Honda Civic. The vehicle sideswiped a concrete barrier on the left then returned to the highway, crossing all lanes to the right. The front of the vehicle impacted a sign and it entered the exit ramp. The vehicle then sideswiped a concrete barrier on the right and departed the roadway. Finally, the vehicle rotated counterclockwise and impacted the concrete base of a light pole with its right side. The vehicle had significant intrusion (39 cm) on the right side, rear of the b-pillar.

    a. Occupant 3: A 3-year-old Male in the second row left seat, belted but without a child safety seat. Injuries included major hemothorax with blood loss > 20%, diaphragm rupture, 9 rib fractures and thoracic cavity injury with massive air leak coded to the other occupant. Right side panel intrusion coded as contributing factor. Occupant-based ISP predicted 8% probability of ISS 15+, actual ISS reported as 59 and the occupant was pronounced fatal at the hospital.

    b. Occupant 4: A 4-year-old Female in the second row right seat, belted but without a child safety seat. Fatality with ISS of 34, cause of death listed as cervical vertebra dislocation, massive bilateral lung contusion, and cerebrum hematoma. Injuries coded to right side panel or the other occupant. Occupant-based ISP predicted 17% probability of injury 15+.

2. CASEID 7817, PSU 24, Vehicle 1, Occupant 4: An obese 43-year-old female belted in second row right seat of 2013 Chevrolet Equinox struck in right rear by 2013 Ford Econoline van while making left turn. Vehicle's rear then impacted guardrail. First impact reported as PDOF 60 and Delta-V 30 kph, second impact had PDOF 160 and Delta-V 9 kph. Multiple rib fractures and hemopneumothorax injuries coded to the seatbelt, pelvic ring fracture coded to intruded door panel. ISS reported as 17, with occupant-based ISP predicting 5% probability of 1SS 15+.

3. CASEID 6591, PSU 13, Vehicle 3, Occupant 2: A 10-year-old male belted in second row left seat of 2014 Honda Accord struck in the front by an oncoming 2014 Chevrolet Malibu that crossed the center line. PDOF reported as 330, with Delta-V estimated to be 61 kph. Seat listed as deformed by cargo. Multiple injuries, including bilateral lung contusions and cervical vertebrae dislocation coded to seatbelt. Contributing factors included 8 to 15 cm seatback deformation. ISS reported to be 19, with occupant-based ISP predicting 18% probability of ISS 15+.

These cases highlight the challenge that second row occupant heterogeneity poses to occupant-based ISP performance. With a wider range of occupant ages (especially children), the second row model must comprehend more variability in occupant-related factors. For example, while the front row models capture the effect of proper restraint use through a binary seat belt variable, the presence of children in the second row make proper restraint use (including forward- and rear-facing child safety seats and boosters) more difficult to comprehend. Children may also have increased likelihood of being out-of-position with respect to restraints during a crash. These effects are illustrated by the two children in case 1 above who were belted, but at ages 3 and 4 should have been restrained in a child safety seat. Proper restraints and positioning may have limited the interaction between the occupants that resulted in some of the serious injuries described, but the model does not currently account for such detail. Having children in the second row also means increased variation in occupant size (with a longer tail of small occupants) and potentially different injury mechanisms.

Case 3 above also highlights the potential impact of cargo on second row occupants, either through direct contact or via seat deformation. Cargo may affect second row occupant outcomes more significantly because of their greater proximity to stored cargo (either in the cargo/trunk area or in unoccupied second row seat positions). While the PDOF spline curves enable different sensitivity to rear/side impacts that may be more likely to dislodge cargo, the effect of cargo is not directly captured as relevant data is not available at the time of crash.

Lower occupancy numbers compound the challenges for a second row model, as few cases of seriously injured second row occupants exist in NASS-CDS or CISS. Table 6 summarizes the combined data set used to validate the second row occupant ISP model. Over this set, the model has a specificity of 96%, but sensitivity of only 33%. Currently, the rear seat sensors required to enable this model are not implemented across the GM fleet, so further research to increase model sensitivity will proceed as new data become available.

Table 6: Combined 2015 NASS-CDS and 2017 CISS 2nd row occupant cases

| | | Row 2 Occupant-based ISP | |
|---|---|---|---|
| | | True | False |
| Actual ISS > 15 | True | 3 | 6 |
| | False | 13 | 286 |

## LIMITATIONS

Several limiting factors affected the development and validation of occupant-based ISP models described in this report. Publicly available NASS-CDS data sets used in fitting the models have known limitations that can affect model accuracy. Specifically, CDS-reported delta-Vs are based on WinSMASH estimates that have been shown to differ from EDR-reported values (Gabler et al, 2012). PDOF inputs based on accident reconstruction may also differ from vehicle-based assessments. Data errors may also exist due to reconstruction uncertainties, investigation limitations or reporting errors. Such issues could result in occupants coded to the wrong seat position, errors in recorded seat belt use, and gaps in age and gender reporting.

The reported validation of model performance using a holdout year of NASS-CDS data shows that models are not over-fit to the input sample, but do not address potential shortcomings of NASS-CDS data for predicting real world performance. Prior studies validating ISP-V2 using other data sets have found these errors to have limited effect on real world model performance (Wang et al., 2017). Future work on occupant-based ISP models should include a similar assessment. This work could be structured to focus particular attention on second row outcomes to address data limitations reported above. In doing so, the additional validation could also test the modeling assumption that injury risks to second row outboard occupants are the same when PDOF is mirrored.

Finally, this report does not address the effect of ISP model improvements on emergency response or occupant outcomes. Such an assessment requires a detailed study that comprehends crash, occupant, emergency response, and hospital factors and is beyond the scope of the current initiative. NHTSA has recently initiated research to better understand the cost and benefit of AACN/ISP in the US (Lee et al., 2019; NHTSA, 2020) which could help quantify the value of model improvements. Another factor that influences AACN/ISP effectiveness is the threshold established for assessing injury risk. As noted above, current field triage guidelines recommend using a 20% risk of ISS 15+ to balance over- and under-triage. The American College of Surgeons' Committee on Trauma is also now considering changes in guidelines that could impact effectiveness (American College of Surgeons, 2021). The model improvements documented in this report seek to provide more complete and accurate data to support EMS as recommended by these health experts.

## CONCLUSION

As automotive manufacturers work to reduce the number and severity of crashes through active safety and AV technologies, work to improve emergency crash response continues around the globe. ISP models have been developed to support emergency crash response in several countries, with model framing and inputs dependent on available data and EMS resources. Although studies to quantify the effect of ISP on occupant medical outcomes are limited, the CDC has identified AACN as an important focus in improving post-crash response. The occupant-based ISP models seek to provide more precise predictions of severe injuries within a vehicle to enable better communication of potential EMS resource needs. Front row models have been shown to improve sensitivity over ISP-V2 with only moderate decline in specificity.

Improvement of second row occupant-based ISP models will require additional case data for second row occupants, especially those with severe injury outcomes. Accurate models for this more heterogeneous population will require additional vehicle data be collected at the time of crash, including data from rear seat sensors and possibly more detailed crash data from SDM event data recorders. These models may also benefit from further exploration of occupant age factors, as the current binary 55+ cutoff may not sufficiently capture effects associated with second row age variation.

Additional future research should focus on understanding how further improvements in model prediction, including predictions at a more granular injury or body region level, could support the work of EMS and hospital personnel. Advances in 9-1-1 technology and data transmission may soon enable vehicle telemetry data and injury predictions to flow directly to medical teams. Work is needed to understand how such information can be effectively communicated to benefit the treatment of vehicle occupants.

## ACKNOWLEDGMENTS

The authors would like to thank John Capp of General Motors and Cathy Bishop of OnStar for their encouragement and managerial support.

## REFERENCES

American College of Surgeons (2021) Field Triage Guidelines Update. Committee on Trauma News, Spring 2021. https://www.facs.org/publications/newsletters/cot-news/spring2021/systems

Bloomberg Philanthropies (2014) Leading the Worldwide Movement to Improve Road Safety. https://assets.bbhub.io/dotorg/sites/2/2014/04/Bloomberg_Road_Safety_Midway_Report_Final.pdf

Buendia, R., Candefjord, S., Fagerlind, H., Bàlint, A., and Sjöqvist, B.A. (2015) On scene injury severity prediction (OSISP) algorithm for car occupants. Accident Analysis and Prevention 81: 211–217.

Gabler, H.C., Hampton, C., and Johnson, N. (2012) Development of the WinSMASH 2010 Crash Reconstruction Code. DOT HS 811 546.

Hundley, T. (2013) How 'Roads Kill': Pulitzer Center Visualizes Global Safety Crisis. http://mediashift.org/2013/09/visualizing-the-global-road-safety-crisis/

Kononen, D.W., Flannagan, C.A., and Wang, S.C. (2011) Identification and validation of a logistic regression model for predicting serious injuries associated with motor vehicle crashes. Accident Analysis and Prevention 43: 112–122.

Lee, E., Wu, J., Enriquez, J., Martin, J., and Craig, M. (2019) Advanced Automatic Collision Notification Research Report. DOT HS 812 729.

Lubbe, N., and Kiuchi, T. (2013) Injury estimation for advanced automatic collision notification (AACN) in Germany. ESAR Conference.

National Center for Statistics and Analysis (2019) 2018 fatal motor vehicle crashes: Overview. Traffic Safety Facts Research Note. Report No. DOT HS 812 826.

National Automotive Sampling System (NASS). National Highway Traffic Safety Administration, https://www.nhtsa.gov/research-data/national-automotive-sampling-system-nass.

National Highway Traffic Safety Administration (2020) ACN/AACN Research Plan Pilot Project. Request for Proposal 693JJ920R000041. https://govtribe.com/opportunity/federal-contract-opportunity/acnaacn-research-plan-pilot-project-693jj920r000041

Nishimoto, T., Mukaigawa, K., Tominaga, S., Lubbe, N., Kiuchi, T., Motomura, T., and Matsumoto, H. (2017) Serious injury prediction algorithm based on large-scale data and under-triage control. Accident Analysis and Prevention 98: 266-276.

Marquez, P. V., Dutta, S., and Bose, D. (2017) The High Toll of Traffic Injuries: Unacceptable and Preventable. World Bank Group. http://documents.worldbank.org/curated/en/374881515180592957/The-high-toll-of-traffic-injuries-unacceptable-and-preventable

Plevin, R.E., Kaufman, R., Fraade-Blanar, L., and Bulger, E.M. (2017) Evaluating the Potential Benefits of Advanced Automatic Crash Notification. Prehospital and Disaster Medicine 32 (2): 156-164.

Sasser, S.M., Hunt, R.C., Sullivent, E.E., Wald, M.M., Mitchko, J., Jurkovich, G.J., Henry, M.C., Salomone, J.P., Wang, S.C., Galli, R.L., Cooper, A., Brown, L.H., and Sattin, R.W. (2009) Guidelines for field triage of injured patients: recommendations of the national expert panel on field triage. Morb. Mortal. Wkly. Rep. 58 (RR-1): 1–35.

Stitzel, J., Weaver, A., Schoell, S., Barnard, R., Talton, J., Martin, R. S., and Meredith, J. W. (2015) Occupant Transportation Decision Algorithm: An Advanced Automatic Crash Notification Algorithm Developed and Evaluated for Motor Vehicle Crash Occupant Triage. 24th Enhanced Safety of Vehicles Conference (ESV): Traffic Safety Through Integrated Technologies.

Wang, S., Kohoyda-Inglis, C., Ejima, S., MacWilliams, J., Zhang, P., Stacey, L., Melocchi, A., Gorman, D., Kral, J., and Joyner, J. (2017) Second Generation AACN Injury Severity Prediction Algorithm: Development and Real-World Validation. 25th International Technical Conference on the Enhanced Safety of Vehicles (ESV): Innovations in Vehicle Safety: Opportunities and Challenges.

Weaver, A. A., Talton, J. W., Barnard, R. T., Schoell, S. L., Swett, K. R., and Stitzel, J. D. (2015) Estimated Injury Risk for Specific Injuries and Body Regions in Frontal Motor Vehicle Crashes. Traffic Injury Prevention 16: 108-116.

World Health Organization (2016) Post-crash response: Supporting those affected by road traffic crashes. WHO.NMH.NVI.16.9. https://www.who.int/violence_injury_prevention/publications/road_traffic/Post-crash_response_booklet.pdf

World Health Organization (2018) Global Status Report on Road Safety 2018. www.who.int/violence_injury_prevention/road_safety_status/2018/en/

Zhang, F. and Chen, C-L. (2013) NASS-CDS: Sample Design and Weights. Report No. DOT HS 811807.

## APPENDIX A

Figure 3 illustrates the ROC curve for the driver (seat position 11) model using weighted training and validation data, with an AUC = 0.899. Figure 4 shows the ROC curve for the model when fit and validated without NASS CDS weights, with an AUC = 0908. The AUC measure is slightly improved, and the curve is smoother when weights are removed.

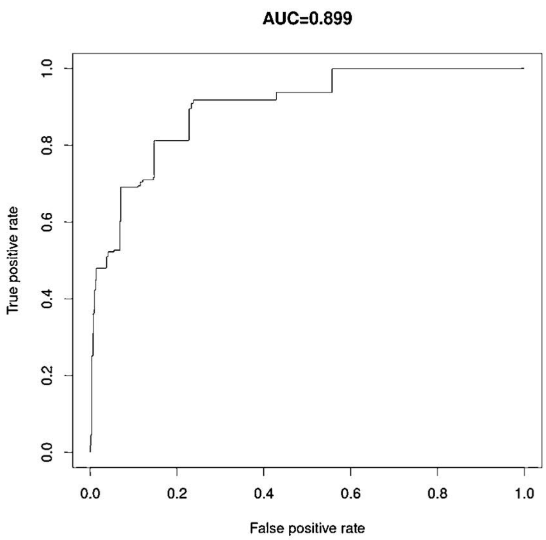


Figure 3: ROC curve for driver (seat position 11) model based on weighted training and validation data

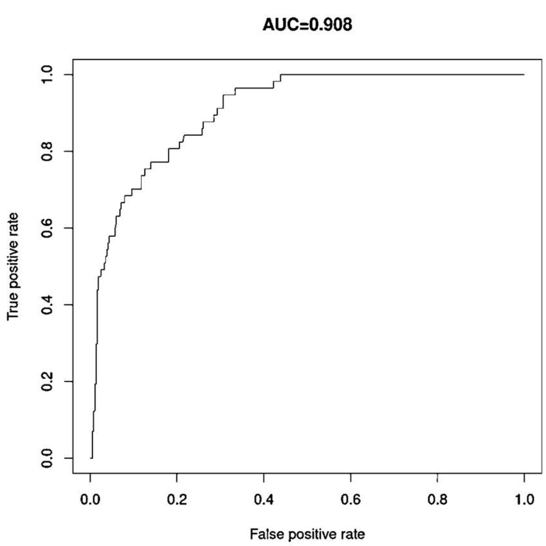


Figure 4: ROC curve for driver (seat position 11) model based on unweighted training and validation data

## APPENDIX B

Model coefficient summaries for the following models are included below:

1. Driver (seat position 11) with interaction term based on unweighted input data
2. Front right passenger (seat position 13) with extrapolated interaction term based on unweighted input data
3. Outboard rear passenger (seat positions 21 and 23) with interaction term based on unweighted input data

Table 7: Seat position 11 model coefficient summary

| Variable | Coefficient | Std. Error | P-Value |
|---|---|---|---|
| Intercept | -11.8958 | 1.5261 | 0 |
| log(delta-V) (mph) | 3.6135 | 0.12 | 0 |
| PDOF | | | |
| spline term 1 | -1.8266 | 2.021 | 0.3661 |
| spline term 2 | -1.5916 | 1.3459 | 0.237 |
| spline term 3 | 1.3778 | 1.6693 | 0.4092 |
| spline term 4 | -4.7214 | 1.4814 | 0.0014 |
| spline term 5 | 2.167 | 1.5479 | 0.1616 |
| spline term 6 | -0.2634 | 1.4938 | 0.86 |
| spline term 7 | -1.8046 | 1.5305 | 0.2384 |
| spline term 8 | -1.2116 | 1.5473 | 0.4336 |
| spline term 9 | -1.2507 | 1.4882 | 0.4007 |
| Belt use | -1.1935 | 0.0794 | 0 |
| Multiple event | 0.3603 | 0.0729 | 0 |
| AGE>=55 | 0.9437 | 0.0824 | 0 |
| Female | 0.0129 | 0.0729 | 0.8602 |
| PDOF and same-row passenger interaction | | | |
| spline term 1 | -0.5855 | 0.4425 | 0.1859 |
| spline term 2 | -0.0651 | 0.0719 | 0.9427 |
| spline term 3 | 0.1858 | 0.6644 | 0.7798 |
| spline term 4 | 0.0292 | 0.4487 | 0.9481 |
| spline term 5 | -0.5555 | 0.4325 | 0.199 |
| spline term 6 | -0.2984 | -0.9627 | 0.3357 |

Table 8: Seat position 13 model coefficient summary

| Variable | Coefficient | Std. Error | P-Value |
|---|---|---|---|
| Intercept | -10.5937 | 1.123 | 0 |
| log(delta-V) (mph | 3.2056 | 0.2289 | 0 |
| PDOF spline term 1 | -1.7927 | 1.2534 | 0.1528 |
| spline term 2 | -0.3588 | 0.7268 | 0.6216 |
| spline term 3 | 1.2932 | 1.3676 | 0.3444 |
| spline term 4 | -5.6001 | 1.1037 | 0 |
| spline term 5 | 0.9244 | 0.9965 | 0.3537 |
| spline term 6 | -3.2683 | 0.9209 | 0.0004 |
| spline term 7 | -1.1369 | 1.2405 | 0.3595 |
| spline term 8 | -1.2802 | 0.8216 | 0.1193 |
| Belt use | -1.0071 | 0.1549 | 0 |
| Multiple event | 0.4639 | 0.1407 | 0.001 |
| AGE>=55 | 1.3627 | 0.1681 | 0 |
| Female | 0.1029 | 0.143 | 0.4717 |

Table 9: Seat position 21 and 23 model coefficient summary

| Variable | Coefficient | Std. Error | P-Value |
|---|---|---|---|
| Intercept | -15.0417 | 3.6105 | 0 |
| log(delta-V) (mph) | 2.7147 | 0.2864 | 0 |
| PDOF spline term 1 | 4.8597 | 4.6818 | 0.2995 |
| spline term 2 | 3.9808 | 3.0955 | 0.1987 |
| spline term 3 | 5.4714 | 3.9335 | 0.1645 |
| spline term 4 | 3.0446 | 3.4389 | 0.3761 |
| spline term 5 | 7.3121 | 3.6629 | 0.0461 |
| spline term 6 | 4.5952 | 3.5273 | 0.1929 |
| spline term 7 | 4.7401 | 3.5947 | 0.1875 |
| spline term 8 | 3.6806 | 3.6443 | 0.3127 |
| spline term 9 | 4.3521 | 3.5062 | 0.2147 |
| Belt use | -1.1028 | 0.1914 | 0 |
| Multiple event | 0.1897 | 0.1941 | 0.3285 |
| AGE>=55 | 1.8401 | 0.2925 | 0 |
| Female | 0.1246 | 0.1952 | 0.5233 |
| Female | 0.1246 | 0.1952 | 0.5233 |
| PDOF and same-row passenger interaction spline term 1 | -0.3775 | 1.2091 | 0.7562 |
| spline term 2 | -1.0588 | 0.9892 | 0.2846 |
| spline term 3 | -0.1827 | 0.5753 | 0.7508 |
| spline term 4 | -0.1967 | 0.4871 | 0.6865 |

## APPENDIX C

Figures 5 and 6 illustrate the relative contributions of each variable to the final right front passenger and second row occupant models, respectively.

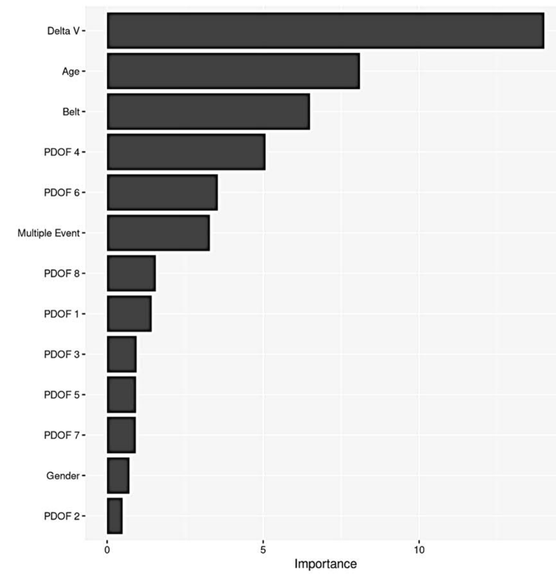


Figure 5: Plot of t-statistics for each variable in the occupant-based ISP model for right front passengers, with PDOF contributions broken out by spline terms

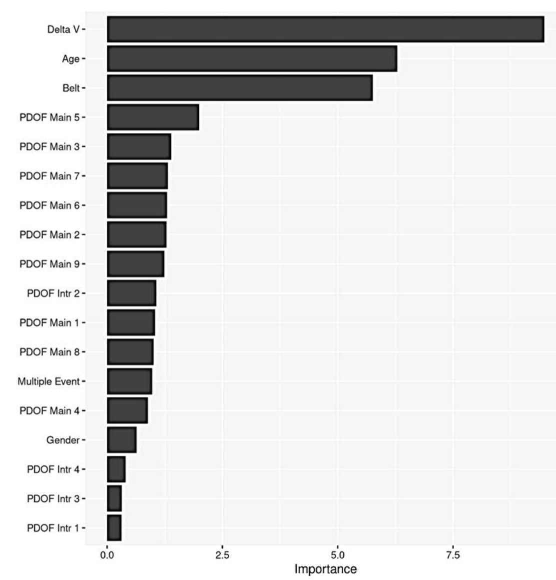


Figure 6: Plot of t-statistics for each variable in the occupant-based ISP model for second row occupants, with PDOF contributions broken out by spline terms