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A Review of Injury Risk Curve Development to Support Human Factors and Ergonomic Design under Extreme Loading Conditions

Lebone Mokgotho, Karabelo Sekhuthe and Dithoto Modungwa
Defence and Security, Landward Sciences
Council for Scientific and Industrial Research
Pretoria, South Africa
lmokgotho1@csir.co.za

Abstract

Conducting risk assessments in underbody blast (UBB) scenarios on landmine-protected vehicles is important for evaluating vehicle safety, crew injury risk, and the effectiveness of blast protection systems. Due to the hazardous, costly, and resource-constrained nature of UBB testing, injury risk assessment commonly relies on survival analysis methods to estimate injury probabilities from limited and censored experimental data. This paper presents a structured review of survival analysis methods used to develop lower-limb injury risk criteria under UBB loading conditions. Parametric, non-parametric, and semi-parametric survival models are reviewed and compared with respect to their assumptions, data requirements, and suitability for constrained experimental environments. Emphasis is placed on their application to injury risk curve development for lower extremity injuries. The review highlights methodological strengths, limitations, and practical implications of model selection for engineering decision-making, including risk threshold definition, test evaluation, and validation of protective systems. A limited illustrative dataset is used to demonstrate the application of selected methods. The findings support more consistent and transparent use of survival analysis techniques in injury risk assessment for extreme loading scenarios.

Keywords
Injury Risk Assessment, Underbody Blast, Survival Models, Injury Risk Criteria

1. Introduction
Given the evolving nature of conflicts and the uncertainty of future warfare, enhancing the safety of military personnel during transport in armored vehicles is of great importance. Improvised Explosive Devices (IEDs) and anti-tank landmines (LV) have become a great threat to deployed soldiers, both mounted and dismounted. An Underbody blast (UBB) is an explosive impact that occurs when an IED/LV detonates beneath a vehicle, causing severe harm to the occupants inside the vehicle. UBB from IEDs on military vehicles impart upward accelerations that focus force into occupants' feet and legs.

Risk assessment in UBB scenarios plays an important role in engineering decision-making, informing vehicle safety evaluations, crew injury risk estimation, design optimization, and the validation of numerical simulation models used in blast protection system design and development. However, experimental investigation of UBB events is challenging. Testing is costly, hazardous, and subject to strict safety and ethical constraints, which severely limit the number of experiments that can be conducted. As a result, experimental datasets are typically small, heterogeneous, and often include censored observations where injury outcomes are not fully observed. These characteristics complicate the use of traditional deterministic thresholds and conventional statistical regression techniques for injury risk assessment.

To address these challenges, probabilistic modelling approaches have been increasingly adopted for injury risk evaluation under extreme loading conditions. Among these, survival analysis has emerged as a suitable framework for modelling injury occurrence as a function of biomechanical response measures and test conditions. Survival analysis methods are specifically designed to handle binary outcomes, censored data, and limited sample sizes, making them well suited to constrained experimental environments such as UBB testing. The output of survival models is commonly expressed in the form of injury risk curves, which estimate the probability of injury as a function of a selected response metric and are widely used to support engineering pass–fail decisions and system-level validation.

Survival analysis is a method used to predict/ describe the survival of a particular observation with respect to an event of interest occurring. Survival analysis methods are used to calculate the probability of surviving a specified event, in this case, surviving a vehicle impact, at a particular time. Survival methods are also capable of handling incomplete and missing data. Particularly, in the UBB case, censored data is always present due to the nature of the test and data collection. Thus, the preference for survival analysis techniques is used to determine the probabilities of injury occurrences.

Survival analysis techniques are described as being either parametric or non-parametric or a combination of both, semi-parametric methods. The focus of the paper is the evaluation of these methods in determining Injury Risk Curves for the lower extremities. Parametric methods are built assuming that the data follows an underlying known distribution, while non-parametric methods are built not assuming a known distribution. Both methods, parametric and non-parametric models, have their limitations. The choice between the two approaches depends heavily on the researchers' expertise, the experiment setup, and the quality of data gathered. Considering that at present, there is no accepted standard method preferred for determining IRC, particularly for applications involving extreme loading environments. The parametric methods of focus of this study are the Weibull, Log-normal and Log-logistic. The non-parametric method of focus of this study is the Consistent Threshold. As such, these methods are the most used in the development of IRCs for lower extremities test under UBB conditions.

From an Industrial engineering and operations management perspective, the development of injury risk criteria under UBB conditions represents a decision-making problem under uncertainty, constrained by limited data, high testing costs, and also safety considerations. Survival analysis methods play a critical role not only in statistical modelling, but also in supporting resource-efficient experimental planning, validation of protective systems, and risk-informed design decisions. A structured evaluation of survival analysis approaches is needed to improve the consistency and defensibility of injury risk assessment practices in this domain.

This paper presents a structured review of survival analysis methods used to develop lower-limb injury risk criteria in underbody blast scenarios. The review focuses on comparing parametric, non-parametric, and semi-parametric models with respect to their assumptions, data requirements, and applicability to constrain experimental testing environments. The strengths and limitations of each approach are discussed in the context of engineering decision-making, with particular emphasis on injury risk curve development. A limited illustrative application is included to demonstrate the practical use of selected survival models.

Problem Statement: Risk assessment in UBB scenarios is an important component of engineering validation for landmine-protected vehicles, where decisions regarding vehicle design, crew protection, and system certification depend on reliable injury risk criteria. However, experimental testing in UBB environments is constrained by safety requirements, high costs, limited test opportunities, and ethical considerations. These constraints result in small sample sizes, censored data, and heterogeneous experimental conditions, which challenge the applicability of traditional deterministic statistical methods for injury risk estimation.

Although survival analysis methods have been increasingly used to address these challenges, there is limited guidance on the selection, interpretation, and comparative suitability of different survival modelling approaches for developing lower-limb injury risk criteria in UBB testing. In practice, model choice is often driven by convention or data availability rather than by a systematic evaluation of methodological assumptions, robustness under constrained experimental conditions, and relevance to engineering decision-making. This lack of clarity can lead to inconsistent risk criteria, reduced transparency in validation decisions, and uncertainty in the interpretation of injury probabilities.

1.1 Objectives
This review paper aims to identify and rank the survival models most appropriate for assessing injury risk in underbody blast scenarios. Additionally, it aims to improve the understanding of each model's limitations and their implications for accurately estimating risk levels in blast-related injuries.

2. Literature Review
2.1 Lower-Limb Injury Assessment in Underbody Blast Scenarios
Due to the proximity of the feet to the floor during an UBB, the lower extremities of vehicle occupants are more susceptible to injury. In a typical UBB explosion, the feet are the first part of the body to absorb the force of the blast (Franklyn & Lee, 2017). This force then travels from the foot, through the ankle, and up the leg, affecting the calcaneus, tibia and fibula bones. During a UBB event, there is a localized deformation of the floor which transmits high axial load to the lower extremity, resulting in injuries. In addition to the floor deformation, the blast also causes global vehicle motion due to the kinetic energy from the soil ejecta and blast dynamics, which further increases the loading on the lower extremities of the occupants.

Loftis et al. (2019) highlights the severity of lower limb injuries in this context. In their research, it was found that the most common skeletal injuries were from feet fractures, accounting for 13% of injuries for service members wounded in action, and tibia/fibula fractures, accounting for 10% of injuries for service members killed in action. A study by Voo et al. (2021) investigated the effects of UBB loading on the occupants and found that severe calcaneus fractures and distal tibia fractures were predominant during high-rate impact loading of the lower legs. These injury patterns motivate the development of quantitative injury risk curves that relate forces, accelerations and strains to the probability of sustaining a fracture. In this review, we examine how statistical methods, more specifically survival analysis approaches, have been used to model lower limb thresholds and risk in military-related UBB scenarios.

2.2 Injury Risk Criteria and Probabilistic Modelling
Understanding the threat level faced by the occupants is important in evaluating UBB events and creating safety guidelines, increasing the survival of occupants and minimizing the severity of injuries to limbs. Characterizing the level of the threat faced is a complex problem. The human body's response due to vehicle impact is a complicated process to characterize due to multiple factors such as the positioning of the occupants in the vehicle, the different responses of impact loadings and position and injury mechanisms experienced by different human parts. There are three main injury mechanisms in vehicle impacts: excessive inertial loading, direct trauma from contact with surfaces, and exposure to environmental factors such as fire, water, smoke, etc.

Therefore, the subdivision of the human body is used when characterising injuries from impact. Characterisation of risk of injury is captured in Injury Risk Curves (IRC) developed from survival analysis methods. IRC are injury-specific curves (or are curves developed for each body part), thus the need to appropriately describe the injury in grave detail. The Abbreviated Injury Scale (AIS) is a system used to describe injuries in a systematic manner that is used by multiple researchers and industries, which was developed by the Advancement of Automotive Medicine (AAAM) – created in 1971 (last time updated in 2015).

In the development of Injury Risk Curves (IRC) for lower extremity injuries, both parametric and non-parametric methods have been employed in various studies. Several studies, such as those by Yoganandan et al. (2021), Peres et al. (2021), Mildon et al. (2018), Pellettiere (2012) and Bailey et al. (2015), have utilised a parametric approach, with the Weibull Distribution being the most used model to describe IRC probabilities. Studies by Yoganandan et al. (2021) and Di & Nusholtz (2005) used the log-normal distribution, Yoganandan et al. (2015) and Mildon et al. (2018) used the log-logistic distribution, and Di & Nusholtz (2003) instead applied the non-parametric consistent threshold method.

One of the key studies by Mildon et al. (2018a) focused on the creation of IRCs for pelvis injuries under lateral impacts, human cadaver tests where the demographics and BMI were considered as covariates. The injury risk curve with the lowest Brier score metric value is selected for the final risk curve. Similarly, Pellettiere (2012) aimed to develop an IRC using data from the Total Human Model for Safety (THUMS) for predicting pelvic fractures under side-impact loading using a validated Human Body Model (HBM), where the HBM is calibrated and validated against PMHS experimental data. Multiple IRCs were determined using different parametric methods, where the best choice of the IRC depended on the loading levels.

Meanwhile, Hostetler & Gayzik (2025) developed IRCs for three common injuries using a validated HBM within underbody blast environments. Due to the limit in experimental data, the study uses validated HBM to simulate the blast-induced environment. The injury response captured where for the foot, ankle, tibia and knee, the strain and stress-based criteria are used to define the injury outcome in bones and soft tissue, thus allowing for the identification of injury level in accordance with the AIS.

In another contribution, Mildon et al. (2018) proposed a novel risk function to predict lower limb injuries, specifically tibia fractures from high axial loading. The model improves prediction by incorporating age, sex and body mass as covariates and using loadings measured by an ATD during military blast testing. These covariates enable more accurate injury probability estimates, as human dynamics change over time.

Voo et al. (2021) focused on investigating the severity, type and injury mechanisms caused by the angle of the knee and ankle of the seated occupant and its influence in the development of IRCs under UBB conditions. Both PMHS and ATDs surrogates are used to see the difference in how varying the angle of the seated surrogates has on the incurred injuries. The study found that ATDs are not posture-sensitive while PHMS surrogates are. Further contributions to injury risk modelling have come from Pellettiere (2012), which defined a process for developing IRCs to quantify the risk of injuries in dynamic environments, focusing on neck injury criteria.

The review by Bailey et al. (2015) proposed an approach to improve injury risk functions for lower extremity injuries under high axial loads. Tibia IRCs at high loading rates, in which researchers often use peak tibia force, are often inaccurate due to inertial effects and load sharing with the fibula. Using PMHS data with age, sex, body mass, and dorsiflexion angle as covariates, the study produced improved injury prediction curves. In addition, Di & Nusholtz (2003) reviewed methods for deriving risk curves from biomechanical data from human impact experiments on surrogates, highlighting different approaches to biomechanical risk assessment. These studies reflect the ongoing evolution of injury risk modelling for lower extremity injuries, demonstrating the use of both parametric and non-parametric approaches to enhance the predictive capabilities of IRCs in various injury scenarios.

Probabilistic modelling approaches have therefore been increasingly adopted to estimate injury risk under dynamic loading conditions. These approaches allow injury probability to be expressed as a continuous function of response magnitude, providing greater flexibility for interpretation and application. Among probabilistic methods, survival analysis has gained prominence due to its ability to accommodate binary outcomes and censored data, which are common in injury assessment studies.

Despite the widespread application of survival analysis methods in injury risk assessment, several methodological challenges are still present. Experimental UBB datasets are typically characterised by small sample sizes, censoring, and variability, which complicate model fitting and comparison. Differences in surrogate selection, instrumentation, and injury definition further contribute to inconsistencies in reported injury risk criteria. Existing studies often focus on applying a single modelling approach without systematically comparing alternative survival models or evaluating their suitability for engineering decision-making under constrained experimental conditions. As a result, there is limited guidance on how model selection influences injury probability estimates, risk thresholds, and validation outcomes.

3. Survival Analysis Methods

Survival analysis is an area of study in statistics used to evaluate events of interest that occur within a set period. Survival analysis methods are used to define the probability of survival beyond time t. Survival analysis methods are the preferred statistical methods used to develop injury risk curves due to their ability to accommodate censored data, being able to switch out the time variable for a different monotonic variable, and the ability to create risk curves that start from zero. Censored data refers to when data is incomplete or missing within the period of interest in reference to the event of interest.

In relation to injury risk assessments, examples of censored data are doubly censored data and interval censored data. Doubly censored data refers to both right and left censoring being present. Where right-censored data refers to no injury and left-censored data refers to either a death occurring or being severely injured. Where censored data may arise in biomechanical UBB tests, using PMHS, censorship may come from the PMHS not being injured at the desired loading value, right-censored data, or when the same PMHS is used in multiple tests, the data is considered interval censored. Interval censoring may be considered as doubly censored data, where left censored level of injury already presents on the PMHS, and right-censored data is when the PMHS is severely injured or dead. In comparison to UBB tests done using ATDs, doubly censored data is used as the ATDs can be reset when involved in multiple tests during the same duration. Below, the general procedure of the survival analysis is described.

Defined variables:

T – random variable of the load-to-event. The random variable T can be any continuous monotonically increasing variable, such as acceleration or time.

U – random variable of the right time-to-censoring.

L – random variable of the left time-to-censoring.

X=max {min{T, L}, U} – random variable of the observation. The survival cumulative distribution function is given by;

$$S(t) = P(T > t) = \int_t^{\infty} f(u)du$$

The corresponding probability density functions for the time to event.

$$f(t) = -S'(t)$$

The hazard function describes the instantaneous rate of occurrence of the event of interest, given the survival until time t.

$$\lambda(t) = \frac{f(t)}{S(t)}$$

Where is the baseline function, which is equivalent to the hazard function for individual I with t=0. The covariates have a multiplicative effect on the hazard function, unlike in the AFT case, which has a multiplicative effect on the timeline. $\Lambda(t)$ is the hazard cumulative distribution function.

$$\Lambda(t) = \int_0^t \lambda(u)du.$$

$$S(t) = e^{-\Lambda(t)}$$

Wanting to observe the effects of the covariates, we consider the regression form. The regression form can be studied by introducing a service distribution by considering the transformation, $T = e^Y$.The transformed time variable is given as;

$$Y = \log(T) = \mu + \sigma W$$

Where μ is the mean of the hazard function, σ is the variance and W is the mean-zero error distribution.

Survival functions are categorised as either parametric, non-parametric, or semi-parametric functions. The focus of this review will be on evaluating how efficiently both parametric and non-parametric functions are in assessing injury risk levels. In addition, evaluating the trends in which survival functions are being used in industry and research with relation to biomechanical tests under UBB conditions.

3.1 Parametric Models

Parametric models refer to models that assume that an underlying distribution exists. These models allow for inference and predictions from the assumed underlying probability distributions. These types of models are preferred over other types of models due to researchers being more familiar with the methodology and being able to estimate the parameters in a more efficient manner.

In UBB-related studies, parametric models are often used to develop injury risk curves that estimate the probability of exceeding a defined injury severity level. Their ability to extrapolate beyond observed data makes them attractive for engineering applications, especially when experimental datasets are limited. Parametric models only perform well when the assumed distribution fits the data. When this assumption is incorrect, injury risk estimates may be unreliable, especially when based on the small datasets common in underbody blast experiments.

3.1.1 Proportional Hazard Model and Accelerated Failure Time Model

Many parametric models are written as accelerated failure time models rather than proportional hazard models. Constant hazard fulfils the proportional hazard assumption, but the other way round, it is not always true. Parametric models are either described as proportional hazard models or as accelerated failure time models. The only models that can be described as both are the Weibull and Exponential models.

Given the hazard of 2 individuals, the ratio between the two hazard functions is constant, $\frac{\lambda_1}{\lambda_2} = e^{\theta}$. Due to this assumption, the model does not allow for a change in the covariate effect over the hazard function. The proportional hazard function assumes the hazard ratio to be constant; thus, the effects of the covariates are constant over time.

Under the proportional hazard model, the hazard function and the survival function are given as;

$$\lambda(\mathrm{t}) = e^{\theta}\lambda_0(\mathrm{t})$$

$$\mathrm{S}(\mathrm{t}) = [S_0(t)]^{e^{\theta}}$$

However, unlike the proportional hazard function, the accelerated failure time model is not restricted by the same assumption and allows for the covariates to change over time. The accelerated failure time model is given as;

$$\mathrm{f}(t) = f_0\left(e^{-\theta}t\right)e^{-\theta}$$

$$\mathrm{S}(t) = \mathrm{S}_0\left(e^{-\theta}t\right)$$

$$\lambda(t) = e^{-\theta}\lambda_0\left(\mathrm{e}^{-\theta}\mathrm{t}\right)$$

Where $\theta = (\beta_1 x_1 + \beta_2 x_2 + \cdots + \beta_n x_n)$, denotes the joint effects of the covariates.

The log-transformed T model under AFT,

$$\log(T_i) = \mu + \beta_1 x_{i1} + \beta_2 x_{i2} + \cdots + \beta_p x_{ip} + \sigma \mathrm{W_i}$$

Where μ is the mean value of the assumed distribution, β_j is the coefficient corresponding to covariate j, where $j = 1,2,\ldots,p$ and W is the error distribution with mean 0 and variance σ.

3.1.1.1 Modelling Process of Data Fitting
First, deciding the distribution that best fits the data. Deciding which parametric distribution to use can be determined using multiple methods, such as evaluating the shape of the data or using parametric models used by past researchers. Second, is determining and evaluating the estimated parameters. A popular method used for determining the unknown parameters is the maximum likelihood estimate. Third, assessing the goodness of fit of the distribution with respect to the data. The Brier Metric Score is used to check whether the chosen covariates are most significant in capturing the effects of the response variable.

3.1.1.2 Maximum Likelihood Estimation Method
The maximum likelihood method is used to determine parameter estimates for parametric models.

The likelihood function for doubly censored data is given by

$$L(t,u,l) = \Pi_i^n\left(f(t_i)\right)^{v_i a}\left(S(t_i)\right)^{v_i b}\left(1 - S(t_i)\right)^{v_{ic}}$$

Where;

$$(v_{ia}, v_{il}, v_{iu}) = \left(\mathbb{1}(\text{when event of interest has occured}), \mathbb{1}(\text{when there is left censoring}), \mathbb{1}(\text{when there is right censoring})\right)$$

The corresponding log-likelihood function is given by;

$$log(L) = \Sigma_{t_i \in T} log\left(f(t_i)\right)\Sigma_{t_i \in L} log\left(S(t_i)\right)\Sigma_{t_i \in U} log\left(1 - S(t_i)\right)$$

3.1.2 Parametric models used in injury risk assessment under UBB:
3.1.2.1 Weibull Model
Assume the failure distribution follows a 2-parameter Weibull distribution, $f \sim Weibull(\lambda, \mathrm{k})$ .The Weibull distribution model is given as;

$$\mathrm{f}_0(t) = \mathrm{k}\lambda^{-k}t^{k-1}e^{-\left(\frac{t}{\lambda}\right)^k}$$

Under the proportional hazard model

$$\mathrm{h_i}(t) = e^{\theta_\mathrm{i}}\mathrm{k}\lambda^{-k}t^{k-1}$$

The hazard function is given a;

$$\mathrm{h}(t) = \mathrm{k}t^{k-1}\left(\lambda e^{\frac{-\theta}{k}}\right)^{-k}$$

Which is the hazard function from the $Weibull\left(\lambda e^{-\theta}, k\right)$. The corresponding survival function is given as;

$$\mathrm{S}(t) = e^{-\mathrm{e}^{\theta}\left(\frac{t}{\lambda}\right)^{k}}$$

Under the AFT model,

$$\mathrm{h}(t) = e^{-\theta} h_0\left(e^{-\theta} t\right)$$

$$\mathrm{h}(t) = \mathrm{k}\lambda^{-k}\left(te^{-\theta}\right)^{k-1} e^{-\theta}$$

Which is the hazard function from the $\mathrm{Weibull}\left(\lambda \mathrm{e}^{\theta}, \mathrm{k}\right)$. The corresponding survival and failure functions are given as

$$\mathrm{S(t)} = \mathrm{e}^{-\left(\frac{\mathrm{te}^{-\theta}}{\lambda}\right)^{\mathrm{k}}}$$

$$f(t) = k\lambda^{-k}\left(te^{-\theta}\right)^{k-1} e^{-\left(\frac{te^{-\theta}}{\lambda}\right)^{k}}$$

3.1.2.2 Log Logistic Survival Model

Assume the failure distribution follows the logistic distribution, $\mathrm{f} \sim \mathrm{Log} - \mathrm{logistic}(\mu, k)$. The log-logistic distribution is given as;

$$f(t) = \frac{1}{1 + e^{-\frac{(t-\mu)}{s}}}$$

Under the AFT mode, the baseline hazard function is given by;

$$\mathrm{h}_0(t) = \frac{\mathrm{kt}^{\mathrm{k}-1} e^{m} u}{1 + t^{k} e^{\mu}}$$

The hazard function is given as;

$$h_i(t) = \frac{e^{\mu - k\theta_i} k t^{k-1}}{1 + t^{k} e^{\mu - k\theta_i}}$$

$$\mathrm{S}(t) = \frac{1}{1 + \left(te^{\mu-\theta}\right)^{k}}$$

Which is the hazard function from $log - logistic(\mu - k\theta_i, k)$.

3.1.2.3 Log-Normal Regression Survival Model

Under the AFT model, the corresponding survival function is given as;

$$S_0(t) = 1 - \Phi\left(\frac{log(t) - \mu}{\sigma}\right)$$

$$S_i(t) = 1 - \Phi\left(\frac{log(t) - \theta - \mu}{\sigma}\right)$$

Under the proportional hazard function, the survival function is given as;

$$S_i(t) = \left[1 - \Phi\left(\frac{log(t) - \mu}{\sigma}\right)\right]^{e^{\theta}}$$

3.2 Non-Parametric Models

The non-parametric methods do not assume about the distribution that the data may or may not follow and have fewer conditions or restrictions that need to be met. These methods provide descriptive estimates of survival or injury probability without requiring an assumed underlying distribution. While non-parametric approaches are robust and relatively simple to implement, they are limited in their ability to support predictive modelling.

3.2.1 Consistent Threshold Method

The consistent threshold method is a non-parametric maximum likelihood method and can handle doubly censored data.

The variables are defined as d_i as the number of deaths or severely injured, the number of losses is defined as l_i. The injury probability function is given by;

$$R_i = \frac{d_i}{l_i + d_i}$$

If $R'_1 \leq R'_2 \leq \cdots \leq R'_n$, then the CT function condition is met, $R'_i = R_i$ for $i = 1, 2, \ldots, n$.

If the condition is not met, for the first i for which $R'_i > R'_{i+1}$, replace l_i with $l_i + l_{i+1}$ and replace d_k with $d_i + di + 1$. Remove R'_{i+1} and recompute R'_i. There will now be $n - 1$ values.

3.3 Comparison of Models

Table 1 below provides an overview of the strengths and limitations of the two survival analysis approaches applied to estimate IRCs under UBB conditions.

Table 1. Parametric and Non-Parametric Models Comparison

Method Type	**Strengths**	**Weaknesses**
Parametric	● Well understood mathematically ● Efficient with limited data ● Interpretable parameters	● Requires correct distribution assumption ● Can bias risk estimates if assumptions fail
Non-Parametric	● No distribution assumptions ● Flexible to complex data features	● Requires a bigger database ● Risk curves may be less smooth as the risk function is a step function or harder to extrapolate

4. Illustrative Application of Survival Analysis Methods

This study utilized ATD data collected using the Council of Scientific and Industrial Research (CSIR) drop test rig. The experimental setup focused on the upper tibia, with the ATD fitted with standard army boots to replicate operational loading conditions. The resulting force–time histories were recorded for each test and used for subsequent analysis.

A limited dataset was employed in this preliminary investigation to demonstrate the application of injury risk curve (IRC) development methodologies. Injury severity was characterized by using the Abbreviated Injury Scale (AIS), with the AIS level of interest selected based on injury severity criteria. The corresponding force threshold for the selected AIS level was defined in accordance with NATO standards. For the purposes of this study, a force threshold of 1900 N was adopted. Test outcomes were classified as censored when the absolute peak force did not exceed the defined threshold. An injury event was defined as the occurrence of an absolute peak force greater than 1900 N.

5. Results and Discussion

Among the fitted models, the Weibull and log-normal distributions produced relatively smooth survival curves, as shown in Figure 1(a) and 1(b). This behaviour indicates stable hazard behaviour across the range of applied force levels. The smoothness of these curves reflects the flexibility of the Weibull and log-normal distributions in representing monotonic or gradually changing injury risk, which is commonly expected in injury risk modelling applications. In contrast, the log-logistic model, shown in Figure 1(c), produced a comparatively less smooth curve, indicating greater sensitivity to the limited data available.

Injury risk curves are often expected to exhibit an S-shaped profile, reflecting a gradual transition from low to high injury probability as the response metric increases. However, in this illustrative application, the dataset was small and contained only a single right-censored observation. As a result, the injury risk curves derived from both the Weibull and log-normal models displayed a concave shape rather than the conventional S-shape form. This outcome highlights the influence of sample size and censoring on the shape of estimated injury risk curves and underscores the importance of cautious interpretation when working with constrained experimental data.

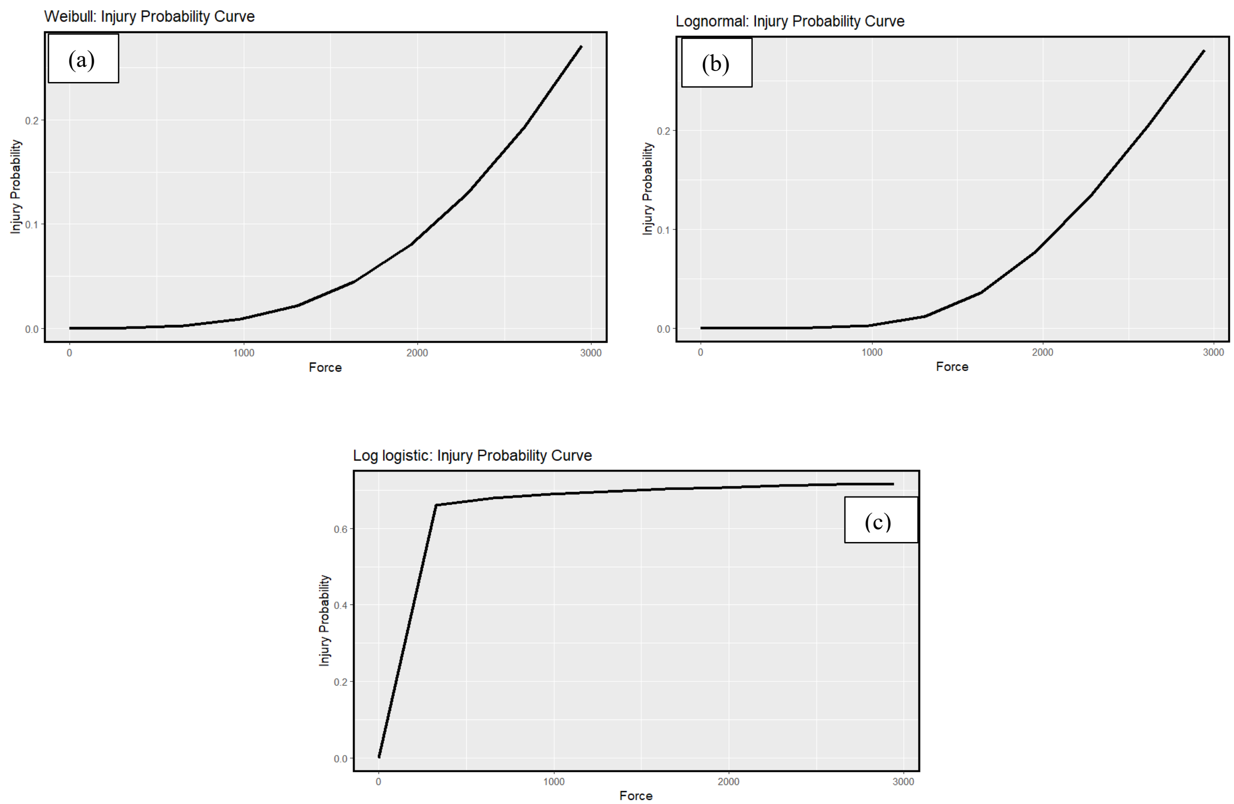

Figure 1. (a) Weibull (b)Log Normal and (c)Log Logistic Injury Probability Curves

Figure 2 presents an example of a consistent threshold injury probability curve. The term "consistent threshold" originates from the statistical approach used to estimate injury probabilities, where model parameters are selected to maximise the likelihood of the observed data (Yoganandan et al., 2014). While this approach is theoretically well founded, its application to very small datasets can lead to unstable results.

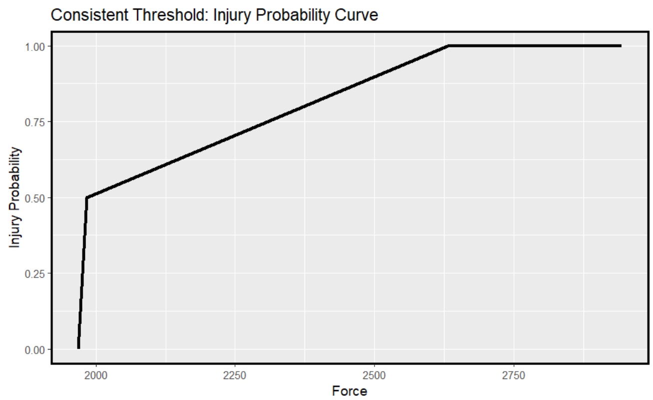

Figure 2. Consistent Threshold Injury Probability Curve

Table 2 refers to the goodness of fit of the three parametric models of interest. The log-normal distribution demonstrates better performance relative to the log-logistic and Weibull models, as evidenced by their lower AIC and BIC values. Both the AIC and BIC evaluate model adequacy by balancing the log-likelihood against the number of estimated parameters. While the AIC is sensitive to sample size and tends to decrease as the sample size increases, the BIC incorporates a penalty for models with larger samples. Consequently, the joint consideration of AIC and BIC provides a more robust basis for model comparison. In addition, the log-normal model yields the highest log-likelihood value, further indicating its superior fit compared to the log-logistic and Weibull distributions.

Table 2. Goodness of Fit Measures

Model	AIC	BIC	Log-Likelihood
Weibull	23.96938	23.5529	-10
Log-normal	23.69175	23.27527	-9.8
Log-logistic	23.89456	23.47808	-9.9

From these results, it can be concluded that there is a need to evaluate survival model behavior alongside data characteristics when developing injury risk curves. Rather than relying on a single modelling approach, comparative assessment of multiple survival models can provide valuable insight into uncertainty.

5.1 Proposed Improvements

Based on the reviewed literature and identified methodological gaps, several improvements are proposed to enhance the development and application of injury risk curves for lower-limb assessment under extreme loading conditions.

i. Survival analysis should be more closely integrated into experimental planning processes. Using probabilistic risk estimates to inform test matrix design, prioritize measurements, and allocate limited testing resources can improve efficiency while maintaining safety and data quality.
ii. The development of guidance or frameworks for survival-based injury risk curve development would support greater standardization across laboratories.

5.2 Validation

In the reviewed literature, validation is usually done by checking whether the models behave in a logical and consistent way. This includes comparing how different models perform across datasets and assessing whether the predicted injury risk follows known injury trends. Parametric, non-parametric, and semi-parametric survival models are evaluated based on whether they produce smooth and realistic injury risk curves, handle censored data correctly, and remain stable when only small datasets are available. Models that are overly influenced by individual data points or produce unrealistic predictions outside the data range are generally considered less suitable for engineering applications.

In this study, validation is further supported by using a limited illustrative example based on experimental data obtained. The aim of this example is not to define final injury thresholds, but to show how selected survival analysis methods can be applied in practice and to examine the consistency of the resulting injury risk curves. The model outputs are assessed for reasonable trends, ease of interpretation, and consistency with established engineering understanding of lower-limb response under extreme loading conditions.

6. Conclusion

This paper reviewed different survival analysis methods used to develop lower-limb injury risk curves for underbody blast scenarios. Because underbody blast testing is dangerous, expensive, and difficult to perform, only small amounts of data are usually available, and some results are incomplete and inconsistent. For this reason, probabilistic modelling methods are important for estimating injury risk and supporting engineering decisions.

The review showed that parametric, non-parametric, and semi-parametric survival models each have their own strengths and weaknesses. Parametric models, especially Weibull-based models, are commonly used because they are flexible, well understood, and can produce smooth injury risk curves even with small datasets. However, their accuracy depends on how well the chosen statistical distribution matches the data. Non-parametric methods are more robust when the correct distribution is uncertain and can represent injury trends realistically, but they are limited in their ability to predict beyond the available data. Semi-parametric models provide a balance between flexibility and ease of interpretation but rely on certain assumptions that must be carefully checked.

References

Bailey, A.M., Mcmurry, T.L., Poplin, G.S., Salzar, R.S. & Crandall, J.R., Survival Model for Foot and Leg High-Rate Axial Impact Injury Data, Informa UK Limited, 2015.

Chirvi, S. & Pintar, F., Human foot-ankle injuries and associated risk curves from under body blast loading conditions, *SAE Technical Papers*, 2017.

Davidsson, J., Carroll, J. & Hynd, D., Set of injury risk curves for different sizes and ages, *Chalmers Publication Library*, 2013.

Di, L. & Nusholtz, G., Comparison of Parametric and Non-Parametric Method Determining Injury Risk, *SAE Technical Papers*, 2003.

Di, L. & Nusholtz, G., Estimation of Injury Risk for Biomechanical Impact Data, *Proceedings of the Thirtieth International Workshop*, 2005.

Grigoriadis, G., Carpanen, D., Webster, C.E., Ramasamy, A., Newell, N. & Masouros, S.D., Lower Limb Posture Affects the Mechanism of Injury in Under-Body Blast, *Ann Biomed Eng*, 47(1):306-316, 2019.

Hostetler, Z.S. & Gayzik, F.S., Lower Extremity Injury Risk Curve Development for a Human Body Model in the Underbody Blast Environment, *J Biomech Eng*., 146(3):031006, 2024.

Mildon, P.J., White, D., Sedman, A.J., Dorn, M. & Masouros, S.D., Injury Risk of the Human Leg Under High-Rate Axial Loading, *Human Factors and Mechanical Engineering for Defense and Safety*, 2018a.

Mildon, P.J., White, D., Sedman, A.J., Dorn, M. & Masouros, S.D., Injury Risk of the Human Leg Under High-Rate Axial Loading, *Human Factors and Mechanical Engineering for Defense and Safety*, 2018b.

Pellettiere, J.A., Development process of injury risk curves, *Proceedings of the 2012 SAFE Symposium*, 2012.

Peres, J., Auer, S. & Praxl, N., Development and comparison of different injury risk functions predicting pelvic fractures in side impact for a Human Body Model, *Proceedings of IRCOBI Conference*, 2016.

Voo, L., Gayzik, S., Baker, A., Hsu, F.C., Pintar, F., Banerjee, A., Yoganandan, N., Bass, C., Cutcliffe, H., Zhang, J., Rupp, J., Drewry, D., Montoya, M., Barnes, D. & Loftis, K., W0063 Guidance Document for Human Injury Probability Curves (HIPCs) Development Biomechanics Product Team, Version 1.4, 2020.

Voo, L., Ott, K., Metzger, T., Merkle, A. & Drewry, D., Severe Calcaneus Injury Probability Curves Due to Under-Body Blast, *Ann Biomed Eng*, 2021.

Webster, C.E. The blast pelvis thesis. Imperial College London, 2017.

Yoganandan, N., Arun, M.W., Pintar, F.A. & Szabo, A., Optimized lower leg injury probability curves from postmortem human subject tests under axial impacts, *Traffic Injury Prevention*, vol. 15, no. sup1, pp. S151–S156, 2014.

Yoganandan, N., Arun, M.W.J., Pintar, F.A. & Banerjee, A., Lower Leg Injury Reference Values and Risk Curves from Survival Analysis for Male and Female Dummies: Meta-analysis of Postmortem Human Subject Tests, *Traffic Injury Prevention*, 2015.

Yoganandan, N., Chirvi, S., Pintar, F.A., Uppal, H., Schlick, M., Banerjee, A., Voo, L., Merkle, A. & Kleinberger, M., Foot–ankle fractures and injury probability curves from post-mortem human surrogate tests, *Annals of Biomedical Engineering*, vol. 44, no. 10, pp. 2937–2947, 2016.

Yoganandan, N., Chirvi, S., Voo, L., Devogel, N., Pintar, F.A. & Banerjee, A., Foot-ankle complex injury risk curves using calcaneus bone mineral density data, *J Mech Behav Biomed Mater,* 2017.

Yoganandan, N., Rooks, T.F., Chancey, V.C., Pintar, F.A. & Banerjee, A., Pelvic Injury Risk Curves for the Military Populations from Lateral Impact, Military Medicine, vol. 186, pp. 424-429, 2021.

Biographies

Lebone Mokgotho holds a Bachelor of Science (Hons) degree in Mathematical Statistics from the University of the Witwatersrand, South Africa. She is currently employed at the Council for Scientific and Industrial Research (CSIR) as a Graduate in Training within the Defence & Security sector. Her research interests focus on survival analysis, particularly in modelling and assessment of crew survivability in military

Karabelo Sekhuthe is a candidate Mechanical Engineer within the Defense and Security Cluster at CSIR where she works with test and measurement with a focus on crew survivability and blast testing. She holds a BScEng (Hons) degree from the University of Cape Town and is currently pursuing a Master of Engineering degree in Biomedical Engineering. Her research interests include material characterization, impact mechanics, and trauma biomechanics.

Dr. Dithoto Modungwa holds a PhD in Electrical and Electronics Engineering from University of Johannesburg, South Africa and was a post-doctoral fellow at Tel Aviv University in Israel. Currently she is a Research Group Leader in Landward Science Competency Area of the Defence and Security Cluster of CSIR. She is currently involved in research and development in vehicle mobility and unmanned systems with applications in the Defence space.