Injury Estimation for Advanced Automatic Collision Notification (AACN) in Germany

N Lubbe*, T Kiuchi**

*Toyota Motor Europe NV/SA , Technical Affairs Planning Dept., Hoge Wei 33, 1930 Zaventem, Belgium
**Toyota Motor Corporation, Vehicle Engineering Development Div., 1200, Mishuku, Susono, 410-1193 Japan

Abstract - This study aimed at developing an injury estimation algorithm for AACN technologies for Germany and compared them to findings based on Japanese data.
The data to build and to verify the algorithm was obtained from the German in-depth Accident Database (GIDAS) and split into a training and a validation dataset. Significant input variables and the generalized linear regression model to predict severe injuries (ISS>15) were selected to maximize area under the receiver operating characteristic curve (AUC).
Probit regression with the input parameter *multiple impact, delta v, seatbelt use* and *impact direction* gave the largest AUC of 0.91. Sensitivity of the algorithm was validated at 90% and specificity at 76% for an injury risk threshold of 2%.
It appears that no major differences between Japan and Germany exist for injury estimation based on *delta v* and *impact direction*. However, far side impact and multiple crash events appear to be associated with a larger risk increase in the German data.

INTRODUCTION

Fatalities from road traffic accidents can be reduced by accident avoidance before the collision, mitigation of consequences during a collision and medical treatment after a collision. Automatic Collision Notification (ACN) describes technologies that establish a communication link with rescue services and forward the position of the vehicle given a collision. The rescue services then decide on appropriate action. These technologies are established in US and Europe and know for example as “ecall” [1].

Advanced Automatic Collision Notification (AACN) describes technologies that exceed ACN functionality by estimating injury outcome based on some crash parameters. Medical rescue services have to dispatch the appropriate unit to the accident scene and transport any injured person to the appropriate medical facility. Appropriate hereby means that injury severity and medical treatment need to match: Treating severe injuries at non-specialized facilities (referred to as under triage) increases fatality risk [2] while treating minor injuries at specialized Trauma centers (referred to as over triage) might overload these and might lead to transport times longer than necessary. The information provided by AACN – an estimation of injury severity – aims at aiding medical rescue services to decide on appropriate action. AACN technologies are established in the USA, where for example OnStar is a system introduced on the market by General Motors in 1996 [3]. Most research concerns road traffic accidents in the USA or Japan. In Germany, AACN functionality is offered by BMW as part of “Connected Drive” since 2007. The “Urgency” algorithm was trained on US data to predict risk of severe injury [4]. It is not clear if the insights from research specific to the USA or Japan can be directly applied to Germany or how AACN technologies can be tuned to work effectively in Germany. Brehme et al. [5] developed an injury prediction tool for Germany based on GIDAS data, which was validated by Hannawald et al. [6]. The tool used logistic regression and a priori defined explanatory variables based on visual inspection of the accident scene to estimate the likelihood of single injuries.

This study aims at developing an injury estimation algorithm for AACN technologies for Germany selecting regression model and explanatory variables as a set of crash parameters for best model fit and compared them to findings based on Japanese data [7].

METHODS

Estimation output: A metric for injury severity

Many metrics to quantify injury severity and estimate fatality risk have been developed. There is vast literature on this topic. A thorough review exceeds the scope of this paper.

The metrics Maximum Abbreviated Injury Score (MAIS) [4,8] and Injury Severity Score (ISS) [9-10] are used to characterize injury severity for a patient. AIS and Mortality Risk Ration (MRR) [11] are used to characterize severity on injury level. For this study, the authors adapt findings of the German Trauma Registry. The RISC score [12] is used to estimate chances of fatality for a patient. Hospital performance is judged comparing actual fatality rates with those estimated by RISC. Further quality assessment is based on the time passed for several treatments for severely injured, whereby severely injured is defined by ISS≥16 [13]. As it is unclear for now how to relate RISC levels to appropriate medical care, the algorithm estimates the event of ISS≥16 and thereby the need for treatment in a specialized Trauma Center.

Estimation input: Variables characterizing crash severity and vulnerability

For the USA, it was recommended to primarily make use of

- Delta v
- Principal direction of Force (PDOF)
- Seatbelt use
- Crash with multiple impact
- Vehicle type

If contact with the occupant is possible, occupant age should also be used to estimate risk of having a severe injury (ISS>15) [9]. These input variables with an addition of occupant gender were used in the injury estimation model by Kononen et al. [10]. Yoshida et al. [7] used delta v and PDOF in a “base model” and added seatbelt use, multiple impact and occupant age in a “full model”.

For this study, all the above mentioned variables were pooled with other variables as candidates for the injury estimation algorithm. Delta v and PDOF were taken from the collision that caused the largest damage to the vehicle. Further variables that potentially can estimate injury outcome were:

- Roll-over event [yes / no]
- Occupant height [cm], weight [kg], age [years] and gender
- Vehicle registration [calendar year]

Candidates were selected based on their expected contribution on injury outcome and their expected availability in the near future. For example, the authors expect occupant characteristics (height, weight age, gender) to influence injury outcome and to be available in the future through personalized car communication. Other variables, such as occupant position, collision partner, or structural engagement were not expected to be available in the near future and thus not included.

The final input variables were determined by backward selection in several estimation models as described in the next section. That means, starting from a given set of variables the one with the highest p-value was removed until all p-values were below 0.1. Amongst the set of variables fulfilling the above condition, the final model was selected based on largest area under the receiver operating characteristic curve (AUC). AUC gives an overall measure of estimation accuracy, with a value of one representing perfect accuracy [14].

Estimation model: Linking input and output

Generalized linear regression models were used to relate injury risk R to input parameter X. Besides the popular logit [4,7,8,10] of the form *Log(R/(1-R))=Xb*, also probit *Norminv(R)=Xb*, and complementary log-log: *log(-log(1-R))=Xb* were modeled. Calculations were performed with Matlab R2013a using glmfit function.
Sensitivity was calculated as the proportion of individuals with the outcome that are correctly classified: True positive / (true positive + false negative). Specificity was calculated as the proportion of individuals without the outcome that were correctly classified: True negative / (true negative + false positive). False positive rate was calculated as the proportion of given alarms that were false: False positive / (false positive + true positive). Similarly, false negative rate was calculated: False negative / (false negative + true negative).

Threshold optimization: Binary response from estimated injury risk

The regression model gives the probability of severe injury between 0% and 100%. A threshold for the decision transport to Trauma Center can be set arbitrarily (for example at 20% [9]) or chosen to minimize overtriage and undertriage [8]. In this study, the transport threshold was obtained through analysis of ROC. The distance of any point of the ROC to the target point was calculated. The distance depends on the injury threshold and is known. The threshold with largest distance to the target was selected. The target was 10% undertriage (1-sensitivity) and 50% overtriage (specificity). These values are recommended in the German Whitebook Medical Care of the Severely Injured [15].

Dataset

The data to build and to verify the algorithm was obtained from the German in-depth Accident Database (GIDAS). GIDAS cases are sampled to be representative for Germany but tend to be biased to higher injury severity [16]. The data used for this study was approximately representative for the injury severity in Germany: National data 2003-2012 for injured passenger car occupants (police reported) recorded fatal injuries in 1.1% of all cases, severe injuries in 14% and slight injury in 85% [17]. The GIDAS dataset for this study contained 1.7% fatal injuries and 19% severe injuries using the same police reported definitions. No weighting factors were applied.

Complete cases from the years 2003-2012 were filtered for front seat occupants >15years in passenger cars and vehicle registration later than year 2000. Each front seat occupant was treated as a separate case. The data was split into a training dataset (to build the algorithm) with uneven case numbers (n=1942) and a validation dataset (even case numbers, n=2048). Some characteristics of the datasets are given in table 1. There was no obvious difference between the sets. For backward model selection, omission of incomplete data was done specifically for each model, depending on the included variables. This means that the number of data differs between models.

Table 1: Characteristics of training and validation data

Variable		Training data	Validation data
Injury outcome	ISS>15	52 (3%)	41 (2%)
	ISS<15	1795 (92%)	1894 (93%)
	ISS unknown	95 (5%)	113 (6%)
DV	Mean	22.2 km/h	22.8 km/h
	SD	15.4 km/h	15.3 km/h
Impact direction	Front	984 (51%)	1067 (52%)
	Near Side	250 (13%)	255 (13%)
	Far Side	191 (10%)	174 (9%)
Belt use		1751 (96%)	1843 (95%)
Occupant age	mean	41 years	42 years
	SD	16 years	17 years

RESULTS

The largest AUC resulted from a probit model with the input parameter *multiple impact, delta v, seatbelt use* and *impact direction.* AUC was 0.908. Best fit model specifications (regression coefficients b, standard error of coefficients and p-value of coefficients) are given in Table 2. The ROC curve is depicted in figure 1. Sensitivity, specificity, false positive rate and false negative rate are depicted in figure 2. Best sensitivity (92%) and specificity (75%) was reached at a threshold of R = 2%.

Table 2: Best fit model specification

Parameter	Unit	b	SE	p-value
Intercept	-	-2.912	0.297	<0.001
Multi impact	Yes = 1, No = 0	0.375	0.157	0.0169
Delta v	Km/h	0.040	0.004	<0.001
Seatbelt use	Use = 1, No use = 0	-0.708	0.238	0.0029
Impact direction	Near side = 1, other = 0	0.512	0.225	0.0231
	Far side = 1, other = 0	0.923	0.208	<0.001
	Front	-	-	-
	Rear	-	-	-

Figure 3 illustrates the regression results. Severe injury risk for a single belted front or rear impact was 5% at a delta v of 50 km/h. When unbelted, the risk more than tripled to 18%. A belted near side impact at delta v of 50 km/h lead to a risk of severe injury of 13%.

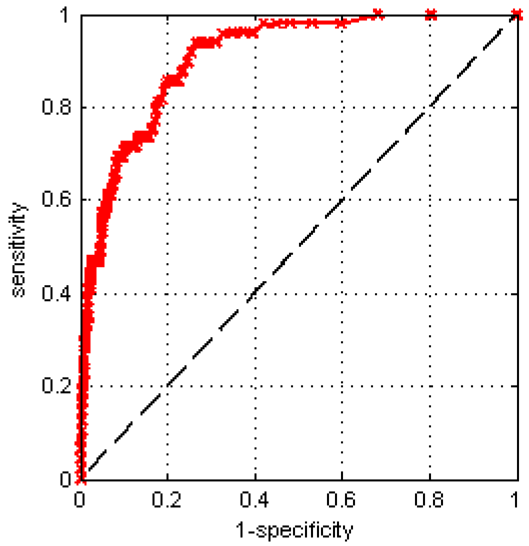

Figure 1: ROC curve of best fit model

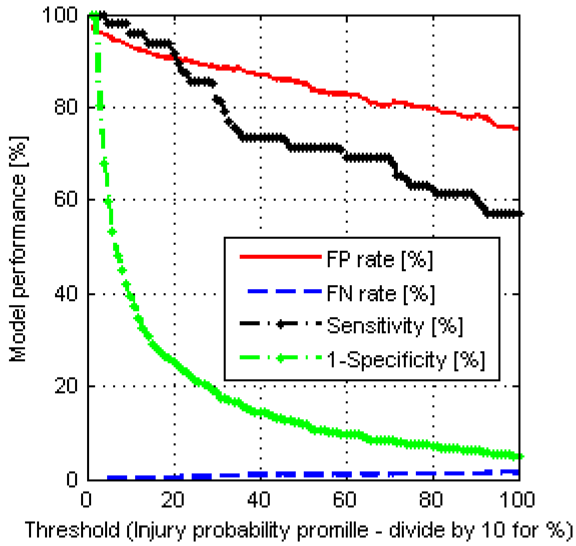

Figure 2: Characteristics of best fit model

The probit model with specifications as given in Table 2 and a threshold for estimating injury of R≥2% was validated against the GIDAS validation dataset. Sensitivity was 90% (target: ≥90%), specificity was 76% (target: ≥50%), false positive rate was 92%, and false negative rate was 0.3%.

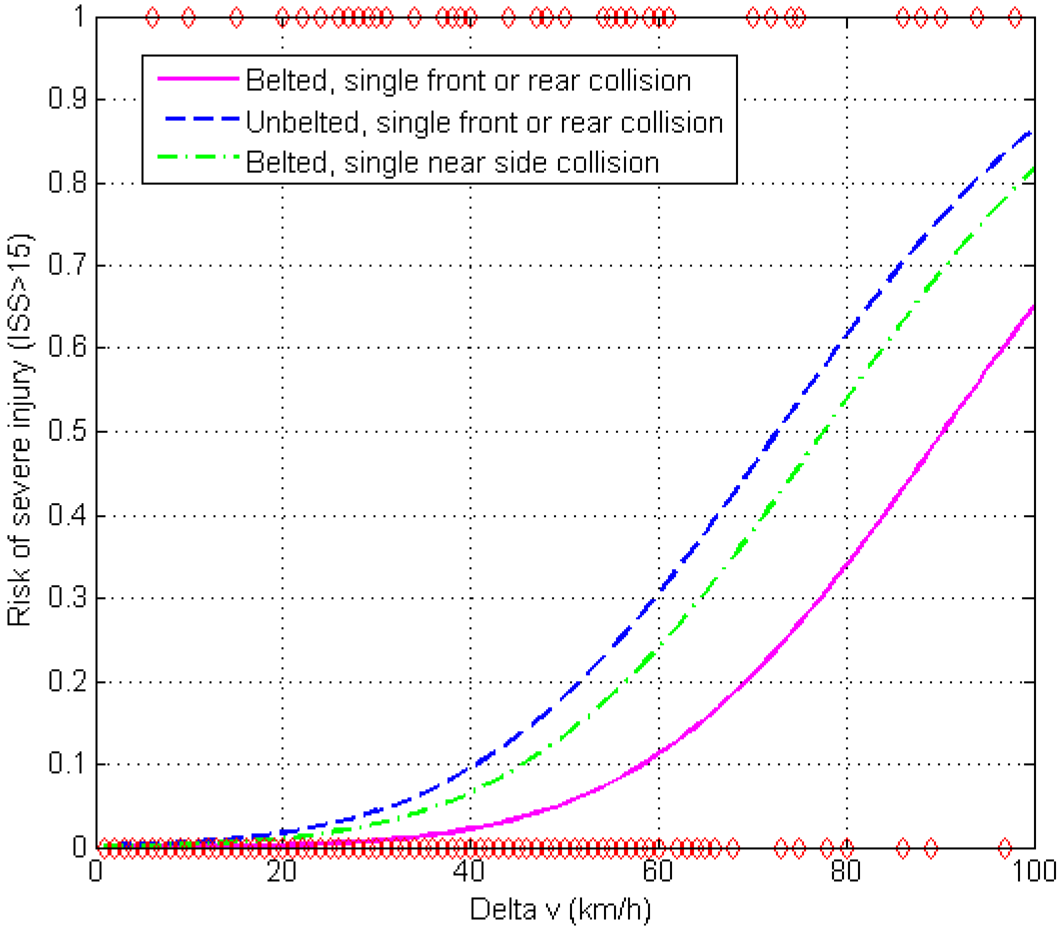

Figure 3: Best fit model injury risk curves

DISCUSSION

There is some indication that far side accidents were associated with a higher probability of severe injuries than near side accidents. In contrast, crash mechanics imply that, due to intrusion and contact injuries, near side impacts are more likely to lead to severe injury than far side impacts. The difference in probability in this study was statistically not significant and therefore might be coincidence. Alternatively, the difference might be due to a high share of cars equipped with advanced near side impact protection, such side airbags (59% of vehicles equipped) which were shown to reduce injuries [18]. Furthermore, results might be confounded with impact angles. In the training dataset of this study, far side impacts occurred more often angled towards the front.

Table 3 summarizes the ten injury estimation models with largest AUC. Number of data points used (#) and severe injuries in the set (# ISS>15) are also given. The type of generalized linear regression model appears to have only marginal influence on result. The top scoring estimation model contained the same variables independent of regression model. Multiple impact ("Multi"), delta v ("DV"), seatbelt use ("SB"), and impact direction (near side impact: "Near", far side impact: "Far" were the most commonly found estimator variables. Roll-over event ("Roll") and vehicle type ("Van" and passenger car ("Pas")) were included in the models ranking 7-10. Differences due to logit, probit or complementary log-log model appear to be of little importance for estimator variable selection and AUC. It can be noted that risk curves did merely differ for risks below 50% as illustrated in figure 4. However, there was no reason not to benefit from the slightly better performance of the probit model, thus probit was proposed and not the commonly used logit.

Table 3: Top ten injury estimation models according to AUC

Model	variables						AUC	#	# ISS>15
Probit	Multi	DV	SB	Near	Far		0.908038	1719	49
Logit	Multi	DV	SB	Near	Far		0.907002	1719	49
c-loglog	Multi	DV	SB	Near	Far		0.906495	1719	49
c-loglog	Multi	DV	SB	Far			0.9054091	1719	49
Logit	Multi	DV	SB	Far			0.90526	1719	49
Probit	Multi	DV	SB	Far			0.905214	1719	49
c-loglog	Multi	DV	SB	Near	Far	Van	0.9038293	1662	46
c-loglog	Multi	DV	SB	Near	Far	Pas	0.9036431	1662	46
Probit	Roll	DV	SB	Near	Far		0.903423	1717	49
Logit	Roll	DV	SB	Near	Far		0.902209	1717	49

Table 4 displays model characteristics for other input variables. Model 1 and model 2 were developed from Japanese data (n=5 090 980) [7] where all variables were significant in logistic regression to estimate police classified injury outcome (severe and fatal injury versus slight and no injury). Model 3 was developed from US data (NASS CDS, n = 14 673) where all variables except vehicle type were significant in logistic regression to estimate ISS>15 versus ISS<15 injury outcome [10]. Note that regression coefficients were computed from the training dataset of this study and not taken from literature.

The model proposed in this study met targeted specificity and sensitivity. This performance can be compared to the injury estimation model 1 to 2 from the literature, using the given parameter and coefficients. Model 3 cannot be compared directly, as parameters are given on vehicle level, not occupant level. In a first step, the threshold was calculated from the training data to maximize positive distance to the target. In a second step, the performance was calculated with the validation dataset

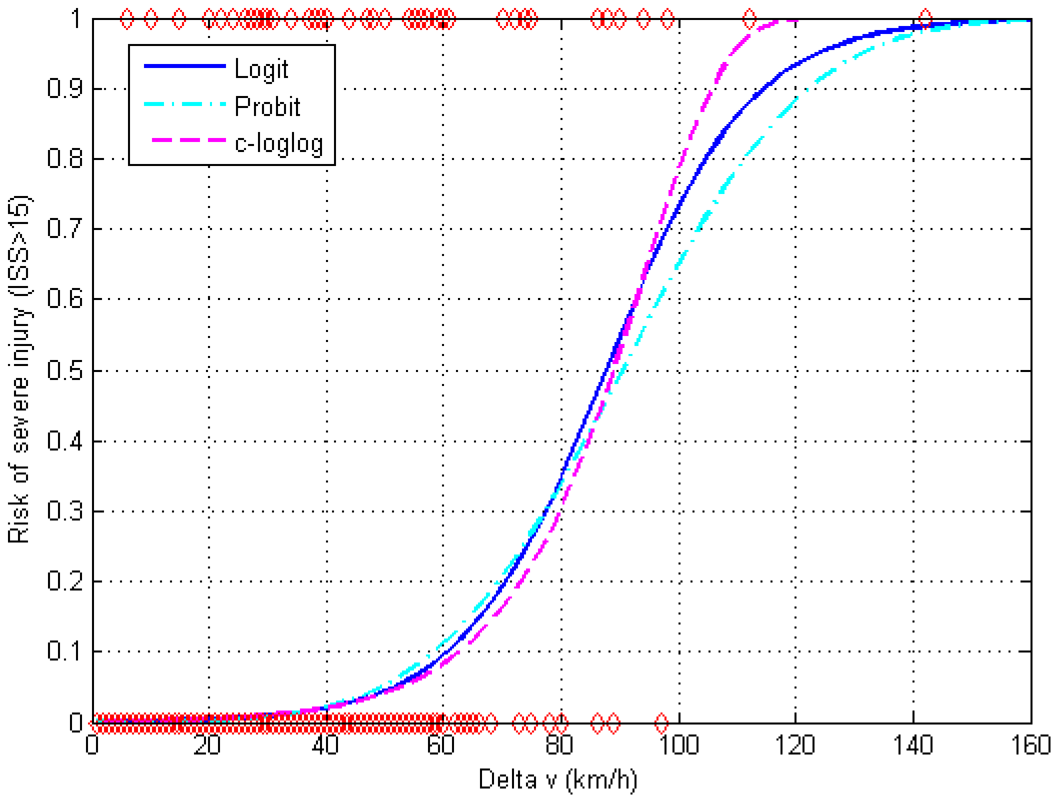

Figure 4: Injury risk curves from logit, probit and complementary log-log regression

Table 4: Model characteristics for alternative input variable selection

Model	Input variables	AUC	#
This study	Multiple Impact, Delta v, Near Side, Far Side, Belt use	0.9080	1719
1(Logit)	Delta v, Front*, Near Side, Far Side	0.8910	1801
2(Logit)	Multiple Impact, Delta v, Front*, Near Side*, Far Side, Belt use, Age*	0.9067	1706
3(Logit)	Multiple Impact, Delta v, Front*, Near Side*, Far Side, Belt use, Age*, Gender*, Vehicle type	0.9041	1647

* not significant at p<0.1

Performance is given in table 5. The "base model" from Yoshida et al. (2012) exceeded targeted specificity and sensitivity. Sensitivity, false positive and false negative rate were comparable to the model developed in this study but specificity was 14% lower.

Using GIDAS data, one or several of the input variables were not significant. A real difference between US, Japan and Germany for injury outcome might be the underlying reason. Insignificant results could also be due to lower case numbers in this study while there is no difference in injury outcome explanation between the countries. The performance of the estimation models from literature with respect to AUC were similar to the best rated ones in this study besides use of non-significant estimator variables. However, the authors believe that the chance of estimating injury outcome based on non-existing relationships is high when using non-significant variables, thus the model in this study was chosen to only contain significant variables.

The injury threshold to decide on transport to a Trauma Center is well below the recommendation of the Recommendations from the Expert Panel of 20% [9]. It might be more meaningful to determine target sensitivity and specificity according to medical, political and other considerations and to compute an appropriate threshold than to set a threshold arbitrarily and to deal with sensitivity and specificity as model outcome.

It appears that no major differences between Japan and Germany exist for severe injury estimation based on delta v and impact direction. The "full model" performance was lower, indicating that the influence of the additional variables might differ between the data from Japan and Germany. When comparing the coefficients for a logistic regression in the variable formulation of Yoshida et al. [7], Table 6 shows differences between the original regression coefficients calculated on the Japanese data and the ones calculated on the German data based on the training dataset for crash direction far side (base model, significant at $p<0.1$) and multiple crash (full model, significant at $p<0.05$). Statistical significance of difference in coefficients was calculated with a two-sided independent sample t-test. One must keep in mind though that the German data fit predicts ISS>15 injury while the Japanese data fit predicts police reported severe injury.

Table 5: Comparative performance of injury estimation models

	Best fit model (this study)	Yoshida et al. (2012) "base"	Yoshida et al. (2012) "full"	Target
Threshold	2%	1.3%	1.3%	-
Sensitivity	90%	92%	82%	≥90%
Specificity	76%	62%	66%	≥50%
False positive rate	92%	93%	94%	-
False negative rate	0.3%	0.4%	0.8%	-
Number of TN	1332	1105	1120	-
Number of TP	35	48	40	-
Number of FN	4	4	9	-
Number of FP	422	690	583	-

Bose et al. [19] pointed out two limitations of regression models used in literature: The inability to capture non-linear effects and the lack of interaction terms. These limitations exist in this study as well. Interaction terms might improve accuracy, but the dataset was deemed too small for meaningful modelling. Modelling of interaction terms and non-linear effects requires future work on a larger dataset. Survival analysis can make use of censoring information in time to failure analyses. One could formulate the injury estimation model as survival regression with for example delta v as "time" variable and other variables as confounders. This would account for delta v not being exact, i.e. a sustained injury might also have been sustained at a lower speed. Survival regression would yield results for the data at hand. But delta v differs from time in one important aspect: Time to failure is a cumulative measure, which means time is gradually increased until failure is reached while delta v is a singular input (dose). Outcome (response) is likely to differ between a single input and cumulative input: Injury might be sustained at lower delta v if collisions are repeated at ever increasing delta v compared to a single collision at a specific delta v. Thus, it is questionable whether survival regression is applicable for the injury estimation model. Non-linear methods should be explored in the future.

As an alternative to backward selection, Akaike Information Criterion (AIC) can be computed on any combination of predictor variables. AIC consists of a term indicating how well the data fits to the model and a penalty term for the number of model variables:

*AIC = -2 * Log likelihood + 2 * (Number of estimator variables)*

For model selection based on AIC, all data with missing information for at least one variable needs to be omitted to keep a constant dataset across models. This would lead to 1104 cases in the training data with 18 cases of ISS>15. Over fitting was likely to be an issue and model selection based on AIC was ruled out for this study.

Table 6: Regression coefficients for Japanese data fit and German data fit

		Base model	German data	SE	Full model	German data	SE
Intercept		-5.326	-5.421	0.541	-4.129	-4.343	0.736
Delta v	<30	-					
	31-40	2.161	1.921	0.453	2.052	1.892	0.472
	41-50	2.99	2.426	0.503	2.858	2.384	0.533
	51-60	3,467	3.480	0.489	3.310	3.509	0.52
	>60	4.175	4.547	0.509	3.995	4.645	0.523
Crash direction	Front	0.257	0.151*	0.576	0.163	0.038*	0.59
	Near side	1.524	1.120	0.659	1.446	1.080*	0.674
	Far side	**1.082**	**2.143**	0.605	0.984	1.890	0.635
	Rear	-					
Belt use	Yes				-1.371	-1.519	0.47
	No						
Multiple crash	Yes				***0.099***	***0.784***	0.328
	No						
Occupant age	<54						
	55-64				0.477	-0.605*	0.66
	>65				0.812	0.413*	0.439

*not significant at p<0.1; Significant differences between Japanese and German fit coefficients at p<0.1 in bold, significant differences at p<0.05 in italic and bold

CONCLUSION

An algorithm to estimate severe injury (ISS>15) for front seat passenger car occupants older than 15years was developed and validated based on GIDAS data. The model with significant input variables and the best estimation results (largest AUC) was found to make use of information about delta v, multiple impact, seatbelt use, and crash direction: Far side and near side impact. Injuries in front and rear-end collisions can be estimated, but did not require a specific regression coefficient. A probit model is proposed, but logit or complementary log-log regressions gave similar results. Sensitivity was 90% and specificity was 76%, meeting target performance.

The “base model” developed by Yoshida et al. [7] for injury estimation in Japan showed a comparable performance using delta v and crash direction information. It appears that no major differences exist for injury estimation in Japan and Germany based on these variables. However, far side impact and multiple crash events appear to be associated with a larger risk increase in the German data. Further research is required to investigate these differences, and to validate the model and estimator selection proposed in this study with a larger dataset.

ACKNOWLEDGEMENTS

The authors would like to thank Mazakazu Chiba (Toyota Motor Corporation, Japan) for discussion and review of manuscript and Erik Rosén (Autoliv Research, Sweden) for comments on the statistical models.

REFERENCES

1. Chauvel C and Haviotte C (2010) “Automatic emergency calls in France”. 4th international Conference on ESAR, September 16-18, 2010, Hannover, Germany
2. DGU (2011) “S3 – Leitlinie Polytrauma/Schwerverletzten-Behandlung” Deutsche Gesellschaft für Unfallchirurgie (federführend) aktueller Stand: 07/2011 AWMF-Register Nr. 012/019. Available at: http://www.awmf.org/uploads/tx_szleitlinien/012-019l_S3_Polytrauma_Schwerverletzten-Behandlung_2011-07.pdf
3. GM (2013). “On Star: Safe & Connected”. General Motors homepage. Available at: http://www.gm.com/vision/design_technology/onstar_safe_connected.html
4. Rauscher S, Messner G, Baur P, Augenstein J, Digges K, Perdeck E, Bahout G, Pieske O (2009) “Enhanced Automatic Collision Notification System – Improved Care due to Injury Prediction – First Field Experience” ESV conference 2009, Stuttgart, Germany, Paper number 09-0049
5. Brehme H, Zwipp H, Hannawald L (2008) “Severe Injuries in Passenger Cars – Development of a Software Tool for Emergency Diagnostics“ 3rd International Conference on ESAR, September 5-6, 2008, Hannover, Germany
6. Hannawald L, Liers H, Brehme H. (2012) „Prediction of severe injuries for the optimization of the pre-clinical rescue period of car occupants“. 5th international Conference on ESAR, September 7-8, 2012, Hannover, Germany
7. Yoshida S, Hasegawa T, Tominaga S, Nishimoto T (2012) “Injury Prediction Model for Automatic Collision Notification Based on Japanese Accident Data” (In Japanese with English abstract). Proceedings of JSAE conference, Vol.42, No.2, paper number 20124219
8. Bahout G, Digges K, Schulman C (2012) “Influence of Injury Risk Thresholds on the Performance of an Algorithm to Predict Crashes with Serious Injuries”. Proceedings of 56th AAAM Annual Conference, October 14-17, 2012
9. CDC (2008) “Recommendations from the Expert Panel: Advanced Automatic Collision Notification and Triage of Injured Patient”. Centers for Disease Control and Prevention, 2008
10. Kononen DW, Flannagan CAC, Wang SC (2011) “Identification and validation of a logistic regression model for predicting serious injuries associated with motor vehicle crashed”. Accident Analysis and Prevention, 43 (2011) 112-22
11. Weaver AA, Barnard RT, Kilgo PD, Martin RS, Stitzel JD (2013) “Mortality-based Quantification of Injury Severity for Frequently Occuring Motor Vehcile Crash Injuries”, Proceedings of 57th AAAM Annual Conference, September 22-25, 2013
12. Lefering R (2009) “Development and Validation of the Revised Injury Severity Classification Score for Severely Injured Patients”. European Journal of Trauma and Emergency Surgery, 2009, Vol.35, pp.437-47
13. DGU (2012) Sektion NIS der Deutschen Gesellschaft für Unfallchirurgie (DGU) / Akademie der Unfallchirurgie (AUC GmbH), „TraumaRegister DGU Jahresbericht 2012“. Available at: http://www.traumaregister.de/images/stories/downloads/jahresberichte/tr-dgu-jahresbericht_2012.pdf
14. Vittinghoff E, Glidden DV, Shiboski SC, McCulloch CE (2005) “Regression Methods in Biostatistics. Linear, Logistic, Survival and Repeated Measure Models” Springer, 2005
15. DGU (2012) German Society for Trauma Surgery. “Whitebook Medical Care of the Severely Injured” 2nd revised and updated edition. Available at: http://www.dgu-

online.de/fileadmin/published_content/5.Qualitaet_und_Sicherheit/PDF/2012_DGU_Whitebook_Medical_Care_2ndEdition.pdf
16. Pfeiffer M, and Schmidt J (2006). „Statistical and methodological foundations of the GIDAS accident survey system" 2nd International Conference on ESAR, Hanover, Germany, pp. 81–87
17. Destatis (2013) Statistisches Bundesamt, "Verkehrsunfälle, Zeitreihen 2012". Article number 5462403127005. Available at: https://www.destatis.de/DE/Publikationen/Thematisch/TransportVerkehr/Verkehrsunfaelle/VerkehrsunfaelleZeitreihenZIP_5462403.zip?__blob=publicationFile
18. Stigson H, and Kullgren A (2011) "Effect of side impact protection in reducing injuries" 22nd ESV Conference, Washington DC, USA, Paper Number 11-0319
19. Bose D, Crandall JR, McGwin G, Goldman J, Foster J, Fine PR (2011) "Computational methodology to predict injury risk for motor vehicle crash victims: A framework for improving Advanced Automatic Crash Notification systems". Transportation Research Part C, Vol.19, pp. 1048-59