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Crashes and Injuries in 2020-2030: Development of a Crash Data Projection Model

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ABSTRACT

The most urgent issues in crash safety research have typically been identified using retrospective, real-world crash data. Methods have been developed to instead project estimates of crash frequency and outcomes in the future, to better identify the issues that are most urgent for crash safety research. With these methods, future crash projections are made by modeling the forecasted effects of transportation trends, safety initiatives, and new technology on retrospective crash cases. As in any predictive model, the results do not predict with certainty what will happen in future crashes: instead, the model offers a picture of the future crashes that would be expected if a comprehensive combination of existing predictions and forecasts affecting transportation safety were applied in a single model, accounting for interactions in the effects of different countermeasures and avoiding double-counting of the benefits of overlapping safety improvements. In spite of the inherent limitations of predictive modeling, the resulting projections are useful in that they can offer a more comprehensive picture of the crashes expected to remain in the future than can be gleaned from analyzing historic data, or by consideration of the effects of individual trends or safety interventions. The objective of this summary is to introduce the modeling methods that have been developed and to provide example projections to illustrate how the model results can be used to identify future research priorities.

INTRODUCTION

Identification of the most urgent issues in crash safety research has typically been based on the most frequent or harmful crash scenarios, occupant types, or injuries in *retrospective*, real-world crash data. In this study, methods have been developed to instead make *predictive* estimates of crash frequency and outcomes in the future to identify the crash, occupant, and injury issues that are most urgent for crash safety research. With these methods, future crash projections are made by modeling the combined, forecasted effects of transportation trends, safety initiatives, and new technology on retrospective crash cases.

The results in this paper come from a version of the projection model that projects future injuries and crashes in 2020 to 2030 based on the best current estimates of the effects of expected safety interventions and countermeasures, as well as population and transportation trends. It is intended to illustrate the application of the model and provide a sample of the analyses that can be performed on model output. Although the model can also be used to explore hypothetical scenarios, alternative predictions, and potential future countermeasures, only a sample of base model results are included in this paper. More comprehensive reports are currently in progress to document the modeling methods and provide detailed results for the base model and alternative versions of the model. Those reports will include full specifications for the model and its components.

METHODS

The following summary describes the basic methods used to develop the projection model. The projection model was based on the concept that individual weighted cases from retrospective crash datasets can be reweighted, and variables in those cases can be modified to reflect how the frequency and outcome of crashes in the future would be changed by shifts in transportation trends and the introduction of safety interventions and policy changes that occurred after the year of the original crash. A brief summary of this case-by-case methodology follows.

The retrospective cases used as source cases in the model were occupants in passenger vehicles from the 2004-2015 National Automotive Sampling System (NASS) Crashworthiness Data System (CDS). The cases were re-weighted using cases from the 2013-2015 NASS General Estimates System (GES) and the 2013-2015 Fatality Analysis Reporting System (FARS) to calibrate crash frequency and distribution to the most recent available counts and to correct the retrospective dataset for inaccuracies introduced by the exclusion of cases with unknown data. Among the excluded cases with unknown data were the occupants in cases in older vehicles in crash year 2009 and later, for whom injury data was not collected. The FARS and GES reweighting procedures targeted accurate counts of crash occupants by injury severity, age group, belt use, and driver/passenger status. Cases were also reweighted to account for the over-reporting of belt use (Kahane, 2018a) and the under-reporting of lower-severity cases (Blincoe et al., 2015). Cases from vehicle model years earlier than 2005 still represented pre-2005 model year vehicles in the projections and therefore were treated separately in the projection model: no vehicle-based countermeasures were applied to these cases. These cases were assumed to be affected only by crash avoidance technology installed on other newer vehicles in the crash and by non-vehicle countermeasures such as infrastructure and policy changes. Occupants in these early-model year cases were downweighted to represent the small percentage of pre-2005 model year vehicles expected to be involved in crashes in 2020 to 2030. The model-year distribution for occupant cases in the future was based on analysis of the vehicle-age distribution among crashes in retrospective data.

As in retrospective studies, there is potential for individual cases with a high weight relative to other cases in a given analysis category to unduly influence projection results. Cases with the potential for unreasonably high leverage on the results were identified by comparing the average case weight in each output analysis category to the distribution of weights among all cases at each injury severity level. The concept is that individual high-weight source cases that have the potential to skew results are downweighted prior to the application of countermeasures, rather than simply being eliminated from the dataset.

Overall Transportation Trends

Overall trends in the number of drivers and passengers exposed to crashes were applied in the model by accounting for historical and predicted shifts in the number of people in each age group in the US population, as well as licensure rates and unemployment rates in those age groups. These factors were found to be better predictors of the annual number of crash exposures in retrospective data than vehicle miles travelled (VMT). Additional transportation trends in the base model were applied to adjust the proportion of crash occupants expected to be restrained by seat belts or child restraints in the future, as well as the proportion in each type of passenger vehicle. These shifts were applied by upweighting some types of cases and downweighting others. The primary sources for information and estimates for the trends coded in the base model are listed in Table 1. Full details for these parameters will be included in the methods report currently in progress.

Table 1. Trends in the Base Projection Model

Trend	Description	Primary Sources
Population Growth by Age Group	Adjustment of the expected future number of occupant crash exposures in each age group as a function of predicted population size, licensure rates, and unemployment rates in that age group in the future. (Relationship between crash exposures and these parameters was developed with a regression analysis of 2007-2015 crash cases.)	Population Projections (U.S. Census Bureau, 2014, U.S. Census Bureau, 2015, U.S. Census Bureau, 2017)
Licensure Rates by Age Group		FHWA Highway Statistics (FHWA, 2014a, FHWA, 2016)
Unemployment Rates by Age Group		IIHS Report (Farmer, 2017a) Monthly Labor Review (Byun et al., 2015) US Labor Statistics (United States Bureau of Labor, 2018)
Vehicle Type	Proportion of cases in each vehicle type adjusted based on projected proportion of occupants in future crashes in cars, car-based SUVs, truck-based SUVs, pickups, and vans.	Annual Energy Outlook 2018 (EIA, 2018) Automotive Trends Report (EPA, 2019) Docket NHTSA-2016-0068 (Puckett et al., 2016) Kahane, Personal Communication (2018b)
Belt Use	Proportion of belted cases adjusted based on estimates that non-belt users will convert to belt users at half the recent historical conversion rate.	NHTSA DOT HS 809 639 (Wang et al., 2003) NHTSA DOT HS 810 777 (Blincoe et al., 2007) NHTSA DOT HS 812 243 (Pickrell et al., 2016) NOPUS (Subramanian, 2017)
Child Restraint Use	Proportion of child occupants in age-appropriate restraints adjusted based on conversion to age-appropriate restraint at half the recent historical conversion rate.	NSUBS: NHTSA DOT HS 810 798 (Glassbrenner et al., 2007) NHTSA DOT HS 810 895 (Glassbrenner et al., 2008) NHTSA DOT HS 811 377 (Pickrell et al., 2010) NHTSA DOT HS 811 718 (Pickrell et al., 2013) NHTSA DOT HS 812 037 (Pickrell et al., 2014) NHTSA DOT HS 812 309 (Li et al., 2016)

Safety Countermeasures and Technologies

Safety countermeasures and technologies were applied to the model using a case-by-case methodology by adjusting the case weight and outcome for every individual case that was expected to be affected by those countermeasures. Each countermeasure in the base model was applied to every case in the dataset that fell within the target population defined for the given countermeasure. The parameters needed to apply each countermeasure were:

(1) A definition of the countermeasure's target population applicable to variables available in the original NASS CDS source cases.
(2) An estimate of effectiveness, in terms of the percentage of target population cases affected by the countermeasure. Where available, variable effectiveness estimates for different target sub-populations were applied.
(3) Penetration of the countermeasure (by vehicle model year or by crash year) during the time period of the original source cases (2004-2015) and estimated for the future target projection years in 2020, 2025, and 2030.

The parameters associated with each adjustment, countermeasure, and trend in the base model in this paper were based on the best estimates available at the time it was run. As improved estimates for model parameters are available or as new countermeasures are identified or developed, they can be applied to the model to improve projections.

The modular structure of the projection model code allows individual countermeasures to be added, excluded, or modified with each run so that many "versions" of output are possible. This section lists the countermeasures and trends included in the base version of the model presented in this summary. Detailed specifications of the parameters used will be included in the methods and results reports that are currently in progress.

Vehicle-Based Crash Avoidance Countermeasures

Crash avoidance countermeasures were applied to occupants in their target populations by adjusting individual case weights to reflect the percentage of these cases that would be prevented in the future. Penetration of the countermeasure was used to adjust this reweighting step. This adjustment was based on estimates of penetration among vehicles in the crash based on model year, as well as among vehicles in the fleet in the targeted projection years. The adjustment was necessary because the addition of a given vehicle-based countermeasure would have no effect on the proportion of vehicles that already had the countermeasure available at the time of the original crash, or on the proportion of vehicles that would still not be expected to have the countermeasure available in the future target year. The model also accounted for the fact that individual occupants may be affected by crash avoidance technologies in other vehicles. Therefore, although the case-by-case model applied countermeasures to individual occupants, the potential installation of crash avoidance technologies was considered for partner vehicles in the crash, as well as for the occupant's own vehicle. The primary sources for the parameters used to code vehicle-based crash avoidance countermeasures included in the base model are listed in Table 2.

Crash Mitigation, Crashworthiness and Occupant Protection Countermeasures

Crash mitigation, crashworthiness and occupant protection countermeasures are not expected to prevent crashes. Therefore, these countermeasures were applied by adjusting the *outcome* of each case in the target population for each countermeasure. This adjustment was accomplished by dividing the case weight between two or more "pseudocases," one with the same outcome as the original case and one or more with adjusted injuries. Depending on the expected effect of the countermeasure, individual injuries in the pseudocases were deleted or modified in severity. In other words, the occupant case was retained, but the outcome modified. The original case's weight was divided among the resulting pseudocases proportionally according to the percentage of future cases expected to be affected by the countermeasure, which was estimated as a function of effectiveness and penetration. All available information on the effects of a given countermeasure were applied to predict its effect on individual injuries in a case, rather than simply adjusting the overall case injury severity. For example, for countermeasures where effectiveness estimates were available for specific body regions, separate adjustments were made to injuries in each affected body region. In the case-by-case model, countermeasure penetration was accounted for as a function of (1) the model year of the occupant's vehicle in the original crash and (2) the expected penetration of the countermeasure among vehicles exposed to crashes in the future projection years. The primary sources for the parameters used to code the countermeasures included in the base model are listed in Table 3 for crash mitigation countermeasures and in Table 4 for crashworthiness and occupant protection countermeasures.

Infrastructure and Policy Countermeasures

Countermeasures such as infrastructure improvements or policy changes were associated with a range of effects on cases in the model. These effects were applied in the model to correspond to the benefits defined in the effectiveness studies available for each individual countermeasure. For example, improved cable median barriers were incorporated by upweighting crashes in some target populations and downweighting crashes in other target populations to reflect varying effects for different crash types. The effects of raising the state maximum speed limits, which were atypical in that they caused a reduction in overall safety, were applied by increasing the case weight of affected cases to reflect the expected increase in crashes in the target population. The primary sources for the parameters used to code the infrastructure and policy countermeasures in the base model are listed in Table 5.

Table 2. Primary Sources of Data for Effectiveness and Penetration Estimates for Crash Avoidance Countermeasures

Countermeasure	Primary Sources for Development of Effectiveness Estimates	Primary Sources for Penetration by Model Year
FMVSS 126: Electronic Stability Control	NHTSA (2007a), Dang (2007), Sivinski (2011), Kahane (2014b)	Sivinski (2011), Webb (2017)
Automatic Emergency Braking with Forward Crash Warning	Najm et al. (2006), Anderson et al. (2012), Kusano et al. (2014b), Fildes et al. (2015), Cicchino (2016), Cicchino (2017a), Cicchino (2019)	Voluntary Commitment (NHTSA, 2016a), NCAP Vehicle Information (NHTSA, 2018b)
NCAP 2004 Static Stability Factor Enhancement	Funk et al. (2012), Pai (2017)	Hershman (2001), Global NCAP (2011), NHTSA (2012), NHTSA (2013)
Blind Spot Detection	Cicchino (2017b), Reagan et al. (2018)	HLDI (2017), NHTSA (2018b)
Lane and Road Departure Warning	Wilson et al. (2007), Sayer et al. (2011), Blower (2014), Kusano et al. (2014b), Kusano et al. (2014a), Kusano et al. (2015), LeBlanc et al. (2017), Cicchino (2017c)	HLDI (2017), NHTSA (2018b)
FMVSS 138: Tire Pressure Monitoring Systems	NHTSA (2005), Sivinski (2012)	Simons (2017), Simons (2018)
Lane Keeping Support	Scanlon et al. (2015), Flannagan et al. (2016), LeBlanc et al. (2017), Wiacek et al. (2017), Sternlund et al. (2017), Reagan et al. (2018)	NHTSA (2018b)
Level 3-5 Automated Driving Systems	Fagnant et al. (2013), Stienstra (2014), Litman (2014), Smith et al. (2015), Fagnant et al. (2015), Singh (2015), Sivak et al. (2015), Yanagisawa et al. (2015), Schoettle et al. (2015), Blanco et al. (2016), Dixit et al. (2016), IIHS (2016), Kockelman et al. (2016), Kalra et al. (2016), Zhao et al. (2017)	Ernst & Young (2014), Litman (2014), KPMG (2015), McKinsey & Company (2016), Lavasani et al. (2016), 2030 IHS Markit (2016), NHTSA (2016b)

Table 3. Primary Sources of Data for Effectiveness and Penetration Estimates for Crash Mitigation Countermeasures

Countermeasure	Primary Sources for Development of Effectiveness Estimates	Primary Sources for Penetration by Model Year
FMVSS 138: Tire Pressure Monitoring Systems	NHTSA (2005), Sivinski (2012)	Simons (2017), Simons (2018)
Automatic Emergency Braking with Crash Imminent Braking	Kusano et al. (2011), Anderson et al. (2012)	NHTSA (2016a), NHTSA (2018b)

Table 4. Primary Sources of Data for Effectiveness and Penetration Estimates for Crashworthiness and Occupant Protection Countermeasures

Countermeasure	Primary Sources for Development of Effectiveness Estimates	Primary Sources for Penetration by Model Year
FMVSS 202: Head Restraints	NHTSA (2004), NHTSA (2007d)	NHTSA (2004), NHTSA (2007d), Simons (2017), Simons (2018)
FMVSS 208: Advanced Airbag Updates (including Phase II 5th female)	NHTSA (2000), NHTSA (2006), Greenwell (2013)	NHTSA (2000), NHTSA (2006)
FMVSS 214: Side Impact Update	NHTSA (2007c), Kahane (2014a)	Simons (2017), Simons (2018)
FMVSS 216: Roof Strength Update	Austin et al. (2003), NHTSA (2007b), Strashny (2007)	Simons (2017), Simons (2018)
FMVSS 226: Ejection Mitigation Update	NHTSA (2011a), NHTSA (2011b),	NHTSA (2011b), Simons (2017) Simons (2018)
FMVSS 301: Rear Impact	NHTSA (2003), Viano et al. (2016)	NHTSA (2003), Pai (2014)
NCAP 2011 Enhancement (Frontal and Side Impact Tests)	Park et al. (2015)	Hershman (2001), Global NCAP (2011), NHTSA (2012), NHTSA (2013), Park et al. (2015), Dang (2017)

Table 5. Primary Sources of Data for Effectiveness and Penetration Estimates for Infrastructure Countermeasures and Policy Changes

Countermeasure	Primary Sources for Development of Effectiveness Estimates	Primary Sources for Penetration by Model Year
Rumble Strips (Edge and Centerline)	Torbic (2009), Himes et al. (2016)	Spears (2017), Satterfield (2019)
Red Light Cameras	Council et al. (2005)	US Census Bureau (2017), IIHS (2018), Goble (2018), NHTSA (2018a)
State Maximum Speed Limit Increases	Parker (1997), Skszek (2004), Kockelman (2006), Mannering (2007), Retting et al. (2008), Elvik (2013), Nelli et al. (2014), Hu (2017)	Nelli et al. (2014), Farmer (2017b)
Cable Median Barriers	Shankar et al. (1996), Ray et al. (2009), Villwock et al. (2010), Hu et al. (2010), Chitturi et al. (2011), Marzougui et al. (2012), Blank (2012), Russo et al. (2016)	Ray et al. (2009), Marzougui (2012), FHWA (2014b)

Application of Countermeasures to the Model

Countermeasures were applied sequentially to avoid double-counting benefits from different countermeasures, i.e., each countermeasure was applied only to the cases remaining after other countermeasures had already been applied. Interactions among countermeasures were accounted for where data was available. For example, improvement in rollover rate with increased SSF (Static Stability Factor) was modeled as a function of ESC (Electronic Stability Control) penetration since SSF effectiveness was reported to vary for vehicles equipped with ESC (Pai, 2017).

As a final step, the resulting projected future cases and pseudocases were aggregated into a projected future dataset for each of the target projection years (2020, 2025, and 2030). Each of the occupant cases in those projected datasets had been adjusted individually to reflect the combined effects of all predicted trends and countermeasures in the model, as well as interactions among those countermeasures. Each case retained variables and parameters from its original corresponding NASS CDS case, including those not affected by countermeasures and those that had been adjusted by the application of trends or countermeasures. Thus, the resulting projected dataset could be disaggregated and analyzed by almost all variables available in the source NASS CDS cases. Additionally, since individual injuries were adjusted when target populations and effectiveness varied by body region or by injury source, the projected outcome in future datasets could be evaluated relative to the many harm measures that can be calculated from NASS CDS injury variables.

Model Output

Since the projection dataset can be analyzed using harm variables available in the source NASS CDS cases, projection model results are presented in this summary in terms of the number of occupants in crashes, as well as in terms of injury by MAIS (Maximum Abbreviated Injury Scale) severity level, cost, and fatality. AIS (Abbreviated Injury Scale) analysis was based on AIS Version 1990/1998 (AAAM, 1998) because the majority of cases in the 2004-2015 source dataset were coded with that version. Source cases coded with a newer version of AIS were converted to Version 1990/1998 using the mapping recommended in the AIS 2005 coding manual (AAAM, 2008). Cost analysis was based on injury-specific estimates from Blincoe et al. (2015) that included medical and emergency services, lost household and wage work, and legal and insurances costs in 2010 dollars, keyed to codes from AIS Version 1990/1998. Fatality counts and rates were estimated based on the change in the expected number of fatalities in the dataset before and after application of trends and countermeasures, using a fatality probability function (Hasija et al., 2006, Mallory et al., 2017). All estimates of outcome in the future projected datasets were plotted with corresponding estimates for the retrospective (2005-2015) period using survey analysis procedures for survey-sampled, weighted data in SAS 9.4 (SAS Institute, Cary, NC). The 95% confidence intervals reported for estimates of the retrospective period could not be calculated for the projections because of the complexity of the adjustments made in those datasets.

Model Evaluation

The model methods have been evaluated using a version of the model to predict 2014 crash outcomes using NASS CDS crash data from 2004 to 2012, reweighted with NASS GES and FARS cases from 2010 to 2012. The 2014 projections were compared to real-world data averaged across 2013 to 2015 to evaluate the reliability of the modeling methods, i.e., how well the model predicted real-world outcomes for that period. Analysis of the evaluation version of the model was limited to very broad categories of crashes and injury severity since there were too few cases in the three-year real-world comparison dataset to evaluate projections of categories broken down by specific combinations of injuries, crash type, and occupant type. Although limited, this evaluation version of the model provided an opportunity to broadly assess the reliability of the modeling methods.

RESULTS

The high-leverage check identified only one case in the source dataset with unreasonably high leverage on the model results. Among seriously-injured (MAIS 3+) occupants in rear impacts, mean trend-adjusted case weight was higher than 25 for the following categories: 0-15 year-old occupants, rear seat passengers, and car-based SUV (CUV) occupants. In comparison, mean trend-adjusted case weight for MAIS 3+ occupants overall was only 9.5, with a mean absolute deviation (MAD) of 12.2. All three of these categories included the same case involving a rear impact with a child in the rear seat of a CUV, with a case weight of 1445.3[1]. This case weight had substantial leverage in these analyses because of the relatively small number of cases in these MAIS 3+ rear-impact cases that were further disaggregated by age, seat position, and vehicle type. As a result, this case was identified as an outlier, with the potential to distort results involving rear impact,

[1] Case year 2015, PSU 43, CASENO 126, VEHNO 2, OCCNO 3

rear seat, and child cases. Instead of completely removing the potential outlier case from the source dataset, this case was downweighted to the mean weight for other cases in the bin of restrained, 0-15 year-old passengers with MAIS 3-5 injuries. After the weight adjustment, the mean case weights for all analysis categories were below the threshold of the mean plus MAD for their corresponding injury severity levels. The following results reflect this outlier adjustment.

Model Evaluation (Projection of 2014 Crashes)

Results of the model evaluation, which used the projection model procedures to project 2014 crashes for comparison to retrospective results averaged over 2013-2015, are shown in Figure 1 to Figure 3. Both the projected and retrospective evaluation results are limited to occupants in vehicles that are less than 10 years old, since the comparison data was based on 2013-2015 NASS CDS cases, which have no injury data for occupants of older vehicles. All results are also limited to cases in vehicles of model year 2005 and later.

When aggregated across all crash and occupant types, the overall distribution of injury severity in the projected 2014 dataset was compared to the real-world 2013-2015 point estimates for the annual number of cases and rate of injury at each severity level in Figure 1. All projected values were well within the 95% confidence intervals (CI) shown for the comparison real-world data from 2013-2015.

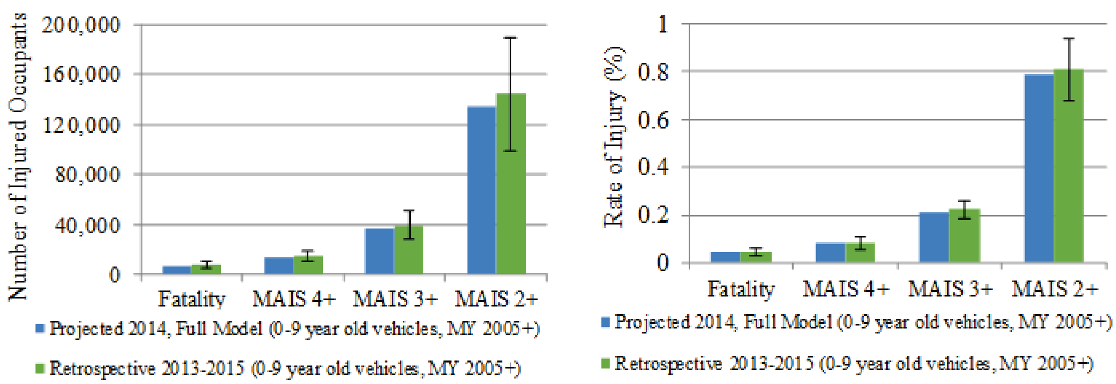

Figure 1. Annual injury frequency and rate by MAIS in evaluation model
(95% CI shown for retrospective data only)

Figure 2 shows the total number of occupants in the dataset by pre-crash scenario category, based on Volpe's more detailed crash-type taxonomy (Swanson et al., 2016). For every pre-crash scenario category, the projected annual number of occupants was within the 95% confidence interval for the annual number estimated from the 2013-2015 real-world comparison data. The relative frequency of different crash types was similar in the projected data and the comparison 2013-2015 data: with the exception of occupants in crashes classified as "other," the rank-order of the number of crashes in each category in the projection matched the rank-order for the retrospective dataset. Rear end, crossing path, and left turn across path/opposite direction crashes accounted for the most occupant crash exposures.

Results were also analyzed by impact direction. Rollovers were identified as those with primary damage from overturn. Frontal oblique crashes were categorized using previously defined methods (NHTSA, 2015) and frontal, side, and rear crashes, defined on similar principals. Limiting the analysis to serious injury cases (MAIS 3+), the projected number of injured occupants is within the confidence interval of the estimated number for each impact direction in the comparison 2013-2015 retrospective data (Figure 3). However, the relative frequency of injuries in different crash types was not the same in the projection and the comparison real world data: while the projection suggested serious injury cases would be more frequent in side impacts than in frontal oblique crashes, the opposite was true in the comparison real-world cases from 2013-2015.

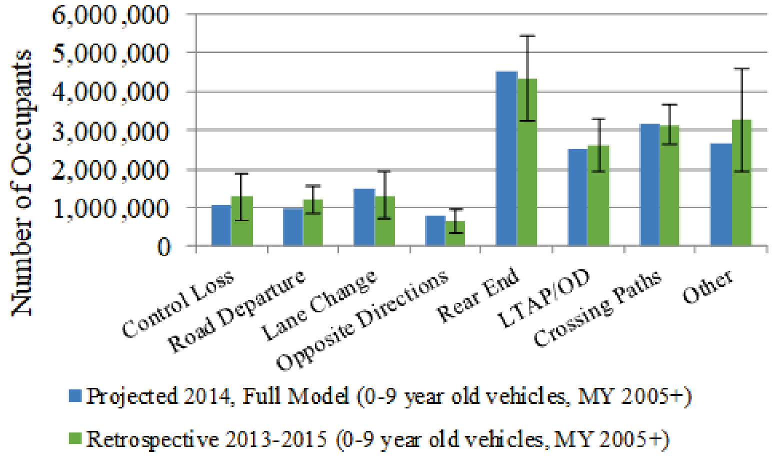

Figure 2. Annual frequency of occupants in crashes by pre-crash scenario (LTAP/OD = left turn across path/opposite direction)

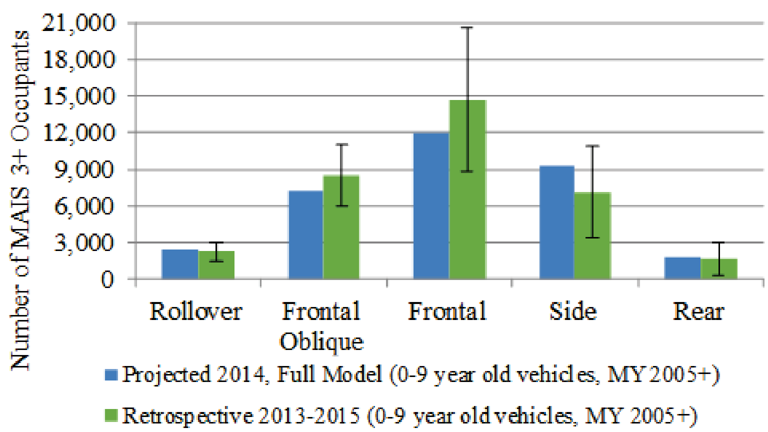

Figure 3. Annual frequency of serious (MAIS 3+) injury cases by impact direction

Further breakdown of 2014 projections by additional injury measures for each category of pre-crash scenario and impact direction showed that injury cases of all severities were reasonably well-predicted by the evaluation model. With few exceptions, the number of injury cases in each crash category and at each injury severity level, as well as the rate of injury among those cases, were within the 95% confidence interval for the comparison retrospective data for 2013-2015. The only exceptions were an overestimate of low-severity rollover cases relative to the retrospective 2013-2015 cases and overestimates of the rate of MAIS 3+ or MAIS 4+ injury among side impact crash occupants. While the overestimate of side impact injury rate estimates changed its relative rank-order with respect to frontal oblique crashes, the overestimate of low-severity rollover cases did not affect the relative frequency of rollovers compared to other impact directions.

Base Model (Projection of 2020-2030 Crashes)

The projection model results are drawn from analysis of the full projected dataset, which was based on source cases from NASS CDS that were reweighted and modified in the steps described in the methods section. The projection model estimates that the annual number of occupants in crashes from 2020 to 2030 will be 2 to 6% higher than the average number in the 2004 to 2015 range (Table 6). In spite of the projected increase in crash exposure, the number of serious or worse injuries (MAIS 3+) is expected to be 24 to 31% lower than in the retrospective period, a trend echoed in analyses by other outcome harm measures. Examples of model projections for 2020-2030, broken down by pre-crash scenario and by impact direction, are shown in Figure 4 to Figure 10. Note that reweighting procedures, such as those to address inaccuracies introduced by exclusion of cases with missing data or undercounting of low-severity crashes, were applied to both the retrospective and projection datasets to allow direct comparison. As a result, the retrospective values are higher than would be reported in a typical NASS-based retrospective analysis.

Table 6. Passenger Vehicle Occupants and Injuries in Retrospective and Projection Datasets (with 95% CI where possible to calculate)

	Retrospective 2004-2015	2020	2025	2030
Occupants in crashes	29,686,195 ± 6,570,393	31,551634	30,737,703	30,190,264
MAIS 3+ injured occupants	100,780 ± 24,627	76,492	71,555	69,937
Fatally injured occupants	25,108 ± 7,408	18,284	16,237	15,811

Base Model Projections by Pre-Crash Scenario (2020-2030)

Analysis by pre-crash scenario category can be used to identify how broad crash patterns have changed since the 2004 to 2015 period. For example, control loss and road departure crashes, as well as associated injuries, are projected to be less frequent in the future by any of the harm measures considered, including the number of occupants in crashes (Figure 4) or the number of occupants with serious or worse injuries (Figure 5). Much of the projected reduction in these crash types relative to the 2004-2015 retrospective period is expected by 2020. In spite of an anticipated reduction in the number of injury cases in opposite direction crashes, opposite direction crashes are projected to be the most frequent crash type among seriously injured occupants in 2020 to 2030 (Figure 5). Opposite direction crashes were projected to take over as the most frequent serious-injury crash type because of the projected drop in control loss and road departure cases.

The number of occupants in rear end crashes, with or without serious injury, is projected to be higher in 2020 than in the retrospective period, followed by a decline in later years (Figure 4, Figure 5). There were no trends or countermeasures coded in the model to *explicitly increase* the number of rear end crash occupant cases, or to *increase the harm* associated with these crashes, so the projected increase in rear end impact harm is simply a result of the upweighting of occupants expected to be in these crashes based on trends associated with factors such as population growth, vehicle type, age, licensure rates, and the improving economy. Future decreases in rear end crashes and injuries between 2020 and 2030 are consistent with the predicted increasing prevalence of automatic emergency braking (AEB) systems. However, the substantial number of occupants still projected to be involved in rear impact crashes and the substantial harm still projected to be associated with rear end crashes is consistent with the expected target population, effectiveness, and penetration of AEB, which reflect that AEB is not expected to eliminate front-to-rear crashes in the foreseeable future.

In contrast to several crash types expected to become less frequent between 2020 and 2030, intersection crashes, such as left turn across path/opposite direction and crossing path crashes, are projected to become more common (Figure 4). These increases reflect that no intersection countermeasures are included in the model because of uncertainty about the adoption of potential technologies such as vehicle-to-vehicle (V2V) or vehicle-to-infrastructure (V2I) communication or vehicle-resident crash-avoidance technologies.

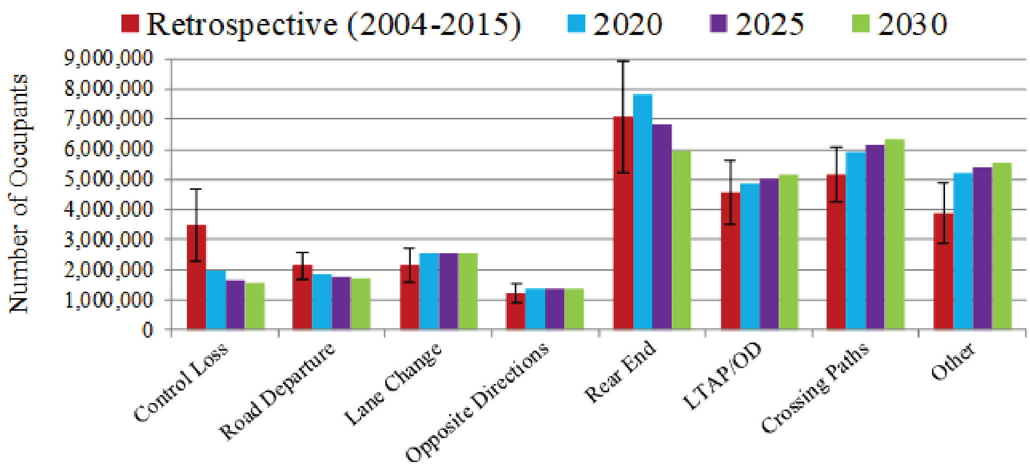

Figure 4. Annual number of occupants by pre-crash scenario
(LTAP/OD = left turn across path/opposite direction)

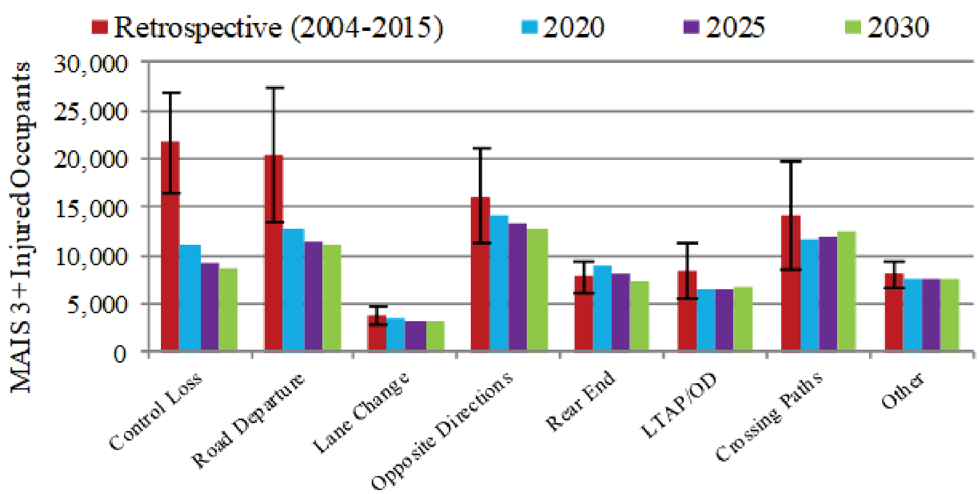

Figure 5. Annual number of seriously injured (MAIS 3+) occupants by pre-crash scenario

Base Model Projections by Impact Direction (2020-2030)

Samples of the analyses that can be performed on data that has been disaggregated by impact direction are shown in Figure 6 through Figure 10. Note that impact direction is defined relative to the occupant's vehicle, e.g., an occupant in a "rear end" impact as classified by pre-crash scenario could be in a rear impact or a frontal impact when classified by impact direction. Note that the total harm to passenger vehicle occupants cannot be estimated from these results since some crashes cannot be identified as being in one of the five defined crash types.

By impact direction, the most dramatic improvements projected in future crash safety are in rollovers, with a substantial drop from the retrospective period to the 2020 projection, and continued decreases in the number of occupants in rollovers (Figure 6), as well as in harm measures such as fatalities (Figure 7), injuries (Figure 8), or cost (Figure 9). Overall injury rate in the remaining rollovers is projected to drop steadily from the retrospective period through 2030, which indicates that rollover prevention is especially effective in the most severe crashes, and/or that occupant protection is expected to improve in the rollovers that will continue to occur (Figure 10).

In contrast to rollovers, the number of occupants in crashes in all planar impact directions is projected to increase between the retrospective period and 2020 (Figure 6). After 2020, projected increases or decreases in planar crashes varied by impact direction as a result of the modeled adoption of countermeasures with varying effects for each crash type. For example, the projected reductions in frontal and rear crashes outpace improvements in other planar directions because of the expected widespread adoption of AEB technology. Projections of injury outcome for each impact direction also vary depending on harm measure, with fatalities (Figure 7) and serious injuries (Figure 8) generally showing more improvement in the future than harm measures that account for more minor injuries. For example, cost-based harm measures (Figure 9**Error! Reference source not found.**), are projected with future increases over 2005-2015 levels for some impact directions because of the influence of AIS 1 and 2 injuries that typically are not captured by other harm measures.

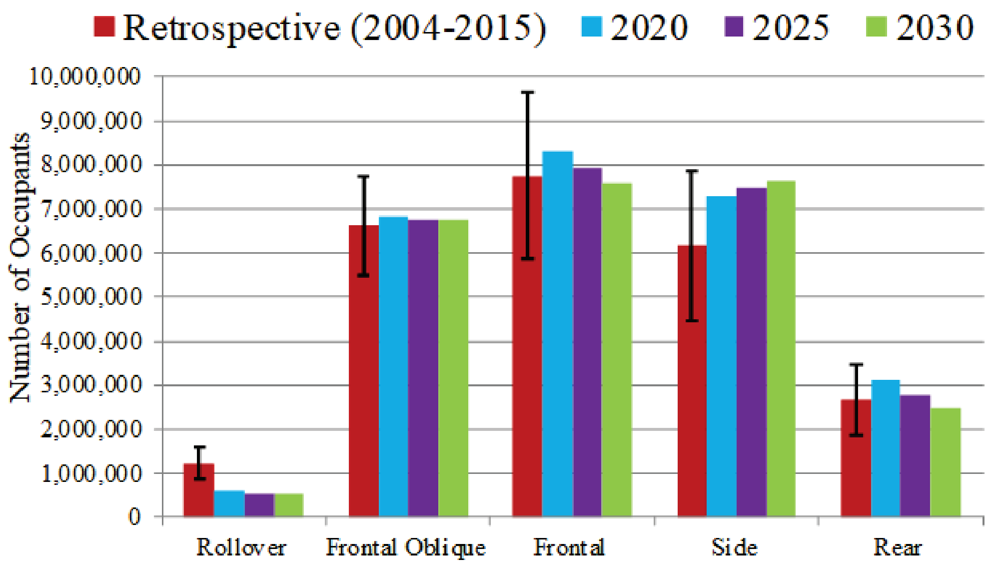

Figure 6. Annual number of occupants in crashes by impact direction

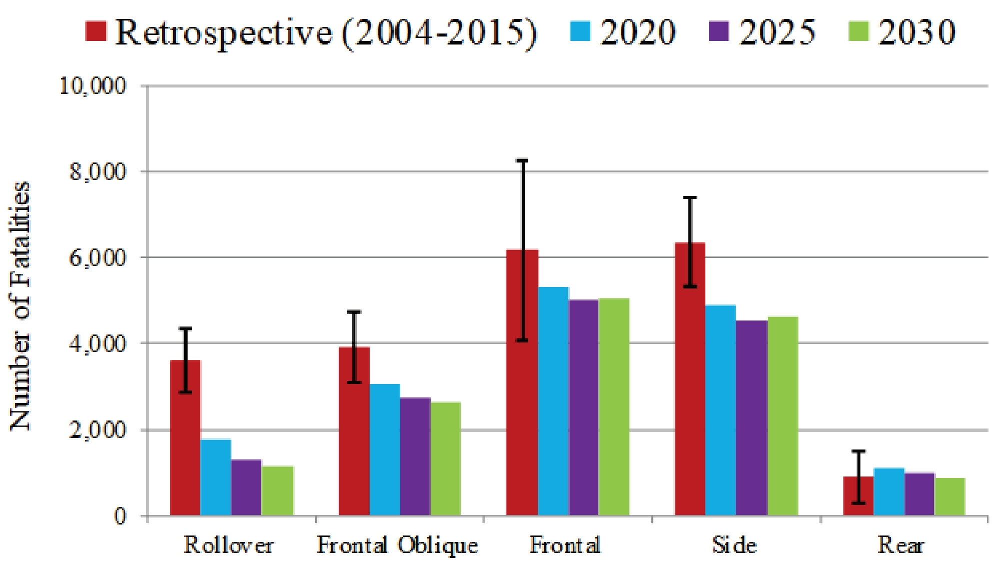

Figure 7. Annual number of fatalities by impact direction

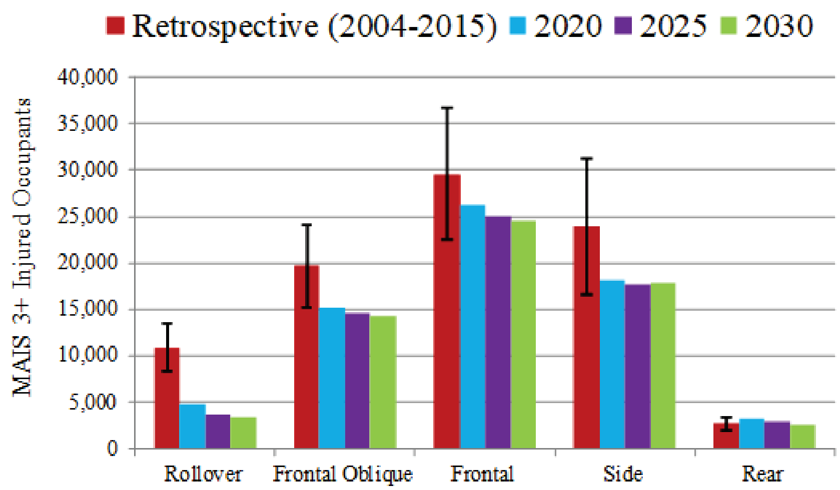

Figure 8. Annual number of MAIS 3+ injured occupants by impact direction

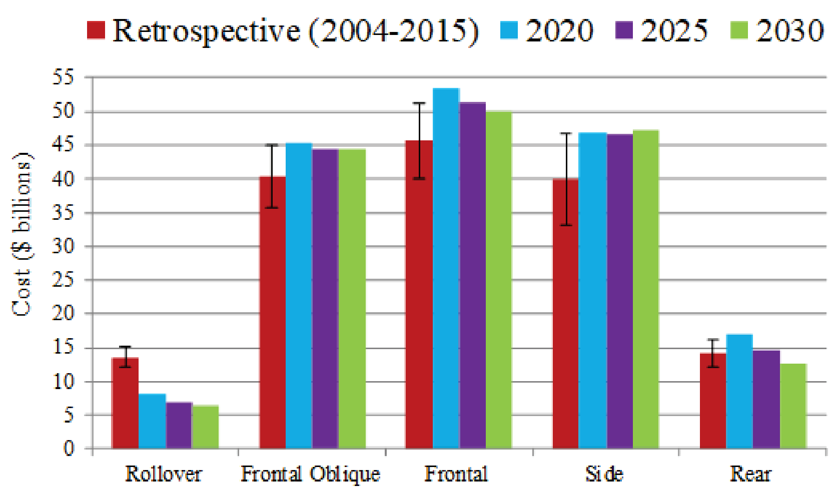

Figure 9. Total annual cost by impact direction

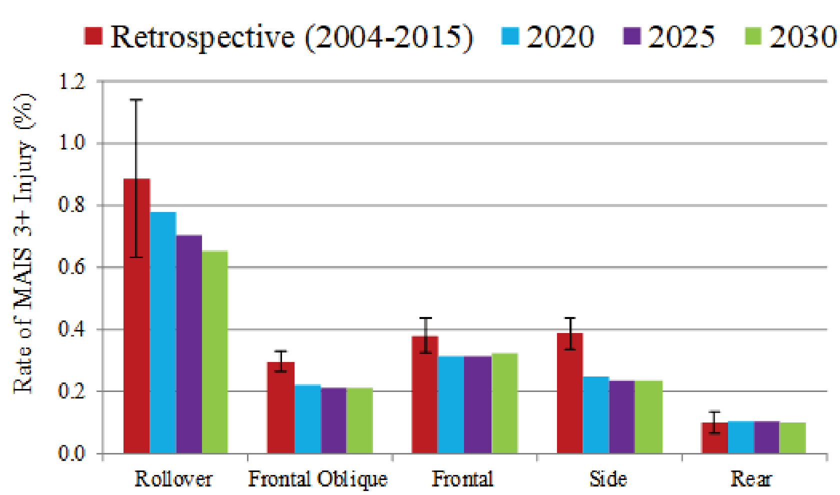

Figure 10. Rate (proportion) of MAIS 3+ injury among occupants by impact direction

DISCUSSION

The projections in this summary are from the base version of the model coded with the predicted effects of transportation trends and safety countermeasures since 2005, as well as best estimates of anticipated future trends and countermeasures (Table 1 to Table 5). The objective of this workshop paper is to introduce the modeling methods developed and to use the sample of included results to demonstrate how the projections can help identify future research opportunities. More comprehensive details on the methods, and additional results from the base model and hypothetical projections, will be available in two separate reports that are currently in progress.

Since there is no future dataset available to *validate* the results of the projection model, the modeling methodology used for the development of the 2020 to 2030 projections was evaluated by splitting the source data years used in the model to compare a projection made using 2004-2012 data to real-world data from 2013-2015. This method is a compromise in that it reduces the data available to make the projection in order to reserve a small number of cases to use as real-world comparison data. Using only three years of data for the comparison dataset limits detailed analysis since the relatively small number of cases precludes disaggregation by multiple variables. Even broad analyses of these cases must be interpreted carefully because of the relatively small number of cases in this three-year dataset. The necessary limitation of the evaluation to cases involving occupants in vehicles that were from model year 2005 and later and were less than 10 years old at the time of the crash further limited the evaluation. However, although the evaluation version of the model cannot be used to definitively validate the model, it was the best option available to broadly assess the overall reliability of the modeling methods in the absence of data for true validation of the model projections.

Overall, the evaluation suggested that the projections were reasonable, insofar as the relatively small dataset of comparison cases can be used to assess the reliability of the model. The only crash categories where the injury projections were outside of the 95% confidence intervals for the comparison real-world data were side impact injury rates for MAIS 3+ and 4+ injuries, and the frequency of overall rollovers and rollovers with MAIS 2+ injury. Ultimately, it was determined that there was insufficient evidence that side impact or rollover crash or injury projections were overestimated to tweak or correct the model to match the comparison data. For all crash categories, but in particular for those identified as outside or near the boundaries of the confidence intervals of the real-world comparison data, model parameters affecting these types of crashes should be reviewed and updated as new information becomes available regarding any potentially related trends or countermeasures.

The absolute counts of injuries and crashes in the retrospective and projected datasets in this study should be compared to other sources with care. For example, since the model covers only occupants in CDS-eligible vehicles, estimates cannot be compared to annual traffic safety statistics that include data on pedestrians, bicyclists, motorcyclists, buses, recreational vehicles, or heavy trucks. Additionally, since cases in the model were upweighted to address undercounting of low-severity crashes, results are not comparable to the total numbers or severity distributions in other NASS GES and NASS CDS studies.

Overall, the number of occupants projected in future crashes is higher than in the retrospective 2004-2015 period. However, in spite of the overall increase in the number of crash exposures, the harm associated with serious or fatal injuries is projected by most measures to be lower in the future than it was in the past. This improvement in future crash outcomes results from the modeled effects of retiring early-model vehicles from the fleet, as well as from recent and expected future crash safety advancements.

Because the model outputs full crash datasets, representing the crashes projected in the future with most of the same variables included in NASS CDS cases, the results can be analyzed by crash, occupant, and injury characteristics. To illustrate how the results can be used, projections in this paper are disaggregated at the crash level by pre-crash scenario and impact direction.

Projection by pre-crash scenario (Figure 4) suggests that the frequency of control-loss and road departure crashes has dropped more than any other type since the 2004-2015 retrospective period and will continue to drop in the future. This projected reduction results from penetration of electronic stability control (ESC) into the fleet, as well as other countermeasures such as tire pressure monitoring systems (TPMS). The highest-frequency scenarios in the retrospective period (rear end, crossing path, and left turn across path/opposite direction), are still expected to be the most frequent in 2030. The results can be used to flag the importance of increased implementation of technologies that could address these crash types. For example, hypothetical versions of the model have been run to explore the effects of accelerated implementation of automated driving systems (which are included in the base version of the model at very low, but realistic, levels of penetration up to 2030) and the implementation of V2V communication (which was not coded in the base version of the model because of uncertainty regarding its widespread adoption). Hypothetical versions of the model have also been used to investigate the potential benefit of non-vehicle-based solutions that could potentially be implemented more quickly, such as red light camera enforcement or conversion of signalized intersections to roundabouts.

Analysis of projected crash outcomes from different pre-crash scenarios in terms of serious injury (MAIS 3+) frequency instead of occupant exposure identifies the most harmful future crash mode as opposite direction crashes (Figure 5). Furthermore, road departure and control loss crashes are still projected to result in a substantial number of serious injury cases in the future, in spite of the expected reductions in overall frequency. This injury analysis suggests a higher priority for road departure, control loss, and opposite direction crash prevention than would be concluded solely from the analysis of case counts, underlining the importance of considering multiple measures of harm in analysis of the projections. Analyzing by additional harm measures beyond those used in this summary, such as a range of AIS injury severities, fatality, attributable fatality, or equivalent lives saved (analogous to the equivalent lives lost harm measure used in benefits analyses), yields an even more detailed picture of the most urgent crash issues in the future.

Analysis of the projections by impact direction suggests that rollover crashes will continue to be important in the future because they will be associated with higher rates of injury than any other crash type (Figure 10). However, planar crashes are projected in the future to contribute a growing proportion of the total injury harm from crashes. The relative harm associated with different crash types is sensitive to the countermeasures applied. For example, anticipated penetration of AEB in the base version of the model noticeably reduces the frequency of frontal and rear impact crashes between 2020 and 2030. However, by any injury measure considered, frontal, frontal oblique, and side impact crashes all contribute substantially to fatalities, injuries, and injury costs in the future. These increases underline the continued need for crashworthiness and occupant protection research for these crash types, even after applying the expected effects of crash avoidance and automated driving system technologies.

Development of effective countermeasures for the broad crash types analyzed in this summary requires more detailed information about the crash parameters most frequently associated with harm. Although the sample projection results in this summary are disaggregated only by pre-crash scenario and impact direction, the full analysis of these results disaggregates them by a variety of variables associated with the crash (e.g., intersection type, roadway type, near/far side, vehicle type), the occupant (e.g. sex, age, seat position, restraint use), and by injury body region.

A report summarizing results for additional versions of the model is in progress. These alternative versions of the model explore the effects of varying predictions regarding transportation trends (e.g., future restraint use and economic trends), the introduction and adoption of potential future safety countermeasures (e.g., V2V communication), or hypothetical conditions (e.g., 100% penetration of advanced technologies, or potential countermeasures that could reduce alcohol-related crashes). The model can also be used to model the effects of rare events such as the COVID-19 pandemic, which is influencing 2020 crash exposures and vehicle sales, which will also affect future penetration of vehicle improvements.

Analysis of weighted, survey-sampled retrospective crash data results is necessarily imprecise. In this crash prediction model, the imprecision associated with the analysis of retrospective crash cases is exacerbated by the modeled adjustments to the case weights and outcomes. These adjustments were based on estimates of the effects of several forecasted trends, as well as estimates of the effectiveness and penetration of multiple safety countermeasures, innovations, and policy changes. The uncertainty in the results is compounded at each stage of adjustments. In addition to these sources of uncertainty inherent to predictive models of this type, the source data available for this predictive model led to additional limitations. For example, projection results for crash types that are excluded or under-sampled in NASS CDS, such as lower-severity cases or cases involving older vehicles, were based on fewer source cases and are therefore associated with especially high uncertainty. In particular, the occupant characteristics associated with crashes involving older vehicles may be underrepresented in the current projections. Additionally, the effectiveness and future penetration of modeled countermeasures were based on available estimates of these parameters. While the estimates for established countermeasures could be based on detailed retrospective analyses, the parameters for recently-introduced and future vehicle technologies were necessarily based on the broad estimates that are currently available. Also, less research was available on many behavioral and program countermeasures, limiting their inclusion in the model. Furthermore, the retrospective cases used as model input are limited to cases from crash year 2015 and earlier because of the termination of NASS CDS and GES data collection. Although future versions of the model may incorporate cases from NHTSA's more recent CISS and CRSS datasets, this model's NASS-based projections of 2020-2030 crashes may be especially useful until there are a sufficient number of CISS and CRSS cases available for retrospective analysis. In spite of the uncertainty associated with making multiple adjustments to survey-sampled retrospective crash data, the value of this projection model is its ability to *combine* the effects of all modeled safety measures, predictions, and forecasts. The model results should not be viewed as a *prediction* of future crashes expected to occur, but as a tool to visualize the combined effects of individual trends, countermeasures, and shifts in transportation safety. The layering of all available forecasts and estimates in the same model is expected to provide a more complete picture of crashes in the future than can be drawn from retrospective data or analysis of any single safety intervention or trend.

CONCLUSIONS

It is acknowledged that the imprecision inherent in sampled real-world crash data is compounded by applying forecasts of future trends and countermeasures, and that transportation safety can be affected by unforeseeable shifts in transportation trends and market forces. In spite of these limitations of predictive modeling, projections from this model offer more comprehensive estimates of crashes expected to remain in the future than can be gleaned from analyzing historic data, or by consideration of the effects of individual trends or safety interventions.

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