Deriving injury risk curves using survival analysis from biomechanical experiments

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Abstract

Injury risk curves from biomechanical experimental data analysis are used in automotive studies to improve crashworthiness and advance occupant safety. Metrics such as acceleration and deflection coupled with outcomes such as fractures and anatomical disruptions from impact tests are used in simple binary regression models. As an improvement, the International Standards Organization suggested a different approach. It was based on survival analysis. While probability curves for **side-impact**-induced thorax and abdominal injuries and frontal impact-induced foot-ankle-leg injuries are developed using this approach, deficiencies are apparent. The objective of this study is to present an improved, robust and generalizable methodology in an attempt to resolve these issues. It includes: (a) statistical identification of the most appropriate independent variable (metric) from a pool of candidate metrics, measured and or derived during experimentation and analysis processes, based on the highest area under the receiver operator curve, (b) quantitative determination of the most optimal probability distribution based on the lowest Akaike information criterion, (c) supplementing the qualitative/visual inspection method for comparing the selected distribution with a non-parametric distribution with objective measures, (d) identification of overly influential observations using different methods, and (e) estimation of confidence intervals using techniques more appropriate to the underlying survival statistical model. These clear and quantified details can be easily implemented with commercial/open source packages. They can be used in retrospective analysis and prospective design of experiments, and in applications to different loading scenarios such as underbody blast events. The feasibility of the methodology is demonstrated using post mortem human subject experiments and 24 metrics associated with thoracic/abdominal injuries in **side-impacts**.

55 **Key words:** biomechanical experiments, confidence intervals, impact loading, probability
56 curves, survival analysis
57

Introduction

Injury risk curves for military and automotive crashworthiness evaluations and for advancing occupant safety are developed using data from post mortem human subject (PMHS) experiments (Arbogast and Maltese, 2015; Petitjean et al., 2015; Rupp, 2015; Salzar et al., 2015; Wang et al., 2015; Yoganandan et al., 2014; Yoganandan et al., 2016; Yoganandan et al., 2013). Simple binary regression models have been used in the literature (Cavanaugh and Yoganandan, 2015; Kuppa et al., 2003; Philippens et al., 2009; Seipel et al., 2001). Survival analyses with different censoring assumptions have been used to develop injury models in biomechanics (Cutcliffe et al., 2012; Kent and Funk, 2004). The ISO/TC22/SC12/WG6 working group of the International Standards Organization (ISO) evaluated parametric and non-parametric methods used by researchers in the automotive field and suggested a unified and improved approach to obtain injury risk curves from retrospective PMHS tests. Survival analysis was recommended because of its ability to accommodate differing censoring status from experimental outcomes. This approach has the substantial advantage of incorporating the biomechanical knowledge beyond simple sensor data into the analysis.

Steps in the ISO approach are: (1) collecting data, (2) assigning censor status, (3) checking for multiple injury mechanisms, (4) separating samples by injury mechanism, (5) estimating distribution parameters, (6) identifying overly influential observations, (7) checking the distribution assumption, (8) choosing the distribution, (9) checking the validity of predictions against existing results, (10) calculating 95% confidence intervals, (11) assessing the quality index, and (12) recommending one curve per body region (Petitjean et al., 2012). The

suggested approach has been applied to derive risk curves for thoracic and abdominal injuries in nearside-impacts (Petitjean et al., 2012). In addition, survival analysis-based probability curves for foot-ankle-leg injuries resulting from the axial loading mechanism differed from simple logistic regression-based risk curves (Yoganandan et al., 2014). While the 12 steps in the ISO procedure appear to be detailed, they do not address all the nuances of the problem and deficiencies.

First, the ISO approach does not discuss the choice of biomechanical parameters for the model since it is common to gather more than one metric in any experiment. The Akaike information criterion (AIC) is the suggested in the ISO approach to choose a statistical distribution. The criterion is an ordinal score which can be used as a simple tool to rank probability distributions, for example, Weibull, log-normal and log logistic. The AIC scores can however, over-fit in a statistical model, and is known in the statistical literature to be asymptotically inconsistent (Findley and Ching-Zong, 2002). The ISO approach also recommends comparing the chosen distribution with a non-parametric fit through visual examination of the Quintile-Quintile (Q-Q) plot and an overlay of the fitted risk curve to a non-parametric risk curve. However, it does not suggest any quantitative measure for comparison.

Further, the ISO recommends the use of the dfbetas statistic to determine overly influential observations. The statistic is a measure of the influence of a data point for each model parameter. It corresponds to the difference between the parameter value when calculated with the data point present and the value when the data point is dropped from the sample. Several versions of this statistic corresponding to different methods of computation are

available. The ISO approach does not suggest methods for identifying outlier(s). The calculation of confidence intervals for survival regression generally relies on asymptotic approximations, for which many established methods exist. The ISO approach does not specify the method to determine confidence intervals.

The objective of this study is to improve these procedures and provide a robust statistical framework to derive risk curves for injury biomechanics and other applications. This effort is attempted to resolve fundamental ambiguities in the ISO approach for deriving risk curves, and it demonstrates the feasibility using an example from published set of experiments. This procedure can be used in sub-component and whole body PMHS tests and for applications to different loading environments including military situations such as underbody blast events, automotive and others. All statistical analysis described can be implemented with commercial statistical packages such as SAS and public license software such as R-code.

Methods

The following steps describe the improved methodology. The flow chart is provided (Figure 1). The words risk and probability are used synonymously throughout the paper.

Input data

Input data includes PMHS information such as demographics, external loading scenarios, injury outcomes and biomechanical metrics. Demographic data such as age and sex, bone mineral density, body mass index, and certain specimen anthropometry (bone or spinal column length for sub-component and stature for whole body PMHS experiments) can serve as categorical or

continuous co-variates. Loading scenarios such as single or repeated applications of the external load can be used to associate the injury or injury severity identified from the experiment with the biomechanical metric. Biomechanical metric(s) can be an individual parameter such as the peak force, deflection, or, combined parameters such as accelerations from different levels of the ribs and spine, associated with the injury mechanism/experiment under consideration. Metrics with no injury are considered as right censored. The metric is treated as left censored if the timing of injury is unknown. In contrast, it is considered as exact or uncensored if the experimental design, instrumentation and signal analysis allow the determination of the precise timing of injury. If repeated tests are included in the experimental design, interval censoring can be used with non-injury and injury outcomes: right censoring associated with the highest severity non-injury test and left censoring associated with the injury test. However, if the repeated testing protocol does not result in injury, the metric from the highest severity test is used as right censored.

1. Choose the most optimal biomechanical metric based on highest Area under the Receiver Operator Curve (AROC): Though multivariate survival analyses have been developed, survival regression often uses one variable as the primary independent variable (often the time variable in medical statistical analyses) (Guo and Rodriguez, 1992). In the presence of several biomechanical metrics, it is therefore important to decide which variable is most likely to produce the best statistical model – the variable best able to distinguish between injury outcomes.

The proposed methodology involves the determination of the AROC for all biomechanical metrics. It represents a measure of the predictive ability of the metric in terms of specificity and sensitivity. The biomechanical metric producing the highest AROC is the most appropriate metric for further analysis.

2. Choose the most optimal candidate probability distribution based on lowest AIC: The next step is to choose the most appropriate probability distribution to be used with survival regression, which is typically done under a non-parametric (distribution free) or under a parametric setup. A parametric setup is often advantageous because of its flexibility and generally results in smoother risk models, i.e., accommodation of differing censor status and covariate combinations (Royston and Parmar, 2002). However, the parametric setup requires additional assumptions: most importantly that the unknown data generating distribution is close to the statistical distribution being used. The Weibull, log-normal and log-logistic are the commonly used distributions with survival regression. For each of these distributions, it is possible to assess fit and the distance from the non-parametric model (described later).

The proposed methodology calculates the AIC for each of the standard probability distributions used in the parametric survival regression models. The candidate probability distribution with the lowest AIC is identified as the most optimal distribution function among the candidates.

3. Compare with Kolmogorov-Smirnov (KS) tests: The proposed methodology involves calculating the KS p-value for that distribution with the lowest AIC. The goodness-of-fit test (based on the distance of the fitted candidate from the non-parametric fit) with very low p-values, i.e., $p < 0.05$, indicate a poorly fitting distribution. If the p-value exceed the set criterion ($p = 0.05$), the next step would be to identify the overly influential observations, described in 4, below. If not, the distribution with the next higher AIC is selected (e.g., log-logistic), and the process is repeated. If all distributions do not meet the criterion, then, the metric associated with the next highest AROC is selected and the entire stated process is repeated, 1, above.

4. Identify overly influential observations based on the dfbetas statistic: This involves deleting one observation/data point 'at a time' and determining the dfbetas statistic. The statistic corresponds to the difference between the coefficients of the model with the inclusion of all data points and the coefficient with one data point excluded from the ensemble. It can be computed on the basis of any moment or parameter of the chosen probability distribution.

The proposed improved methodology involves computing the statistic based on the location, shape and scale. The excluded data point is considered to be overly influential when the value of the statistic exceeds the magnitude defined as follows: $2/\text{square root}$ of the sample size of the ensemble (Belsley et al., 1980). All overly influential sample points might represent erroneously recorded observations. Therefore, they all should

be checked carefully for accuracy by the team that conducted the actual experiments and raw data analysis. In the absence errors, the experimental group and the subject matter expert should decide regarding the exclusion of any of these overly influential observations, while underscoring that exclusion(s) might lead to leptokurtic distributions and under-represented data variance.

5. Determine confidence intervals (CI) and Normalized Confidence Interval Size (NCIS): The methodology involves the determination of the CI for the risk curve obtained in the previous step using the delta method, an asymptotic normal approximation for the distribution of the estimated risk (Parr, 1983). The NCIS quantifies the mean and upper and lower CI curves at discrete probabilities. It is defined as the ratio of the width of the CI to the magnitude of the predictor variable/stimulus from the chosen model at a specific risk level. It is given by the following equation (UL and LL represent the upper and lower limits of the CI and μ represents the mean value of the metric at the chosen risk level). A lower NCIS magnitude is associated with a tighter confidence interval at the chosen probability level.

$$NCIS_{risk \%} = \frac{(CI_{UL} - CI_{LL})_{risk \%}}{\mu_{risk \%}}$$

Application to **side-impact** PMHS experiments

The improved methodology is demonstrated using experiments conducted at the Medical College of Wisconsin, a dataset used to derive injury criteria for the ES2-re anthropomorphic

test device (Kuppa et al., 2003). Briefly, experiments were conducted using whole body Post Mortem Human Subjects (termed as specimens or PMHS) to determine side-impact responses simulating automotive environments. Different velocities, padding and rigid load wall conditions, offsets, and supplemental restraint systems, i.e., with and without side-impact airbags, were used. Specimens were seated erect on a custom Teflon-coated seat, fixed to the sled platform. A stationary load-wall was rigidly attached to the sled platform at the left end of the seat, as viewed from its back. The sled delivered the pre-chosen impact velocity to the seat and specimen. The specimen traversed laterally from right to left and contacted the load-wall upon the application of the lateral acceleration pulse from the sled equipment. The test setup is shown (Figure 2). Biological outcomes consisted of injury and non-injury information, identified during autopsy and imaging techniques.

All specimens were subjected to single lateral impact loading. A total of 24 metrics were chosen from 30 tests to demonstrate the feasibility of the proposed methodology (Table 2). They included data from different types of sensors: accelerometers for the Thoracic Trauma Index (TTI), peak pelvic acceleration and average spinal acceleration (ASA), and load cells for the thoracic and pelvic forces. Non-injury outcomes were considered as right and injury outcomes (based on MAIS 3+ classification) were considered as left censored data points. The left censoring status was assigned because the timing of injuries to the thorax and abdomen could not be precisely determined from experimental data.

Results

Statistical analysis was conducted using the R-studio software, version 0.99 (R Studio, Inc.). The AROC ordered from highest to lowest is shown (Figure 3). Based on the paradigm shown in Figure 1, TTI was chosen as the most appropriate metric as it had the highest AROC that satisfied the KS p-value criterion. Table 3 shows the results of the analysis. The AIC outputs for the TTI metric were 36.57, 36.89, and 36.95 for the Weibull, log-normal and log-logistic distributions, and hence, the Weibull distribution represented the best distribution among those assessed. The influential observation was found to be associated with data points 22 for both shape and scale, and 25 for scale. However, none were deleted because they were deemed to be accurate from a biomechanical viewpoint. In other words, all data points or test numbers were considered in the subsequent survival analysis. The 95% CI curves obtained using the delta method and the mean risk curve for the predictor variable are shown (Figure 4). The NCIS at 5, 10, 20, 50, 80, and 90% risks are given in Table 4.

Discussion

As stated in the introduction, the objective of this study was to develop an improved methodology to derive injury risk curves using survival analysis. An experimental dataset widely used for injury criteria and computational modeling was selected to demonstrate its feasibility (Kuppa et al., 2003; Vavalle et al., 2013). The methodology was At the outset it should be acknowledged that the ISO working group was tasked to recommend a process for determining injury criteria in the form of probability curves for automotive applications, and the consensus-driven approach was a result of a multi-year collaborative work from an international team of researchers (including the first author of this paper). The

recommendation of the working group (WG6 referred in the introduction section) has been used to derive risk curves from **side-impact** sled tests and foot-ankle-leg PMHS experiments (Petitjean et al., 2012; Yoganandan et al., 2015,a-b). While applying to other body regions and loading environments, it was deemed necessary to re-examine this approach and ensure that the methodology is clear, more general and robust. This was the impetus for the current study.

The use of survival analysis techniques is in accordance with the original recommendation because of the inclusion of censored data. Many metrics are routinely gathered and or derived during post processing from PMHS experiments, and the efficacy of the metric describing a complex biomechanical PMHS impact test is generally not known. The first step is therefore to choose the most appropriate metric from this pool that predicts injury outcomes. The identification of the most optimal metric based on the AROC output is an important and first deviation from the ISO approach. The present statistical analysis assists in the post processing phase, and may also have implications in designing future experiments of similar complexity and or loading. More importantly, however, it underscores the need to gather similar data from physical models if the overall experiment is designed to derive injury assessment risk curves for anthropomorphic test devices, routinely used to improve human safety and crashworthiness in automotive and military environments. The present methodology can therefore, be effectively used for dummy design, evaluation, injury criteria and human safety.

The input data selection involves identifications of likely injury metrics and status, stemming from the same hypothesis, loading paradigm and injury mechanism and severity. It should be

noted that all metrics should be available for each test from the entire experimental dataset (in this study a reduced set was used to ensure this feature). The selection of the group of metrics should be decided by the user. In the event of a missing data point for a specific metric, e.g., TTI, then (1) all data is removed for the subject/cadaver that has the missing TTI information or, (2) all TTI data is removed completely for all subjects/cadavers. The sample size decreases by one in the former option. In the latter option, the number of candidate metrics reduces while maintaining the sample size. This underscores the importance of gathering the full set of biomechanical metrics for each specimen, a factor not emphasized in the current ISO approach.

The assignment of censoring statuses for injuries and non-injuries are based on sensors used in biomechanical experiments: exact censoring used when injury timing is known from experiments, else, left censoring, and interval censoring for repeated tests on the same specimen. Exact censoring can be used with confidence if instruments such as strain gages and or acoustic emission sensors are included in the experimental design and the injury is well characterized using these sensors. For example, a strain gage sensor may provide surface profiles of local deformations of bone, it may not be fully adaptable if fractures initiate from distances farther away from its physical location and to soft tissue injuries such as ligaments and discs. The biomechanical community has yet to develop a consensus for processing acoustic emission signals, which depend on factors such as rate of load application and type of experimental model (isolated long bone, vertebral body, segmented spinal column), as widely varying methods have been suggested based on other disciplines and applied in biomechanical studies (Arun et al., 2014; Cormier et al., 2008; Cormier et al., 2011; Funk et al., 2002; Lockner,

1993; McKay and Bir, 2009; Shridharani JK et al., 2014; Van Toen et al., 2012). From this perspective, it will be prudent to resort to the left censoring scheme to identify injury data points for the development of human injury probability curves from survival analysis. However, the left censored assignment for injury data results in lower estimates. This is a desirable feature for crashworthiness and safety applications.

The newly introduced procedure using the AROC and KS statistics provide important additional statistical information. For example, the AROC statistic is a single measure of the overall predictive accuracy of the model. It is free of distributional or model assumptions, while other parameters such as the Wald statistic used in biomechanics literatures relies on asymptotic approximations (Kuppa et al., 2000). With the same underlying sample, it is meaningful to compare the AROC between methods and different models, for evaluating predictive ability. The ROC curve is obtained by plotting the true positive rate against the false positive rate. The area of the perfect ROC curve is one. The ROC curve with an area of 0.5 indicates that the model is no better at predicting than random guesses.

A distinct advantage of the use of the AROC statistic is that in large datasets it could be made more robust by dividing the sample into training and test sets: the training set on which the survival analysis is fitted and the test set on which AROC is evaluated based on the fit, but was blinded (un-used) during the actual fitting. Cross validation analysis can be done using the held-out sample method which can be used to further reduce over-fitting the distribution (Picard and Cook, 1984; Shao, 1993). The AROC cannot be computed in certain cases, termed as edge

cases. These edge cases involve experimental designs wherein all specimens are tested to injury levels, i.e., no non-injury data points. However, if such a situation arises, the adopted experimental design underscores the need to obtain additional data or alter the methodology such that a reasonable combination of injury and no injury data are obtained. If data acquisition precisely points to the time of injury and consist of only injury tests, the AROC parameter can be ignored for risk curve development for the specific metric associated with the timing issue. Because PMHS tests are often designed to extract more than one mechanical metric as shown in the demonstration dataset, other metrics may be considered left censored which should allow the use of AROC in a carefully planned experimental design.

The KS measures provide quantitative statistical information (Daniel, 1990). Hence, it was selected to assess the best underlying distribution for the specific biomechanical injury metric. The distance- based p-value reflects the difference between the fitted distribution and the nonparametric fit, a quantitative measure for the visual overlay plot, currently recommended in the ISO approach. These visual plots can be used in the qualitative diagnosis of a model. So, this feature is also maintained in the present method. The chosen p-value of 0.05 for the acceptance criterion for KS is often used, but, the end user can tailor the p-value to individual requirements.

The specification of the approximation method to determine the CI of the injury risk curve further provides clarity and statistical robustness to the description of injury risk curves. The recommended delta method has better asymptotic accuracy and variance estimates than a

direct normal approximation for the CI (Parr, 1983). This process tends to produce wider intervals at the tails, resulting in wider NCIS magnitudes. The risk curve confidence is therefore more conservative than for a conventional logistic regression. This method has been applied in recent studies as an extension of the ISO recommendation (Yoganandan et al., 2015; Yoganandan et al., 2014).

The definition of the quality index for the CI data was arbitrary in the ISO approach. In contrast, the NCIS in the present methodology provides a quantitative measure so that the end user can select different threshold values at discrete probabilities, or combine the NCIS data at different risk levels or ranges to achieve individual goals. This feature is attractive in military **data/datasets**. Further, no specific quality indices or their range are proposed because user(s) may have differing objectives. While the choice of the 95% interval is standard in many disciplines, the end user can alter this **value**. For example, the United States military can use this method as its application is different from automotive crashworthiness. Thus, the improved methodology is clearer, and has increased generalizability, flexibility and robustness to derive most optimal human (PMHS) or physical model (dummy/manikin) injury probability curves from a pool of fundamental/recorded and derived data/observations biomechanical experiments. This process may be efficaciously used in retrospective and prospective analysis of impact data from biomechanical tests and in future experimental designs for applications in different crashworthiness disciplines to advance human safety in different environments.

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Figure captions

Figure 1: Flow chart of the statistical process to derive risk curves.

Figure 2: Schematic of the sled test set up for PMHS experiments.

Figure 3: AROC rank ordered by metric.

Figure 4a: A. Injury risk curve for selected metric, TTI, showing 95% confidence intervals.

Figure 4b: Dfbeta plots

Figure 4c: Q-Q plot of the resulting selection.

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Table 1: Data from PMHS sled tests (Kuppa et al., 2003)

ID	lhx_f	abd_f	pel_f	Hdmax	Hdavg	HVmax	HVC	Fdmax	Fdavg	FVmax	FVC	HVavg	HVCavg	FVavg	FVCavg	TTI	ASA	spu	spl	rspu	rspl	riu	rli	pel	MAIS*
6	13033	3139	6893	0.176	0.173	8.6	1.1	0.299	0.267	16.8	1.1	6.13	0.81	14.78	0.95	154	45	51	54	54	56	135	174	57	2
15	7487	3525	8663	0.271	0.226	5.3	1	0.412	0.332	8.8	2.1	4.49	0.74	7.39	1.72	170	63	73	93	74	112	60	130	51	3
31	8682	3759	7745	0.281	0.262	6.1	1.1	0.406	0.366	6.7	2.7	5.64	0.96	6.47	2.04	178	54	56	91	61	95	89	161	56	4
32	9025	3584	8556	0.274	0.224	4.6	0.9	0.421	0.343	6.2	2.8	4.26	0.75	5.6	2.08	180	56	71	62	77	64	129	194	51	4
33	6504	4303	9153	0.268	0.213	11.5	2	0.411	0.365	16.1	6.9	9.75	1.63	13.3	4.97	153	51	58	57	77	64	114	46	44	3
4	3498	1970	5618	0.114	0.104	3.3	0.3	0.176	0.163	5.2	0.5	2.87	0.24	4.78	0.46	154	72	23	68	24	70	37	62	32	0
14	4160	2301	5190	0.32	0.264	5.3	1.2	0.409	0.356	6.7	1.5	4.56	0.96	6.21	1.23	142	34	46	29	49	34	63	111	37	4
18	3691	2187	7869	0.214	0.185	4.7	0.8	0.318	0.259	6.6	1.3	3.77	0.64	4.89	0.87	153	30	42	51	48	53	81	106	35	3
21	4133	2018	7893	0.203	0.148	4	0.6	0.305	0.253	6.2	1.2	3.16	0.36	5.05	0.87	155	23	33	38	34	39	92	111	35	1
35	3046	1634	6012	0.275	0.235	4.2	0.8	0.384	0.320	4.8	1.5	3.61	0.57	3.99	1.08	133	16	22	37	22	38	92	166	51	2
16	3482	758	9067	0.107	0.075	2.5	0.1	0.191	0.148	4.1	0.4	2.48	0.14	3.4	0.3	129	28	26	31	27	32	44	65	23	2
7	16338	3888	9905	0.239	0.219	7.1	1.9	0.395	0.364	10.9	2.2	6.68	1.44	10.16	1.83	158	51	94	62	94	90	88	140	76	2
8	7225	3668	19104	0.292	0.225	10.9	2.3	0.41	0.346	9.7	2.1	8.57	1.46	9.2	1.85	172	34	111	74	117	87	135	125	60	4
11	4395	2393	21071	0.27	0.270	3.9	1	0.37	0.370	7.2	1.2	3.16	0.42	6.33	0.75	202	71	56	54	57	55	132	106	66	3
12	7447	2250	19336	0.291	0.255	6.8	1.5	0.412	0.376	11.8	2.6	6.44	1.29	10.93	2.2	231	125	103	103	112	109	142	164	67	5
3	4975	5314	3372	0.243	0.212	6	1.4	0.394	0.350	7.3	1.9	5.51	1.01	6.74	1.52	160	26	49	51	50	57	183	112	55	3
19	4997	3095	5945	0.215	0.189	5.5	0.8	0.374	0.317	9.2	2.2	4.97	0.64	8.33	1.8	164	46	52	63	54	66	102	95	41	0
20	5744	3414	8972	0.235	0.215	5.2	0.8	0.364	0.325	6.7	1.7	4.58	0.6	6.47	1.25	195	33	47	41	47	50	183	67	46	3
29	4773	2725	9350	0.217	0.152	6.7	1	0.329	0.221	6.4	1.6	4.96	0.6	5.22	0.97	121	17	82	45	82	53	156	167	58	0
30	2992	2735	5456	0.293	0.256	17.6	3.9	0.431	0.391	26	11.8	13.94	3	22.91	9.5	167	22	77	66	77	89	163	278	47	4
34	3769	1990	7339	0.266	0.239	6	1.2	0.407	0.332	6.4	1.7	5.21	0.98	5.57	1.32	142	57	48	59	49	60	121	102	46	4
36	3896	2648	10891	0.207	0.177	11.9	2	0.332	0.278	15.5	3.2	10.45	1.55	14.07	2.7	181	81	66	80	72	84	114	111	57	2
22	4256	8083	4744	0.074	0.066	3.4	0.2	0.117	0.103	4.4	0.4	2.8	0.14	3.79	0.3	150	41	39	41	44	47	121	115	42	3
24	3891	7236	3413	0.144	0.135	4.7	0.5	0.2	0.186	5.3	0.9	4.37	0.41	4.96	0.71	143	43	44	61	52	64	115	130	88	2
26	1704	6905	2847	0.22	0.190	7.9	0.8	0.33	0.300	9.8	1.9	4.92	0.58	7.4	1.41	119	23	57	50	61	52	70	99	62	3
9	3657	559	10838	0.279	0.245	5.5	0.9	0.359	0.324	8.3	1.4	4.77	0.72	7.15	1.1	189	33	79	35	80	38	139	44	54	4
28	9329	532	7787	0.184	0.158	9	1	0.25	0.220	12.2	1.9	7.93	0.87	10.56	1.57	124	11	56	41	63	49	90	94	41	2
38	5112	1680	9229	0.154	0.120	3	0.2	0.229	0.200	3.6	0.5	2.52	0.14	2.75	0.38	111	16	22	18	27	46	28	46	53	0
41	4280	1930	9998	0.284	0.230	6.5	1.2	0.384	0.320	9.5	2	6.06	0.93	8.5	1.62	116	23	22	36	26	37	29	43	60	2
42	3078	2358	7226	0.16	0.150	8	0.9	0.272	0.230	12.2	3	7.06	0.8	10.44	2.06	146	37	28	47	33	50	26	40	51	2

*: MAIS 0= no injury

Table 2. Metric definitions from Table 1 (Kuppa et al., 2003)

Metric	Unit	Definition	Metric	Unit	Definition
abd_f	N	Normalized max abdominal wall force	HVCavg	m/s	Same as FVCavg but with half-width
ASA	g	Average spinal acceleration	Hvmax	m/s	Same as Fvmax but with half-width
Fdavg	mm	Average full-width deflection, normalized	pel	g	Pelvis acceleration
Fdmax	mm	Max full-width deflection, normalized	pel_f	N	Normalized max pelvis wall force
Fvavg	m/s	Average velocity of full-width deflection measure	rl	g	Normalized left lower rib acceleration
FVC	m/s	Max velocity*compression derived from full width	rlu	g	Normalized left upper rib acceleration
FVCavg	m/s	Average velocity*compression derived from full width	rspl	g	Normalized resultant lower spine acceleration
Fvmax	m/s	Max velocity from full-width deflection measure	rspl_u	g	Normalized resultant upper spine acceleration
Hdavg	Ratio	Same as Fdavg but with half-width	spl	g	Normalized lateral lower spine acceleration
Hdmax	Ratio	Same as Fdmax but with half-width	spl_u	g	Normalized lateral upper spine acceleration
Hvavg	m/s	Same as Fvavg but with half-width	thx_f	N	Normalized maximum thoracic wall force
HVC	m/s	Same as FVC but with half-width	TTI	g	Thoracic trauma index

Table 3: Summary of statistical results

No	Variable	AROC	AIC			KS p value		
			LL	LN	WB	LL	LN	WB
3	Fdavg	0.857	39.19	39.92	37.62	< 0.05	< 0.05	< 0.05
9	Hdavg	0.839	38.33	39.12	36.62	< 0.05	< 0.05	< 0.05
4	Fdmax	0.830	40.59	41.11	39.26	< 0.05	< 0.05	< 0.05
10	Hdmax	0.826	39.32	40.03	37.81	< 0.05	< 0.05	< 0.05
24	TTI	0.763	36.95	36.89	36.57	Not computed	Not computed	0.2365

Results after applying statistical paradigm presented in Figure 1. The selected metric, TTI, is shown in bold. P-values below 1×10^{-4} are shown as zero. Results are shown for metrics in the order of the highest AROC and following the flow chart shown (Figure 1), results the analysis is stopped after meeting all specified criteria. WB was used for the TTI metric to derive the risk curve and obtain NCIS because the AIC was the lowest. Hence, it was not necessary to compute the KS statistic for the LL and LN. LL: log logistic, LN: log normal, WB: Weibull, KS - Kolmogorov-Smirnov

Table 4: Normalized confidence interval size (NCIS) and data for the TTI (g) metric based on Weibull distribution, survival analysis.

Risk Level	NCIS	Lower Bound	Mean	Upper Bound
0.05	0.87	62	95	145
0.25	0.38	108	130	158
0.50	0.21	137	153	170
0.90	0.34	161	190	225
0.95	0.40	163	199	243

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Figure 1

Figure 1: Flow chart of the statistical process to derive risk curves.

Figure 2

Figure 2: Schematic of the sled test set up for PMHS experiments.

Figure 3

Figure 3: AROC rank ordered by metric.

Figure 4A

Figure 4B

Figure 4C

Figure4D