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An enhanced method for evaluating the effectiveness of protective devices for road safety application

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ABSTRACT

This paper presents an enhanced probabilistic approach to estimate the real-world safety performance of new device concepts for road safety applications from the perspective of Powered Two-Wheeler (PTW) riders who suffer multiple injuries in different body regions. The proposed method estimates the overall effectiveness of safety devices for PTW riders by correlating computer simulations with various levels of actual injuries collected worldwide from accident databases. The study further develops the methodology initially presented by Johnny Korner in 1989 by introducing a new indicator, Global Potential Damage (GPD), that overcomes the limitations of the original method, encompassing six biomechanical injury indices estimated in five body regions. A Weibull regression model was fit to the field data using the Maximum Likelihood Method with boundaries at the 90% confidence level for the construction of novel injury risk curves for PTW riders. The modified methodology was applied for the holistic evaluation of the effectiveness of a new safety system, the Belted Safety Jacket (BSJ), in head-on collisions across multiple injury indices, body regions, vehicle types, and speed pairs without sub-optimizing it at specific crash severities. A virtual multi-body environment was employed to reproduce a selected set of crashes. The BSJ is a device concept comprising a vest with safety belts to restrict the rider's movements relative to the PTW during crashes. The BSJ exhibited 59% effectiveness, with an undoubted benefit to the head, neck, chest, and lower extremities. The results show that the proposed methodology enables an overall assessment of the injuries, thus improving the protection of PTW users. The novel indicator supports a robust evaluation of safety systems, specifically relevant in the context of PTW accidents.

1. Introduction

Establishing injury metrics represents a crucial first step in safety research, but it is also essential to correlate these metrics with the likelihood of injury. Two methods can be employed to establish this correlation: one involves the definition of an absolute threshold that the injury metric must not exceed, while the other entails defining a probability distribution function that quantifies the injury risk. The first method has been the standard approach of running tests in a controlled laboratory environment with the evident advantage of using a pass/fail standard to analyze the outcomes (Korner, 1989). However, the second method has the advantage of giving a probability of injury, which is a more realistic criterion..

The evident drawback of the pass/fail method is that the measured limits offer too much simplification in some instances, and generally, it does not apply to all individuals. Such a method assumes that all individuals have the same ability to tolerate injuries and that injuries only happen when the impact severity threshold is met or exceeded. This assumption presents evident limitations because factors like age, sex, weight, and height are recognized to impact a person's vulnerability to injuries (Chong et al., 2007; Klug et al., 2023; Korner, 1989; Richardson et al., 1996; Ryan et al., 2022). Thus, a more appropriate methodology for evaluating protection performance is a probability approach that considers the entire range of crash severities and describes the distribution of the injury risk.

To the authors' knowledge, the first attempt in this direction was made in 1978, when the quantity of risk in sustaining an injury, advocating for distributions of crash speeds rather than for unique values, was proposed with the name of Injury Probability Integral (Searle et al., 1978). In the same work, road safety was defined as "inherently a statistical subject, concerned with probabilities and trade-offs, with correlations and significance", and the authors pointed to single-test configurations as responsible for making it lose this definition. Therefore, a probability-based approach is the most appropriate for a robust

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evaluation of the safety performances.

Such a probabilistic approach was originally published by Johnny Korner in 1989 for Volvo Car Corporation (Korner, 1989). His article outlined a technique for evaluating the overall effectiveness of safety designs across the range of crash severities. By correlating accidents with laboratory test data, a dummy response function can be developed and converted into an injury probability versus crash severity function for a specific safety device and a selected crash mode, namely a specific impact configuration. The overall injury reduction of the safety device can be easily assessed by using the crash severity distribution of that crash type.

The primary strength of Korner's approach is the possibility of evaluating a device concept even before its introduction to the market by correlating real-world accident data and laboratory tests or computer simulations; the primary limitation was that Korner considered only one injury mechanism at a time. Specifically, he chose the Thoracic Trauma Index (TTI) to correlate with the side impact test of car-to-car accidents, as he deemed TTI the best estimator of thoracic injuries (Korner, 1989).

However, the protection of the whole body is utterly important, especially for riders, for the following motivations: 1) high mortality rate is not related to a single critical body region (Directorate General for Mobility and Transport, 2018; Amadasi et al., 2016); 2) multiple injuries on two or more body regions are consistently represented in crashes involving Powered Two-Wheeler (PTW) riders (Aarts et al., 2016); 3) protective devices, such as leg protectors, may lead to augmented injuries due to a transfer-of-injury mechanism (Bracali et al., 2019; Pallacci et al., 2019; Rogers and Zellner, 1998; Tadokoro et al., 1985).

Consequently, the most relevant scientific literature, from the authors' perspective, that directly cited Korner's method in the following thirty-four years was revised to acknowledge any possible development of the original method, question the method itself, and seek its limitations or possible advances.

The first study in chronological order was published by Hugo Mellander, who demonstrated that with Korner's method, it was possible to infer expected injury reduction in real accidents for a new device concept called SIPS (Side Impact Protection System) from dummy measurements in tests (Mellander et al., 1989). Later on, Hans Norin published four works where he replaced laboratory tests with computer simulations and mathematical models mapping the tolerance levels versus crash severities and occupants' heights (Norin, 1998, 1994; Norin et al., 1995; Norin and Isaksson-Hellman, 1995). In 2003, Tony Laituri retrieved Korner's method and defined an accumulated injury risk metric (AccIR) to estimate the number of drivers sustaining at least one AIS3 + injury (i.e., serious injury on the Abbreviated Injury Scale, cfr. Paragraph 2.1.3) by weighting the maximum risk among the head, neck, and chest (Laituri et al., 2003): the evident limitation was that each simulation event accounted only for the riskiest injury, underestimating accidents with multiple injuries. In 2005, Korner's method was acknowledged as a fundamental step in the global safety improvement that car occupants had faced in the last thirty years (Isaksson-Hellman and Norin, 2005). In particular, the possibility of correlating real-world crash data with laboratory data was remarked, and the benefits of having in-depth crash databases were highlighted. The benefits of reliable crash data were also mentioned by Magdalena Lindman and Emma Tivesten while estimating autonomous braking systems (Lindman and Tivesten, 2006). Since active safety systems were addressed in their work, Korner's method was implemented with the further assumption that adding a system to reduce the speed of a vehicle would not affect the injury risk in that vehicle but would instead alter the probability density function of crash severity regardless of injury outcomes, i.e., the exposure density. The effectiveness of the device was, therefore, expressed in terms of accidents avoided. In 2010, two decades after the prediction (grounded on Korner's method) by Mellander of a 50 % decrease in AIS3 + chest injuries with the SIPS bag, Lotta Jakobsson demonstrated with an actual reduction in injury of 45 % that the previous prediction was accurate and correct (Jakobsson et al., 2010). Two years later, Richard Morgan retrieved Korner's method in Laituri's variation, using MADYMO simulations to calculate child dummy response over the entire range of field data (Morgan et al., 2012). His field-based methodology focused on child safety design toward a more far-reaching system approach where the entire range of side-impact crash severities and occupant variability were considered. A significant limitation of his work was that the injury risk curves for children were scaled from their adult counterparts and not directly derived from the database. One year later, Andras Bálint developed his work using a dose–response method to estimate the number of injured occupants (i.e., the response) from the injury risk and crash frequency (i.e., the dose) functions, in a similar fashion to what Korner established (Bálint et al., 2013). However, Bálint explicitly claimed that no attempt was made to construct a combined assessment for different injuries and that each injury reduction was not estimated by the typical biomechanical indices but with a points and scores system. In 2015, Mikael Ljung Aust acknowledged Korner as the eminent forefather of prospective studies, typically used to predict the effectiveness of a system before it is deployed in real-world traffic (Ljung Aust et al., 2015). Recently, Jordanka Kovaceva published two articles, introducing a novel application of Bayesian inference so that information from counterfactual simulations is updated with observations from real-world testing (Kovaceva et al., 2022, 2020). In her papers, Korner's method is relegated only to the calculus of the number of people sustaining an injury of the given severity within the selected set of relevant real-world crash scenarios, like in a dose–response approach. As in Lindman's and Tivesten's study, Kovaceva's studies focused on active safety systems; hence, the effectiveness of those systems was evaluated by the exposure variation after introducing the device.

Collective limitations of the presented works encompass that: 1) no study developed new injury risk curves for the sample accidents but preferred exploiting existent literature to infer the risk of injury of specific body regions; 2) as in Korner (Korner, 1989), the estimate of injury reduction was always based on a single injury estimator without adopting a comprehensive evaluation of all body regions. The present study has the ambition to overcome all these limitations, updating the original Korner's method to estimate a combination of injuries on different body regions and develop tailored injury risk curves for PTW users. The updated method will be applied to a prospective application of a passive safety concept device correlating field data with computer simulations to showcase the methodological improvements in a specific crash mode. The tested device is the Belted Safety Jacket (BSJ) (Grassi et al., 2018b). The device has already shown promising potential in previous preliminary studies conducted through a comparative estimate with multi-body (MADYMO) simulations (Perticone et al., 2023a, 2023b). In those papers, the research question around its performance was already answered upon variation in twenty-five crash configurations, closing speeds up to 81 km/h, three PTW styles and five body regions. This manuscript exploits the same virtual setup for MADYMO simulations but focuses on the development of a novel probabilistic approach and the demonstration of its capabilites by examining the effectiveness of the BSJ in a selected subset of accidents. The BSJ is subjected to rigorous examination in the context of real-world head-on PTW-to-car accidents, giving insight on their probabilistic nature, and returning a final unequivocal value of its effectiveness based on the distribution of injuries collected from real-world databases and expressed by injury risk curves.

2. Materials

Hereafter, the paper presents the material definition of the necessary data and resources for applying the methodology to the BSJ case study, while a detailed description of the methodology is provided in the "Theory" section.

2.1. Data collection

Three databases were considered in this study. One of them was extrapolated from the ISO 13232 (ISO 13232–2, 2005), which in turn is made up of two separate datasets: one containing 211 accident cases from Hannover (Germany) (Otte, 1980) and the other including 410 accident cases from Los Angeles (U.S.), (Hurt et al., 1981). To increase the amount of data available in the dataset, the ISO requires that any additional dataset meet specific criteria. These criteria include: (1) involving at least 200 accidents between PTWs and passenger cars, (2) selecting accidents randomly from all available incidents within the region, (3) conducting thorough analyses of the incidents and creating detailed accident reports that include onsite measurements and reconstruction, and (4) having access to minimum impact variables such as identification data of the vehicles involved (collision category, vehicle type, and engine size), contact points (CPs), relative angle, impact speeds, injury data, helmet use, and protective clothing.

The Motorcycle Accident In-Depth Study (MAIDS) (MAIDS, 2009) and the German In-Depth Accident Study (GIDAS) databases were considered in compliance with the above criteria. The MAIDS was created by the Association of European Motorcycle Manufacturers (ACEM) with the support of the European Commission to conduct an extensive in-depth study of motorcycle and moped accidents during the period 1999–2000 in five sampling areas located in France, Germany, Netherlands, Spain, and Italy. A total of 921 accidents were documented and coded, with approximately 2000 variables for each. The GIDAS database has collected data since mid-1999 from road crashes in Dresden, Hannover, and surrounding rural areas. Approximately 2000 accidents of all kinds of road users are collected annually in the regions Dresden and Hanover (Germany).

Abiding by ISO 13232 and serving for the scope of the present paper, only PTW-to-car accidents were selected from these databases.

2.1.1. Crash mode and crash severity

The most representative configuration of PTW-to-car crashes is still a matter of debate, as it depends on how the geometry of the vehicles is discretized. According to ISO 13232–2, head-on collisions (i.e., accidents where the front wheel of the motorcycle hits the front bumper of the car) were the most frequent in number of occurrences. Other studies ranked it second to lateral accidents (PTW front impacting car door panel) but only if the door panel of the car is considered for its entire length (from the front to the rear bumpers) as found out in GIDAS and RASSI (Otte et al., 2015; Puthan et al., 2021), otherwise head-on accidents are still the most frequent, as in MAIDS and PIONEERS databases (Grassi et al., 2018a; Mensa et al., 2020). Hence, for the case study of this paper, head-on collisions were selected as the reference crash mode.

Closing speed (ISO 12353-1, 2020) was selected as the proxy for crash severity since, during a collision, riders are usually ejected from their PTWs, and therefore delta-V was not recognized as a valuable crash severity parameter. The closing speed, instead, calculated as the component, along the approach direction, of the relative velocity between the two vehicles before the impact, was considered appropriate to build injury risk curves for riders in a recent study (Ding et al., 2019).

Furthermore, Levene's test was conducted on closing speed variances to verify their independence to ensure that the riders' injuries at a given closing speed depended only on the chosen crash severity and not on the source databases. The test stated that the null hypothesis that the variances were equal across all the databases could not be rejected, Table 1..

Table 1
Kruskal-Wallis's and Levene's tests for the homogeneity of the speed distribution.

	ISO – MAIDS	ISO – GIDAS	MAIDS – GIDAS
Kruskal-Wallis's test	$p_{value} = 0.597$	$p_{value} = 0.113$	$p_{value} = 0.217$
Levene's test		$p_{value} = 0.189$	

A further assessment with the Kruskal-Wallis's test was conducted to check the speed means, as speeds are typically not normally distributed in traffic accidents but are skewed (Cherta et al., 2019). Also, in this case, the p-values in the output from the test showed that the null hypothesis that the speeds were equal across all three databases could not be rejected, Table 1.. Given these statistical tests and the inclusion criteria expressed above (2.1), the three databases were merged.

2.1.2. Data processing

A harmonization was necessary as the 2679 collected accidents were arranged in their original database format, with different variables discretizing their geometry configurations. In compliance with the oldest, MAIDS and GIDAS were converted to match the ISO format, which divided the car side into three parts, or CPs, and the bumpers into two parts, central and lateral, for seven CPs. Similarly, the PTW was divided into four parts: front, rear, and sides. The last variable needed to sketch the accident completely was the relative heading angle (RHA) (i.e., the angle between the vehicle center lines at the time of contact). Since symmetrical collisions were believed to entail the same level of risk for occupants, CPs on the left side of the opposing vehicle (OV) were reclassified as the right side, and the associated motorcycle (MC) side CP was reversed. Consequently, the associated RHA codes were reclassified to give a specular image of it. This categorization, as required in ISO 13232, served to minimize the total number of configurations used to sort the accident databases.

Once the three databases complied with the same geometry variables, the ISO sampling policy was applied to return a comparable and homogeneous dataset of accidents, namely, L3 vehicles (i.e., maximum design speed over 45 km/h and engine capacity more than 50 cm^3), passenger car as OV, PTW without pillion rider, rider in seated position at impact, and testable configuration, that means feasible to reproduce with ease in test or simulations. With such filters, the original dataset was limited to 1412 valid accidents, of which 297 related to head-on cases, i.e., with the frontal MC wheel hitting the frontal OV bumper. In this subsample, the driving speed of each vehicle at collision was checked, and the outliers removed, ensuring a final $\pm 2.698\sigma$ interval (i.e., considering the upper and lower fences of the boxplot whiskers) and leaving 274 valid cases, which were tested before merging in accordance with paragraph 2.1.1. Besides, the accidents with an RHA deviation of more than $\pm 15^\circ$ from the collinearity between PTW and car (i.e., 180°) were discarded for the repeatability of the test and because belts are generally found more effective in collinear full-frontal impacts (Walz, 2003). Thus, the final sample counted 40 accidents from the three merged databases, Table 2..

2.1.3. Injury classification

The scientific 6-degree scale created by the Association for the Advancement of Automotive Medicine (AAAM, 2018) was used to classify the severity of injuries. This scale assigns an Abbreviated Injury Scale (AIS) grade to each injury, determining the degree of severity for different body regions as well as for the entire body with the maximum AIS (MAIS).

The MAIDS injury data were originally coded according to AIS1990/rev.2005 and the GIDAS with AIS1990/rev.2015. On the other hand, the

Table 2
Dataset used in this study.The "÷" sign is here used to denote range of values.

	ISO + MAIDS + GIDAS
Crash mode	Head-on (MC wheel to frontal OV bumper)
Sample size	N = 40 accidents
RHA	$165^\circ \div 195^\circ$
OV speed	0 m/s ÷ 16.4 m/s
MC speed	0 m/s ÷ 25.3 m/s
Crash severity (Closing speed)	5.3 m/s ÷ 41.7 m/s
AIS level	AIS2+ (rev. 1990)

ISO 13232 database, being the oldest, scored injuries with the 1990 revision. Since a univocal correspondence exists only from newer revisions to older ones and not vice versa, MAIDS and GIDAS were recoded to comply with ISO 13232 and create a homogeneous dataset also from the point of view of injury assessment. This study considered injuries from the level "moderate" upwards (AIS2 +), Table 2..

2.2. Simulation set-up

A virtual environment was built to simulate crashes and elicit responses from numerical dummies. The aim was to establish a correlation between actual injuries sustained in the real world and damages recorded in laboratory tests, which was a key aspect of Korner's methodology. The accuracy of the laboratory estimates was critical in this regard, but achieving a one-to-one replica of the real world was not essential as the methodology employed probabilistic approaches that enabled meaningful comparisons without the need for an exact counterpart. Details on the virtual setup and model characterization are provided in two previously published papers (Perticone et al., 2023a, 2023b); hence, in the following sub-Paragraph 2.2.1, the main aspects are reported to elucidate the means for the conducted simulations.

2.2.1. Computer models

The PTWs were modeled in MADYMO to encompass three distinct styles: sport-touring, scooter, and sport, as illustrated in Fig. 1.. Considering their varied sizes and shapes, these styles were selected to represent the current circulating fleet observed in the five European countries in MAIDS. The MAIDS observations indicated that scooters were the most prevalent, accounting for 38 % of the cases reported in both exposure and accident data. The second and third most common PTW styles were sport and sport-touring (the latter referred to as "conventional" in the MAIDS), with 15 % and 14 %, respectively (MAIDS, 2009). Thus, these three PTW styles were considered in this study.

PTW models were modeled in MADYMO employing ellipsoids and facet surfaces. These formulations are both rigid and possess identical contact characteristics, diverging only in their geometric representation. The Geo Metro model, provided online by NHTSA (former NCAC archive) and representative of a small urban car, was selected as the OV because of its low computational effort and broad utilization in recent crash studies (Baranowski and Damaziak, 2021; Bourdet et al., 2021; Kunc et al., 2014; Meng et al., 2020), and it meets all normative requirements to be used in numerical simulations (Bruski et al., 2019). Furthermore, the selection of the Geo Metro was substantiated by a recent study (Perticone et al., 2023c), which found that when assessing collisions between cars and PTWs from a trajectory perspective, there is no particular preference for any specific front-end design among family cars, roadsters, and multi-purpose vehicles. The car model was imported as finite elements, as shown in Fig. 1., to reproduce deformations around the contact point with a high level of detail. The Motorcyclist Anthropometric Test Device (MATD) was chosen as the helmeted rider of every PTW. The dummy wore the BSJ (Grassi et al., 2018b), i.e., the device under assessment, Fig. 1..

The BSJ is a Personal Protective Equipment (PPE) concept that comprises a vest equipped with safety belts at the back, linked to the PTW. A computer model of the BSJ comprises four belt segments affixed to a ring, which connects to the motorcycle frame through a cable that passes through a slip ring and enters the retractor. The vest is a flexible polyamide fabric similar to that used in automobile seatbelts, as the slipring and retractor are from automotive implementation. In the event of rapid deceleration, the retractor releases the seatbelt to a predetermined length, and the cable glides through the slip ring while the seatbelts apply pressure to the vest, securing the rider and reducing the consequences of an impact with the OV.

2.2.2. Configuration runs and injury indices

For a strong correlation between field data and simulations, it is essential that the latter accurately capture the range of vehicle speeds observed in the former. To this end, Table 2. was used to divide the vehicle speeds into sampling increments of approximately 4.2 m/s (equivalent to 15 km/h), and a combination matrix was constructed to generate pairs of accidents to simulate. The MC and OV speeds were respectively divided into five and seven increments, resulting in a total of thirty-two combinations in nine closing speed increments, excluding the three combinations in which both vehicles had a null speed or a resulting closing speed outside the range of crash severities delimited in the accident dataset. Altair HyperStudy was employed to parameterize the model with the identified speed pairs, and the simulations were executed in MADYMO twice for each PTW (for the cases with and without the BSJ) for a total of 192 simulations. As a result, each speed pair represented a point on the spectrum of crash severity established through the field data, and no simulations exceeded either the vehicle speed or closing speed ranges observed in the field data.

Upon completion of 500 ms of simulation, as required in ISO (ISO 13232–7, 2005), automated post-processing was performed to extract the relevant parameters of interest. Six separate injury indices were evaluated as required by the Standard (ISO 13232–5, 2005), including the Generalized Acceleration Model for Brain Injury Threshold (GAMBIT) (Newman, 1986), the Head Injury Criterion (HIC) (Versace, 1971) using the 15 ms formulation, the Neck Injury Index (NII) in its extended form for motorcycle riders (Auken et al., 2005), as opposed to the simplified version typically used for car drivers, (Eppinger et al., 1999), the Chest deflection, and the Viscous Criterion (VC) (Lau and Viano, 1986), which were measured in upper and lower sternum locations, the pelvis residual penetration, and finally, the occurrence of tibia and femur fractures, evaluated at exceeding the threshold values given in the ISO 13232.

3. Theory

Hereafter, a method is presented for predicting the real-world safety performance of a new device concept over the whole range of crash severities where injuries occur. This section is made up of four main parts. The first part exclusively summarizes the paper authored by Korner (Korner, 1989), showing how to create a relationship between the crash severity indicator and the probability of suffering a specific injury on the AIS scale (e.g., AIS2+, AIS3 +). Starting from the second

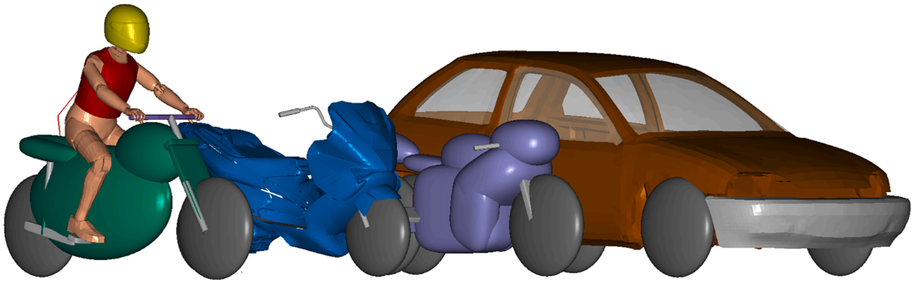

Fig. 1. The three PTWs, the car, the helmeted MATD, and the BSJ used in this study.

part, this manuscript presents a threefold novel contribution to the previous methodology. The second part introduces the simultaneous effect of multiple injuries in different body regions and a new parameter capable of correlating these injuries with whole-body MAIS values. The third part fits a regression model to the newly defined parameter to express an adequate relation with the crash severity indicator when multiple tests are conducted at the same crash severity level. The last part introduces confidence boundaries to the statistical distribution developed in the previous section.

In the following sections, the apostrophe will mark the cases where the safety device is introduced to differentiate the "modified design" from the "baseline design", i.e., the case without the device. Moreover, the term damage will refer to the biomechanical indices estimated from the dummies, while the term injury will denote the bodily harm suffered by real riders and reported in the field data with AIS scores.

3.0.1. Korner's method (Korner, 1989)

This section describes a procedure to predict the overall effect of a protective device over the whole range of crash severities for a selected crash mode. This 'overall effect' is calculated as the percentage effectiveness with respect to the case without the device. The effectiveness (E) is defined as:

$$E = \frac{P(I) - P^{'}(I)}{P(I)} \bullet 100 \tag{1}$$

where $P(I)$ is the injury risk over the range of crash severity of a given crash mode, and it represents the overall probability of injury for a road user exposed to a collision. From a mathematical point of view, it is the integral of the quantity $p(x, I)$ over the whole range of crash severity (x), which expresses the joint probability that crash severity takes a value in the interval $(x, x + dx)$ and that the occupant sustains injury. The integrand is defined as:

$$p(x, I)dx = P(I|x) \cdot s(x)dx \tag{2}$$

where $s(x)$ is the crash severity distribution, which depends solely on field data, and it is supposed to remain unchanged for passive safety technology after the introduction of the device.

Therefore, the quantity to be calculated is the injury probability function $P(I|x)$, which is obviously modified by the presence of the device, being the conditional probability of injury at a given crash severity level. This quantity can be obtained by fitting a probability model to the real-world injuries if these are defined as dichotomous values (e.g., AIS 0–2 and AIS 3–6 or analogous). In this study, as Korner did, the Weibull parametric cumulative distribution (CDF) is implemented:

$$W(x) = P(I|x) = 1 - exp\left[-\left(\frac{x}{a}\right)^{\beta}\right] \tag{3}$$

Thus, the objective is to find the scale (α) and the shape (β) parameters that best represent the field data. The Maximum Likelihood Method (MLM) (Fisher, 1925) is adopted to solve this problem:

$$L(\alpha, \beta) = \prod_{l=1}^{n} f(x_l) \tag{4}$$

or, equivalently, since the function L has its maximum simultaneously with $ln(L)$, the log-likelihood form:

$$ln[(L(\alpha, \beta))] = \sum_{l=1}^{n} ln[f(x_l)] \tag{5}$$

where the $f(x_l)$ is the probability density function (PDF) of the cumulative Weibull distribution over a continuous random variable $x_1, x_2, \cdots, x_n$, namely:

$$f(x_l) = \frac{\beta}{\alpha^{\beta}} x_l^{\beta-1} exp\left[-\left(\frac{x_l}{a}\right)^{\beta}\right] \tag{6}$$

Once $P(I\,|\,x)$ has been calculated with such procedure, the injury probability function after the introduction of the device $P^{'}(I\,|\,x)$ has to be predicted to evaluate the effectiveness (1). At this stage, establishing a correlation between accident data, represented by $P(I\,|\,x)$, and simulated data permits the derivation of an injury probability function, denoted by $P(I\,|\,d)$, which is linked to the response amplitudes of the dummy, $d(x)$ and $d^{'}(x)$, computed respectively for the baseline design and the modified design during two simulation campaigns. Supposing that the chosen cumulative distribution function has the Weibull form, and the dummy response $d(x)$ is represented by a power function (see 3.1.2), then the injury probability function takes the form:

$$P(I|d) = 1 - exp\left[-\left(\frac{\left(\frac{d(x)}{a}\right)^{\frac{1}{b}}}{\alpha}\right)^{\beta}\right] \tag{7}$$

The $P(I\,|\,d)$ is still an injury risk predictor, but the injury probability correlates with the dummy response in lieu of the crash severity. Now, it follows that $P^{'}(I\,|\,x)$ can be obtained in the opposite sense, applying $P(I|d)$ to the new dummy response $d^{'}(x)$, by means of a double variable change. $P(I)$ and $P^{'}(I)$ can be found by the integration of (2) and the effectiveness as in (1).

3.0.2. Global potential damage (GPD)

The objective of this section is the development of Korner's method to overcome the limitation of studying the effect of a design modification on one injury and, thus, a single body region at a time, which is detrimental in the assessment of safety devices intended for the protection of the whole body. Accounting for multiple injuries requires the replacement of the AIS with the MAIS in (3) to account for all the body regions of interest. However, the necessary implication of this change is that the maximum level of injury on the whole body cannot correlate anymore with a specific dummy response for a chosen body region. Hence, the challenge is to find an appropriate measure to express the dummy responses, $d(x)$ and $d^{'}(x)$, so that they can account in simulations for all the body regions for which the MAIS is estimated. The proposed measure, called Global Potential Damage (GPD), is the weighted $(\overline{w}_j)$ sum of the normalized injury indices $(\overline{d}_{ij})$:

$$(GPD)_i = \sum_{j=1}^{N} \overline{d}_{ij} \bullet \overline{w}_j \tag{8}$$

The pre-requisite to calculate this quantity is a matrix made by M rows of the simulated runs and N columns of those injury indices included in the study, selected to comprehensively appraise the overall injury sustained for the given crash mode. The normalization is then performed for every injury j across the maximum of the M rows as:

$$\overline{d}_{ij} = \frac{d_{ij}}{(d_j)_{max}} \tag{9}$$

where the denominator represents the maximum value across the M simulations of the j^{th} index.

The weights in (8) are the results of merging different sets of weights to account for diverse needs and accurately calculate the GPD. One possible approach, indeed, is to initially attribute equal importance to each body region (BR). However, if more than one injury index is associated with the same body region (e.g., GAMBIT and HIC for the head), then the weight for that region must be subdivided proportionally among each index. Therefore, the first set of weights is:

$$w_j^1 = \frac{1}{\#BRs \bullet \#injuryindices(j)perBR} \tag{10}$$

Furthermore, it is necessary to consider that certain injury indices may exhibit a quasi-constant pattern across simulations for a specific crash mode, i.e., remaining similar and hovering around a mean value. Consequently, the variability around the maximum value for the j^{th} column may be limited and incorporating such an index may cause a bias in the results, as the normalized index will frequently be at its maximum value. Therefore, a measure of its scatter can be assessed using Shannon's entropy (Shannon, 1948), where the entropy e is defined as:

$$e_j = -\frac{\sum_{i=1}^{M}\left(r_{ij} \bullet ln\left(r_{ij}\right)\right)}{ln(M)} \tag{11}$$

being r_{ij} the injury index normalized for each run with the sum of the M rows as:

$$r_{ij} = \frac{d_{ij}}{\sum_{i=1}^{M} d_{ij}} \tag{12}$$

Once the entropy has been calculated for every injury index, the second set of weights is defined so that a unitarian entropy for a null scatter will return a null weight and vice versa:

$$w_j^2 = \frac{\left|1 - e_j\right|}{\sum_{j=1}^{N}\left|\left(1 - e_j\right)\right|} \tag{13}$$

Another crucial point is that sometimes, a great scatter in injury indices, i.e., high entropy values, can occur around values far from the levels of significance (l_j) which are typically identified in the literature, Table 3.. Thus, a third set of weights is produced by measuring the ratio between the mean of the injury index and its level of significance:

$$w_j^3 = \frac{\frac{1}{l_j} \bullet \sum_{i=1}^{M} d_{ij}}{\sum_{j=1}^{N}\left|\sum_{i=1}^{M} d_{ij}\right|} \tag{14}$$

Finally, the k sets of computed weights are merged into the set of ($\overline{w}_j$) weights to fulfill all the mentioned necessities:

$$\overline{w}_j = \frac{\prod_{h=1}^{k} w_j^h}{\sum_{j=1}^{N}\prod_{h=1}^{k} w_j^h} \tag{15}$$

Table 3

Injury limits per body region. The 50% AIS3 value was chosen in this study as the level of significance.

Body region	*Injury Index*	*l_j = 50 % AIS3*	*Reference*
Head	*GAMBIT*	*0.95*	(Kramer and Appel, 1990)
	HIC 15	*700*	(Prasad and Mertz, 1985)
Neck	*NII*	*6*	(Auken et al., 2005)
Thorax	*Chest Deflection (mm)*	*50*	(Mertz et al., 1991)
	Viscous Criterion (mm/s)	*1250*	(Lowne and Janssen, 1990)
Abdomen	*Abdomen penetration (mm)*	*115*	(Rouhana et al., 1990)
Lower extremities	*n. of fractures on femurs and tibias*	*2 out of 4*[1]	–

[1] In fracture assessment, a discrete sequence and Boolean logic are utilized to distinguish between the presence or absence of a fracture. AAAM recognizes an AIS3 score for femoral and open tibial fractures. Therefore, to ensure consistency with the rest of injury indices, we established a criterion whereby half of the bones being broken resulted in an assignment of 50% AIS3.

3.0.3. Regression model

Once the GPD is calculated, each simulation returns a unique value to express the global damage estimated by the dummy. However, since from paragraph 2.2.2, each speed interval contains more than one occurrence, a regression model needs to be built to express the dummy response as a single function that associates each value of crash severity with a value of the new indicator, GPD. Assuming a power function ($a \bullet x^b$) to represent the dummy response, a non-linear regression model is fit to the predictor variable (x) to calculate, with the Levenberg-Marquardt non-linear least squares algorithm (Seber and Wild, 2003), the best coefficients (a,b), which represent the simulation results with a constant error ε, i.e., $y = d(x, (a, b)) + \varepsilon$.

Furthermore, if more than one vehicle is considered at a time, as the three PTWs in this study, without any further action, it stated the underlying assumption that each vehicle has the same relevance, i.e., the same frequency in the field data, which is usually unrealistic. In order to address this issue, the frequency data derived from the MAIDS dataset, as previously discussed in paragraph 2.2.1, were used as observation weights when fitting the model function. The observation weights were defined such that a weight of, e.g., two would increase the importance of an observation twofold in the sum of squares of residuals for the desired dummy response function. Consequently, the observation weights on $(GPD)_i$ will be as many as the number of vehicles considered.

3.0.4. Confidence boundaries

This paragraph delineates the construction of a confidence band for each of the cumulative distribution functions $P(I|x)$ and $P'(I|x)$, given a percent confidence value.

Let x be a continuous random variable with cumulative distribution function $F(x, \theta)$ dependent on a vector θ of k unknown parameters. In direct analogy to the standard definition of a confidence region, a $100(1-\overline{\alpha})$ percent confidence band, B, is defined as a region in the $x-y$ plane, in which the graph of the unknown true CDF will entirely lie with probability $1-\overline{\alpha}$. Suppose that a $100(1-\overline{\alpha})$ percent confidence region R has already been constructed and that θ has its values in it. Then, considering the graph $y = F(x, \theta)$ in the $x-y$ plane, we look at how this varies as θ varies. These varying graphs will sweep out an S-shaped region, B, which is the confidence band. As the actual value of θ lies in R with probability $1-\overline{\alpha}$, it follows that the probability of one of the graphs within the confidence band B representing the unknown true CDF of x is at least $1-\overline{\alpha}$. Thus, B serves as a confidence band for $F(x,\theta)$. In essence, the method entails the identification of R, a region for θ with a confidence level of $1-\overline{\alpha}$, where $\theta = (\alpha, \beta)$, since the CDF has the form of a two-parameter Weibull function from (3). Let γ be the value for which:

$$P[Q(\theta) \le \gamma] = 1 - \overline{\alpha} \tag{16}$$

A confidence region R for the unknown θ can be established by including all the θ satisfying: $Q \le \gamma$. Therefore, it is essential to determine $Q(\theta)$. There is not a unique option for it, but in the case of small sample sizes, the Profile Likelihood Ratio (PLR) is usually a suitable choice (Cheng and Iles, 1983):

$$Q(\theta) = -2 \bullet ln\left(\frac{L(\theta)}{L(\widehat{\theta})}\right) = \chi_k^2(\overline{\alpha}) \tag{17}$$

being $\chi_k^2(\alpha)$ the chi-squared statistic for k degrees of freedom and a requested confidence interval of $\overline{\alpha}$, and $\widehat{\theta} = (\widehat{\alpha}, \widehat{\beta})$, the Maximum Likelihood Estimates of θ, which are known after (5) is solved. Consequently, the primary objective is to determine the values of the parameters α and β (i.e., θ), which are the sole unknown variables. Unfortunately, these values must be inferred numerically due to the absence of a closed-form solution for a two-variable equation. One established approach is to fix one parameter while iteratively solving for the other. Following this approach, the likelihood ratio confidence bound for the shape parameter (β) is calculated as:

$$L(W(\alpha,\beta)) = \beta^n \alpha^{-n\beta} \prod_{i=1}^{n} x_i^{\beta-1} exp\left[-\sum_{i=1}^{n}\left(\frac{x_i}{\alpha}\right)^{\beta}\right] \tag{18}$$

The upper and the lower bounds of the $100(1-\overline{\alpha})$ confidence interval for β are then given by the largest and the smallest values of the solution set of the inequation in (16), or equivalently:

$$PLR(\beta) > exp\left[-\frac{\chi_k^2(\overline{\alpha})}{2}\right] \tag{19}$$

or, applying (17):

$$L(W(\widetilde{\alpha},\beta)) > L(W(\widehat{\alpha},\widehat{\beta}))\bullet exp\left[-\frac{\chi_k^2(\overline{\alpha})}{2}\right] \tag{20}$$

where $\overline{\alpha}$ is the maximum likelihood estimator of α, obtained in closed form for a fixed value of β. Subsequently, the identical process is reiterated, with the parameter β kept constant to derive the confidence limits for the parameter α.

4. Results

The results are presented as a case study exemplifying the implementation of the above-mentioned method on the BSJ. The device is tested to verify its capacity to restrain riders, preventing or lowering the injuries in head-on collisions.

As might be expected, the results showed that the GPD has a positive correlation with the collision speed: higher velocities lead to greater injuries overall, Fig. 2.. The solid line represents the regression function, which correlates the crash severity with the GPD observations weighted to account for the three PTW styles, whereas the two dotted lines represent the confidence bounds for the regression curve at 99 % confidence. The coefficient of determination R^2 indicates that the model explains approximately 61 % of the variability in the response variable GPD for the case without the BSJ and 71 % for the case with it. This variability depended primarily on the outcomes exhibited by the scooter, with the highest GPD values among the three styles. Sport-touring and sport styles reported similar values, slightly higher for the former, but with comparable variances. Further, the vertical scatter depended on the speed pairs within each speed interval since the combination matrix introduced in 2.2.2 combined different vehicle speeds in the same closing-speed interval.

The BSJ showed a manifest reduction in GPD along the spectrum of crash severities for the considered crash mode, irrespective of the PTW style. The vertical scatter decreased, with a more similar outcome among the PTWs. From the comparison of the regression curves, the maximum reduction (-0.13) occurred at 22.6 m/s, while the minimum (-0.09) was at 8.3 m/s.

The effectiveness assessment (ISO 12353-1, 2020) of the BSJ was conducted in the tridimensional form initially introduced by Korner. The two dummy response functions illustrated in Fig. 2. were plotted in the crash severity versus the GPD plane, as presented in Fig. 3.. The correlation between the probability of sustaining a MAIS2 + injury based on the overall damage received by the dummy in simulations was depicted in the Injury Risk versus GPD plane. Lastly, the third plane showed the two injury risk curves obtained under two different scenarios, namely without (Baseline Design) and with (Modified Design) the BSJ as a function of the crash severity. The two dotted lines delineated the 90 % confidence interval for the injury risk curves.

According to the results, the BSJ demonstrated an effectiveness of 59.4 %, which indicates that the risk of injury across the entire range of speeds for the selected crash mode was more than halved by the device. Despite the singular effectiveness value, the injury risk curves of the two scenarios did not intersect, ensuring that the BSJ maintained a lower level of maximum injury risk in all speed ranges.

In addition, the effect of the BSJ was also assessed individually on each body region to double-check whether the positive effectiveness calculated through the GPD was in agreement with those estimated with one injury mechanism at a time. The results indicate that the presence of the BSJ had a noticeable positive impact on the head, neck, and chest regions, as demonstrated by a reduction in injury indices and a decrease in the variability among PTW styles, Fig. 4.. However, the BSJ resulted in a slight increment in the abdominal region, which nonetheless remained below the significant threat level (50 % AIS3), as mentioned in Table 3.. The analysis of bony fractures in the lower extremities was conducted separately for tibias and femurs, Table 4.. The BSJ did not cause any new fractures when worn but decreased the odds of suffering from a femur or tibia fracture by 79 % and 61 %, respectively. The odds ratio analysis at the 90 % confidence boundary confirmed a statistically significant inverse correlation between exposure to the BSJ and the probability of leg fractures. In other words, individuals wearing the BSJ have 0.2 times, for femurs, and 0.4, for tibias, the odds of experiencing lower extremity fractures compared to those who do not wear it.

5. Discussion

Building upon Johnny Korner's, 1989 methodology, this study introduces an enhanced method to assess the real-world safety performance of innovative road safety device, focusing on injuries across various body regions to address riders' needs. The approach combines computer simulations with real injury data from global accident databases to gauge the overall effectiveness of rider safety devices through a novel indicator called GPD. This approach is applied to a case study to predict the real-world safety performance of a new device concept for PTW riders, demonstrating its potential in reducing the risk of injury.

The method proposed in this manuscript considered multiple tests within every speed interval, running more speed pairs for each closing

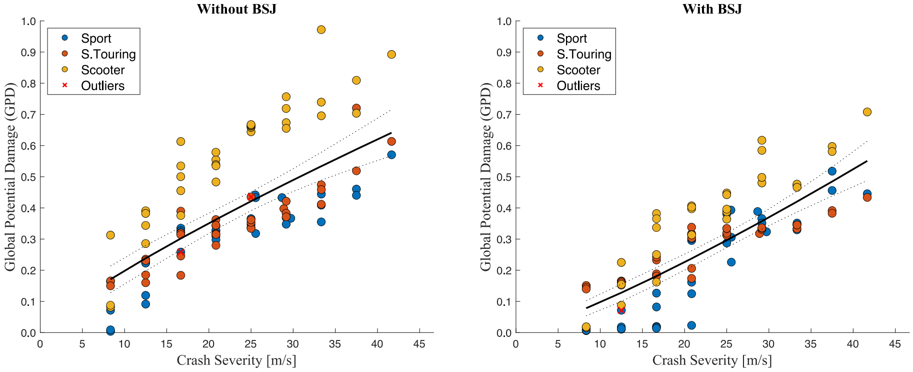

Fig. 2. Dummy responses with and without the Belted Safety Jacket with the regression functions represented by solid lines.

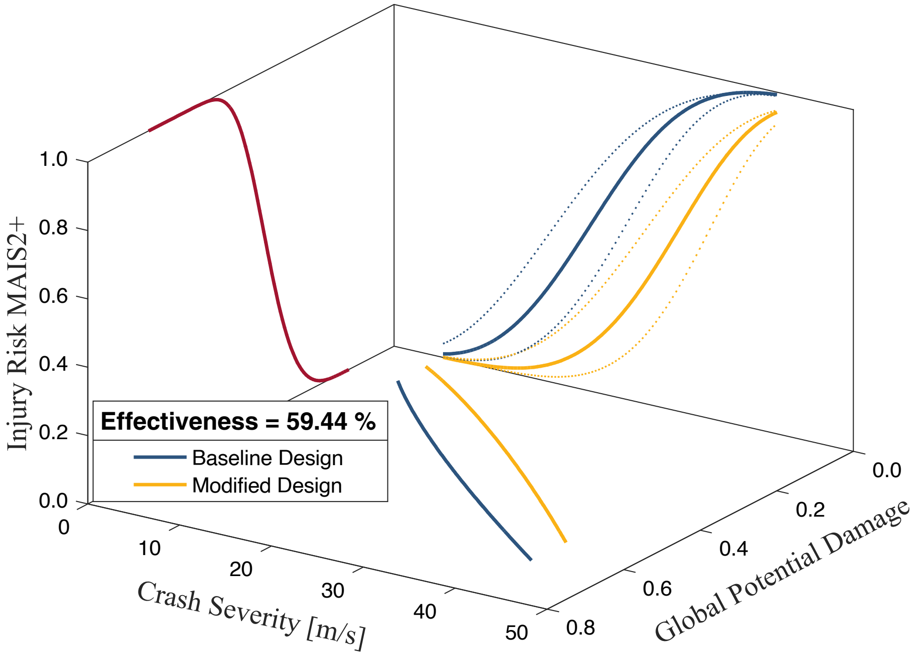

Fig. 3. Effectiveness of the BSJ in frontal accidents.

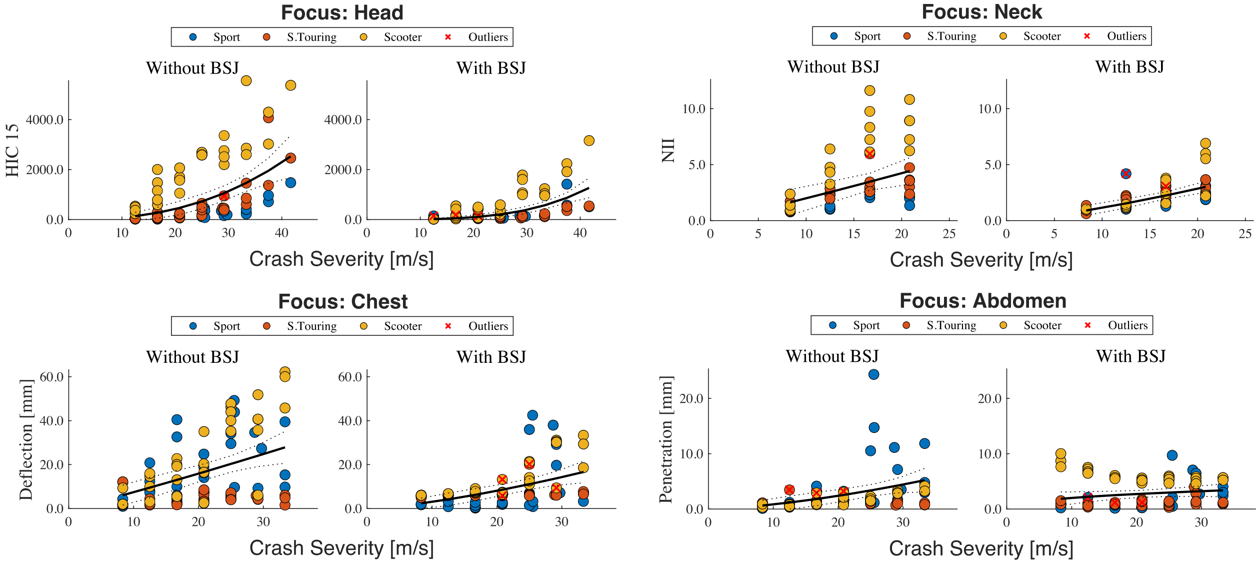

Fig. 4. Dummy responses with and without the BSJ per body region.

Table 4
Fracture counts on lower extremities with and without the BSJ.

	N. of avoided fractures	*N. of caused fractures*	*Odd with BSJ*	*Odd without BSJ*	*Odd ratio (Confidence bounds 90 %)*
Femurs	*27*	*0*	*3.1*	*14.8*	*0.0 < 0.2 < 0.8*
Tibias	*33*	*0*	*1.6*	*4.1*	*0.0 < 0.4 < 0.8*

speed and simulating every run per PTW. This enhanced the quality of safety assessments, providing a more robust evaluation of the device behavior across a broader range of real-world conditions. In fact, even when the crash severity is discretized in intervals, a standard test may not capture the full spectrum of performance for the device (Horsch, 1987), and a more comprehensive range of configurations is recommended (Viano, 1988). The implemented weighting technique allowed for a comprehensive estimate of the examined subsample, improving the original method by considering multiple vehicles and replicating simulations for various crash severity levels. Moreover, the method is applicable beyond PPE assessments, extending to vehicle modifications where significant improvements in the coefficient of determination R^2 of the regression model are expected since a single make or model is considered in those cases.

This study also proposed an enhancement to overcome the limitation of examining a single body region at a time. An important condition of applying Korner's method was that the injury assessment parameter could adequately represent the mechanism producing human injury in real-world accidents. However, this requirement entailed two consistent drawbacks. On one side, it required the need for large databases on which to rely: a drought of real-world accident records entailed poor population representation by the injury risk curve. As a consequence, a rough conditional probability of injury given a crash severity level $P(I|x)$ led to a flawed assumption on the conditional probability of injury given the dummy response $P(I|d)$ and then an uncertain injury risk curve when the device was introduced $P'(I|x)$. On the other side, there was a vital need for the dummy response to strongly correlate with the selected injury. In other words, Korner's method demanded high confidence that the chosen injury assessment parameter was a good indicator of the injured body region. Unfortunately, biomechanical indices are often based on specific physical quantities that correlate only with specific trauma. For instance, the Head Injury Criterion is broadly recognized as valid for head injuries but is limited to linear acceleration, which correlates well with head injuries such as skull fractures, not traumatic brain injuries (TBI) (Feist et al., 2009; Prasad and Mertz, 1985). Hence, as already recommended (Benetton, 2017), it would be beneficial to consider more than one index at a time to correlate with the AIS level sustained on the head, unless not to limit the sample base to one specific injury mechanism at a time, such as skull fractures or tissue hematomas. Nevertheless, with such a limitation, the sample base would necessarily shrink with a heavy repercussion to the statistical strength of the correlation.

To overcome both these limitations, the GPD was proposed as a global injury indicator to observe the weighted outcome over all the considered body regions. In the transition from the use of AIS to MAIS, in fact, it becomes unnecessary to split the sample selected for crash mode into many subsamples as the body regions. Such a segmented approach was implemented in Fig. 4. as further assessment, but, indeed, the number of real-world accidents was insufficient to derive injury risk curves for each body region. In particular, the head and the chest occurred in six accidents, the neck for three, and the abdomen for two. From this perspective, the improvements guaranteed by the GPD were the possibility to consider more than one injury index (or body region) at a time, which in turn led to a broader base sample, passing from the AIS to the MAIS scale. It is indeed worth noting that one of the European Union's objectives for this decade has been to establish a 50 % reduction target for serious injuries in addition to road fatalities (General, 2020) and that, furthermore, riders are particularly concerned about sustaining multiple injuries in multiple body regions during accidents (Aarts et al., 2016). In addition, compared with previous attempts (Laituri et al., 2010, 2003), the levels of risk for each injury index were not inferred from literature but entirely derived from field data with the construction of novel injury risk curves $P(I|x)$. Additionally, the weighted sum of injury indices through the GPD did not focus only on the maximum risk across body regions as Laituri's AccIR but accounted for each considered index, avoiding underestimating the global risk in case of multiple and minor injuries. In this regard, it is worth mentioning that other injury indices share similar limitations to AccIR, e.g., the Injury Severity Score (ISS), New Injury Severity Score (NISS), and even the MAIS itself, or use specific medical parameters like in the Revised Trauma Score (RTS) or Trauma and Injury Severity Score (TRISS), that are not always available on accidentological databases.

Furthermore, in developing this work, a review of the most appropriate distribution function for the data representation and its associated confidence boundaries was also performed. In fact, since the 1980 s, several statistical methods have been applied to generate risk curves: parametric methods using Logistic, Weibull, Normal, Lognormal, or Loglogistic distributions, the Mertz/Weber method (Mertz and Weber, 1982), and the Certainty Method (Mertz et al., 1996). However, in general, many authors agreed that there is no one best injury risk curve for suiting bio-mechanical data sets (Banglmaier et al., 2006; Kent and Funk, 2004; Nakahira et al., 2000; Prasad et al., 2010; Wang et al., 2003); hence, the Weibull distribution was chosen in continuity with Korner's. Similarly, the Maximum Likelihood Method was chosen to represent these types of biomechanical data, which need to be considered in a probabilistic way, being by nature censored (Ran et al., 1984). Fare clic o toccare qui per immettere il testo.Similarly, the choice of using a likelihood estimator to build confidence boundaries was supported by other studies (Cheng and Iles, 1983; Koch, 1988; Mahdi, 2012) and, therefore, chosen in continuity with the MLM already implemented for the cumulative Weibull distribution function, knowing that censored data are advantageously handled by the Maximum Likelihood Method (Ran et al., 1984).

The last contribution of this study relates to the nature of the GPD, dependent, in turn, on the set of weights proposed in 3.1.2. The possibility of its customization makes it able to describe the sample of data as needed by scientists and adapt to biomechanical applications as for other several selection problems where multi-criteria decision methods are used (Dwivedi and Sharma, 2022; Yannis et al., 2020). The GPD is neither a measure of a specific injury (i.e., it is not a new injury index) nor an absolute measure of the damage estimated by the dummy. Conversely, the GPD measures the variation, over the given sample for a specific crash mode, of the weighted sum of selected injury indices between the case with and without the protective device. Consequently, the GPD depends on the given datasets and changes with it, not being an absolute indicator. That is to say that two identical values referred to two different datasets do not account for the same damage. In light of this, the GPD is not a consistent measure of the injury sustained, as the same value may not yield the same result for different populations. Nevertheless, the generation of the new injury risk through the GPD was deemed appropriate since the study aimed to emphasize the reduced (or increased) probability of injury resulting from the introduction of a protective device. Additionally, it is essential to highlight that the significant strength of the method is the a priori evaluation of a new device concept. In fact, the injury risk functions used to calculate device effectiveness depend solely on crash severity rather than on the GPD, a substitution variable in this method. In contrast, the overall injury risk $P(I)$ is derived from the population involved in a given crash mode, $P'(I)$ is not, and cannot be as the protective device (the BSJ in this study) has not yet been implemented in real-world traffic. The GPD, indeed, allows for a direct comparison between the cases with and without the device, expressing an evident variability in terms of global damage received by the numerical dummy, and its absolute values are not relevant for the evaluation of the effectiveness. The $P(I|d)$, and, consequently, the GPD, serves only as a variable to compare dummy responses, and in this regard, even Korner stated that "only if the test set-up is equivalent to real-world accidents if the crash severity and injury assessment parameters are valid and accurately measured, and if the injury probability function $P(I|d)$ is developed from a representative accident sample, $P(I|d)$ may be considered universally applicable also to other sets of data and other test procedures" (Korner, 1989); otherwise it remains valid only for internal assessments.

Regarding the three sets of weights proposed, each of them has a different effect on the GPD. The first set of weights (10) ensures equitable distribution among body regions, avoiding potential bias towards regions that may benefit from device presence. The second set (11) makes the GPD depend on the entropy of each index. Hence, the GPD neglects those indices whose value is not altered by the introduction of the device. In those cases, the entropy equals zero, and, as a result, those indices are not included in the GPD, not being an appropriate measure of the damage variability encountered by the dummy. The last set, (12), ensures that the entropy of each injury index is accounted for solely within the bounds of its significance level (i.e., 50 % AIS3), thus precluding the undue influence of injury indices that exhibit significant fluctuations within the confines of trivial values (e.g., abdominal penetration ranging from 1 mm to 10 mm). In light of this formulation, the GPD facilitates the generation of more meticulously assessed, well-grounded, and comprehensible decisions. The use of GPD supports the organization, management, and simplification of a large amount of technical information and data, often available in transportation research problems and accidentological databases.

Eventually, in this study, as in Korner's, a primary limitation was in the collected data, dependent solely on the crash severity, i.e., the closing speed, and lacking several other parameters. Although the closing speed is one of the explanatory variables known to influence injury risk substantially (Lubbe et al., 2022), injury risk functions are statistic estimates of the probabilities of several types of injuries (or severities) for a prescribed population associated with various levels of stimuli. The stimuli could be forces, moments, deflections, velocities, accelerations, or combinations of these measures, and their associated tolerance levels are based on the population's age, size, and sex. Concerning age, it is known that injuries are more tolerable during the third decade of life since every decade of life after 20 may lead to an increase in injury severity of 0.6 AIS units for the same crash severity (Schmidt et al., 1974). Regarding sex, human tolerances also vary among women, who may experience a sudden drop in bone strength around the age of 50 (Aldman et al., 1983). Also, the different sizes of individuals may impact injury risk, leading taller occupants to hit different parts during collisions (Norin and Isaksson-Hellman, 1995). Therefore, when conducting experimental work, it is crucial to consider the significant scatter in the response to trauma for each population being examined, leading to a notable variation in injury tolerance levels. However, the closing speed was taken as the only crash severity parameter to account for injury risks due to the lack of such information made explicit in the collected data albeit indirectly contemplated via injury risk functions, and only the 50th male percentile was considered in this study since this is the unique available size for MATD, although the use of a single size dummy cannot fully reflect the range of variables present in the real world (Bull and Mackay, 1978; Perez-Rapela et al., 2020). The development of dummies and injury criteria remains a priority in the future to improve the quality of safe vehicles (Norin, 2010).

6. Conclusion

This research introduces a highly refined and comprehensive prospective methodology to evaluate the real-world safety performance of road safety protection devices, particularly addressing the need of PTW riders, who are exposed to a broad spectrum of injuries that may occur across various body regions during an accident with passenger cars. Instead of assessing singularly different safety aspects, this approach takes a holistic view, including different body regions, PTW styles, combinations of speeds, and injury indices. By correlating computer simulations with actual injury data sourced from global accident databases, the method assesses the performance of safety devices through the novel GPD indicator, that concurrently consider all the above-mentioned safety aspects.

Its potential to proactively evaluate the real-world performance of protective devices became clear, by applying the methodology to the BSJ case study in head-on PTW-to-car accidents. The BSJ showed a manifest reduction in GPD across crash severities, irrespective of the PTW style, showing an overall effectiveness of 59.4 % for riders' MAIS2 + injury risk. Positive GPD effectiveness aligned with single injury mechanism estimates. The BSJ notably reduced head, neck, and chest injuries, without causing new fractures but decreasing femur and tibia fracture odds by 79 % and 61 %, respectively. Statistical analysis confirmed a significant inverse correlation between BSJ exposure and leg fracture probability.

The utilization of GPD offers a clear path forward for making more robust data-driven decisions regarding the adoption and enhancement of protective devices, with evident potential for every road users.

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CRediT authorship contribution statement

A. Perticone: Conceptualization, Data curation, Formal analysis, Investigation, Methodology, Software, Visualization, Writing – original draft. **D. Barbani:** Resources, Supervision, Writing – review & editing. **N. Baldanzini:** Methodology, Project administration, Resources, Supervision, Validation, Writing – review & editing.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

The authors do not have permission to share data.

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References

AAAM, 2018. Abbreviated Injury Scale: 2015 Revision.

Aarts, L.T., Commandeur, J.J.F., Welsh, R., Niesen, S., Lerner, M., Thomas, P., Bos, N., Davidse, R.J., 2016. Study on Serious Road Traffic Injuries in the EU.

Aldman, B., Mellander, H., Mackay, M., 1983. The Structure of European Research into the Biomechanics of Impacts, in: Stapp Car Crash Conference. SAE International, San Diego (USA). doi:10.4271/831610.

Amadasi, A., Cerutti, E., Spagnoli, L., Blandino, A., Rancati, A., Gallo, C., Mancini, E., Rizzi, V., Cattaneo, C., 2016. The toll of traffic-related fatalities in a metropolitan Italian area through the experience of the Department of Legal Medicine. Int J Inj Contr Saf Promot 23 2 , 197–205. doi:10.1080/17457300.2014.992347.

Auken, R. Van, Zellner, J., Smith, T., Rogers, N.N., 2005. Development of an improved neck injury assessment criteria for the ISO 13232 motorcyclist anthropometric test dummy, in: International Technical Conference on the Enhanced Safety of Vehicles (ESV). NHTSA, Washington (USA).

Bálint, A., Fagerlind, H., Kullgren, A., 2013. A test-based method for the assessment of pre-crash warning and braking systems. Accid Anal Prev 59, 192–199. https://doi.org/10.1016/j.aap.2013.05.021.

Banglmaier, R.F., Wang, L., Prasad, P., 2006. Influence of interval censoring and bias on injury risk curve development. Int. J. Mater. Prod. Technol. 25 (1–3), 42–63. https://doi.org/10.1504/ijmpt.2006.008273.

Baranowski, P., Damaziak, K., 2021. Numerical simulation of vehicle–lighting pole crash tests: Parametric study of factors influencing predicted occupant safety levels. Materials 14, 11. https://doi.org/10.3390/ma14112822.

Benetton, D., 2017. Evaluation of head and brain injury using empirical and analytical predictors in Human Body Model. In: First International Roadside Safety Conference. Transportation Research Board, San Francisco (USA), pp. 795–802.

Bourdet, N., Cherta, B.O., Deck, C., Meyer, F., Willinger, R., 2021. Impact conditions of motorcyclist per body segment. Int. J. Crashworthiness 26 (5), 568–576. https://doi.org/10.1080/13588265.2020.1766176.

Bracali, A., Baldanzini, N., Barbani, D., Pierini, M., Maffe, F., 2019. Design of an after-market lower limb protector for scooters: Preliminary estimation of effectiveness. In: Procedia Structural Integrity. Elsevier B.V, pp. 448–454. https://doi.org/10.1016/j.prostr.2020.02.041.

Bruski, D., Burzyński, S., Chróścielewski, J., Pachocki, Ł., Witkowski, W., 2019. On the validation of the LS-DYNA Geo Metro numerical model. MATEC Web of. Conferences 262, 10001. https://doi.org/10.1051/matecconf/201926210001.

Bull, J.B., Mackay, G.M., 1978. Some Characteristics of Collisions, the Population of Car Occupant Casualties and Their Relevance to Performance Testing. IRCOBI, Lyon (France).

Cheng, R.C.H., Iles, T.C., 1983. Confidence bands for cumulative distribution functions of continuous random variables. Technometrics 25 (1), 77–86. https://doi.org/10.1080/00401706.1983.10487822.

Cherta, B.O., Llari, M., Afquir, S., Martin, J.L., Bourdet, N., Honoré, V., Masson, C., Arnoux, P.J., 2019. Analysis of trunk impact conditions in motorcycle road accidents based on epidemiological, accidentological data and multi-body simulations. Accid Anal Prev 127, 223–230. https://doi.org/10.1016/j.aap.2019.03.006.

Chong, M., Sochor, M., Ipaktchi, K., Brede, C., Poster, C., Wang, S., 2007. The Interaction of 'Occupant Factors'' on the Lower Extremity Fractures in Frontal Collision of Motor Vehicle Crashes Based on a Level I Trauma Center'. Journal of Trauma: Injury, Infection & Critical Care 62 (3), 720–729. https://doi.org/10.1097/01.ta.0000222577.43192.a6.

Ding, C., Rizzi, M., Strandroth, J., Sander, U., Lubbe, N., 2019. Motorcyclist injury risk as a function of real-life crash speed and other contributing factors. Accid Anal Prev 123, 374–386. https://doi.org/10.1016/j.aap.2018.12.010.

Directorate General for Mobility and Transport, 2020. Eu road safety policy framework 2021 - 2030. Next steps towards “Vision Zero.” doi:10.2832/261629.

Directorate General for Mobility and Transport, 2018. Preparatory work for an EU road safety strategy 2020-2030. doi:10.2832/15318.

Dwivedi, P.P., Sharma, D.K., 2022. Application of Shannon entropy and CoCoSo methods in selection of the most appropriate engineering sustainability components. Cleaner Materials 5, 100118. https://doi.org/10.1016/j.clema.2022.100118.

Eppinger, R., Sun, E., Bandak, F., Haffner, M., Khaewpong, N., Maltese, M., Kuppa, S., Nguyen, T., Takhounts, E., Tannous, R., Zhang, A., Saul, R., 1999. Development of improved injury criteria for the assessment of advanced automotive restraint systems - II.

Feist, F., Jürgen, G., Arregui-Dalmases, C., Pozo, D., de Dios, E., Lopez-Valdes, F., Deck, C., Willinger, R., 2009. Pedestrian Collisions with Flat-Fronted Vehicles: Injury Patterns and Importance of Rotational Accelerations as a Predictor for Traumatic Brain Injury (TBI). In: In: International Technical Conference on Experimental Safety Vehicles (ESV). SAE International. https://doi.org/10.4271/PT-152/3.

Fisher, S.A., 1925. Statistical Methods For Research Workers, First. ed. Oliver & Boyd (Edinburgh).

Grassi, A., Baldanzini, N., Barbani, D., Pierini, M., 2018a. A comparative analysis of MAIDS and ISO13232 databases for the identification of the most representative impact scenarios for powered 2-wheelers in Europe. Traffic Inj Prev 19 (7), 766–772. https://doi.org/10.1080/15389588.2018.1497791.

Grassi, A., Barbani, D., Baldanzini, N., Barbieri, R., Pierini, M., 2018b. Belted Safety Jacket: a new concept in Powered Two-Wheeler passive safety. Procedia Struct. Integrity 8, 573–593. https://doi.org/10.1016/j.prostr.2017.12.057.

Horsch, J.D., 1987. Evaluation of Occupant Protection from Responses Measured In Laboratory Tests, in: SAE International Congress and Exposition. SAE International, Detroit (USA). doi:10.4271/870222.

Hurt Jr., H.H., Ouellet, J.V., Thom, D.R., 1981. Motorcycle accident cause factors and identification of countermeasures. Los Angeles, California.

Isaksson-Hellman, I., Norin, H., 2005. How thirty years of focused safety development has influenced injury outcome in Volvo cars. In: Annual Proceedings - Association for the Advancement of Automotive Medicine. AAAM, Boston, MA, pp. 63–77.

ISO 13232-2, 2005. Motorcycles — Test and analysis procedures for research evaluation of rider crash protective devices fitted to motorcycles — Part 2: Definition of impact conditions in relation to accident data.

ISO 13232-5, 2005. Motorcycles — Test and analysis procedures for research evaluation of rider crash protective devices fitted to motorcycles — Part 5: Injury indices and risk/benefit analysis.

ISO 13232-7, 2005. Motorcycles — Test and analysis procedures for research evaluation of rider crash protective devices fitted to motorcycles — Part 7: Standardized procedures for performing computer simulations of motorcycle impact tests.

ISO 12353-1, 2020. Road vehicles — Traffic accident analysis — Part 1: Vocabulary.

Jakobsson, L., Lindman, M., Svanberg, B., Carlsson, H., 2010. Real World Data Driven Evolution of Volvo Cars’ Side Impact Protection Systems and their Effectiveness. Ann Adv Automot Med 54, 127–136.

Kent, R.W., Funk, J.R., 2004. In: Data Censoring and Parametric Distribution Assignment in the Development of Injury Risk Functions from Biochemical Data. International, Detroit (USA). https://doi.org/10.4271/2004-01-0317.

Klug, C., Bützer, D., Iraeus, J., John, J., Keller, A., Kowalik, M., Leo, C., Levallois, I., Putra, I.P.A., Ressi, F., Schmitt, K.-U., Svensson, M., Trummler, L., Wijnen, W., Linder, A., 2023. How much does the injury risk between average female and average male anthropometry differ? – A simulation study with open source tools for virtual crash safety assessments. Accid Anal Prev 193, 107328. https://doi.org/10.1016/j.aap.2023.107328.

Koch, M., 1988. Recent work with a method for the fitting of injury versus exposure data into a risk function. In: Conference Proceedings International Research Council on the Biomechanics of Injury. IRCOBI. IRCOBI, Bergisch-Gladbach, Germany, pp. 23–34.

Korner, J., 1989. A Method for Evaluating Occupant Protection by Correlating Accident Data with Laboratory Test Data, in: SAE International Congress and Exposition. SAE International, Detroit (USA). doi:10.4271/890747.

Kovaceva, J., Bálint, A., Schindler, R., Schneider, A., 2020. Safety benefit assessment of autonomous emergency braking and steering systems for the protection of cyclists and pedestrians based on a combination of computer simulation and real-world test results. Accid Anal Prev 136. https://doi.org/10.1016/j.aap.2019.105352.

Kovaceva, J., Bärgman, J., Dozza, M., 2022. On the importance of driver models for the development and assessment of active safety: A new collision warning system to make overtaking cyclists safer. Accid Anal Prev 165. https://doi.org/10.1016/j.aap.2021.106513.

Kramer, F., Appel, H., 1990. Evaluation of Protection Criteria on the Basis of Statistical Biomechanics. IRCOBI, Bron (France).

Kunc, R., Omerović, S., Ambrož, M., Prebil, I., 2014. Comparative study of European tunnel emergency-stop-area-wall protection measures. Accid Anal Prev 63, 9–21. https://doi.org/10.1016/j.aap.2013.10.020.

Laituri, T.R., Kachnowski, B.P., Prasad, P., Sullivan, K., Przybylo, P.A., 2003. A Theoretical, Risk Assessment Procedure for In-Position Drivers Involved in Full-Engagement Frontal Impacts, in: SAE World Congress & Exhibition . SAE International, Detroit (USA). doi:10.4271/2003-01-1354.

Laituri, T.R., Henry, S., Sullivan, K., Nutt, M., 2010. Considerations of “combined probability of injury” in the next-generation USA frontal NCAP. Traffic Inj Prev 11 (4), 371–381. https://doi.org/10.1080/15389581003739685.

Lau, I.V., Viano, D.C., 1986. The Viscous Criterion - Bases and Applications of an Injury Severity Index for Soft Tissues. In: Stapp Car Crash Conference. SAE International, Warrendale. https://doi.org/10.4271/861882.

Lindman, M., Tivesten, E., 2006. In: A Method for Estimating the Benefit of Autonomous Braking Systems Using Traffic Accident Data. International, Detroit (USA). https://doi.org/10.4271/2006-01-0473.

Ljung Aust, M., Jakobsson, L., Lindman, M., Coelingh, E., 2015. In: Collision Avoidance Systems - Advancements and Efficiency. International, Detroit (USA). https://doi.org/10.4271/2015-01-1406.

Lowne, R., Janssen, E., 1990. Thorax injury probability estimations using production prototype EuroSID.

Lubbe, N., Wu, Y., Jeppsson, H., 2022. Safe speeds: fatality and injury risks of pedestrians, cyclists, motorcyclists, and car drivers impacting the front of another passenger car as a function of closing speed and age. Traffic Safety Research 2 (000006), 1–26. https://doi.org/10.55329/vfma7555.

Mahdi, S., 2012. One-sided confidence interval estimation for Weibull shape and scale parameters. Revista De Matemática: Teoría y Aplicaciones 12 (1–2), 61. https://doi.org/10.15517/rmta.v12i1-2.251.

MAIDS, 2009. Motorcycle Accidents In Depth Study - Final Report 2.0.

Mellander, H., Ivarsson, J., Korner, J., Nilsson, S., 1989. Side Impact Protection System - A Description of the Technical Solutions and the Statistical and Experimental Tools, in: International Technical Conference on Experimental Safety Vehicles (ESV). NHTSA, Göteborg (Sweden).

Meng, Y., Hu, W., Untaroiu, C., 2020. An examination of the performance of damaged energy-absorbing end terminals. Accid Anal Prev 147, 105789. https://doi.org/10.1016/j.aap.2020.105789.

Mensa, G., Piantini, S., Baldanzini, N., del Mar Rasines, M., Parera, N., Pierini, M., Marco, P., Zampieri, P., Silvia, F., 2020. PIONEERS Deliverable 1.3 - Future trends in accident scenarios and ISO 13232 review.

Mertz, H.J., Weber, D.A., 1982. Interpretations of the Impact Responses of a 3-Year-Old Child Dummy Relative to Child Injury Potential, in: International Technical Conference on Enhanced Safety of Vehicles (ESV). NHTSA, Kyoto (Japan).

Mertz, H.J., Prasad, P., Nusholtz, G., 1996. Head injury risk assessment for forehead impacts, in: International Congress & Exposition. SAE International, Michigan (USA). doi:10.4271/960099.

Mertz, H.J., Horsch, J.D., Horn, G., Lowne, R.W., 1991. Hybrid III Sternal Deflection Associated with Thoracic Injury Severities of Occupants Restrained with Force-Limiting Shoulder Belts. In: International Congress & Exposition. SAE International, Detroit (USA). https://doi.org/10.4271/910812.

Morgan, R.M., Scullion, P., Nix, L., Kan, C.-D., Nagabhushana, V., Shanks, K., Tangirala, R., 2012. Injury Risk Investigation of the Small, Rear-seat Occupant in Side Impact. SAE International Journal of Passenger Cars - Mechanical Systems 5 1 , 2012-01–0092. doi:10.4271/2012-01-0092.

Nakahira, Y., Furukawa, K., Niimi, H., Miki, K., 2000. A combined evaluation method and a modified maximum likelihood method for injury risk curves, in: Conference Proceedings International Research Council on the Biomechanics of Injury, IRCOBI. IRCOBI, Montpellier (France), p. 147.

Newman, J.A., 1986. A Generalized Acceleration Model for Brain Injury Threshold (GAMBIT). IRCOBI, Zurich (Switzerland).

Norin, H., 1994. Correlation of occupant injuries in traffic accidents and dummy responses in mathematical simulations. Accid Anal Prev 26 (3), 277–286. https://doi.org/10.1016/0001-4575(94)90001-9.

Norin, H., 1998. Estimating crash performance for new car design. Int. J. Crashworthiness 3 (1), 37–44. https://doi.org/10.1533/cras.1998.0059.

Norin, H., 2010. Field data-A base for the development of safe vehicles. In: Conference Proceedings International Research Council on the Biomechanics of Injury. IRCOBI. IRCOBI, Hanover, Germany, pp. 3–14.

Norin, H., Isaksson-Hellman, I., 1995. Injury potential prediction of a safety design feature: A theoretical method based on simulations and traffic accident data. Saf Sci 19 (1), 45–56. https://doi.org/10.1016/0925-7535(94)00058-B.

Norin, H., Koch, M., Ryrberg, S., Svensson, S.E., 1995. Combining accident data and laboratory simulation data reduces the risk for sub-optimized safety systems in cars. Saf Sci 19 (1), 57–69. https://doi.org/10.1016/0925-7535(94)00060-G.

Otte, D., 1980. A Review of Different Kinematic Forms in Two-Wheel- Accidents-Their Influence on Effectiveness of Protective Measures. In: Stapp Car Crash Conference. SAE International, Troy (USA), pp. 561–605. https://doi.org/10.4271/801314.

Otte, D., Facius, T., Wiese, B., 2015. Accident Characteristics and Influence Parameters of Severe Motorcycle Accidents in Germany, in: SAE World Congress & Exhibition. SAE International, Detroit (USA), pp. 1–11. doi:10.4271/2015-01-1466.

Pallacci, T., Baldanzini, N., Barbani, D., Pierini, M., 2019. Preliminary effectiveness assessment of an airbag-based device for riders’ leg protection in side impacts. Procedia Struct. Integrity 24, 240–250. https://doi.org/10.1016/j.prostr.2020.02.021.

Perez-Rapela, D., Forman, J.L., Huddleston, S.H., Crandall, J.R., 2020. Methodology for vehicle safety development and assessment accounting for occupant response variability to human and non-human factors. Comput Methods Biomech Biomed Engin 24 (4), 384–399. https://doi.org/10.1080/10255842.2020.1830380.

Perticone, A., Barbani, D., Baldanzini, N., 2023a. Enhancing rider safety through Personal Protective Equipment: investigating the influence of Powered Two-Wheeler styles on the performance of the Belted Safety Jacket (Reviewed: waiting for approval). Traffic Inj Prev.

Perticone, A., Barbani, D., Baldanzini, N., 2023b. Preliminary evaluation of a passive safety device concept for the protection of riders. Int. J. Crashworthiness. https://doi.org/10.1080/13588265.2023.2272306.

Perticone, A., Nardomarino, V., Baldanzini, N., 2023c. Influence of car front-end designs on motorcyclists’ trajectory in head-on and side-on-head crashes (In production), in: Conference on Engineering Mechanical Design and Stress Analysis (AIAS). Morressier, Genova.

Prasad, P., Mertz, H.J., 1985. The Position of the United States Delegation to the ISO Working Group 6 on the Use of HIC in the Automotive Environment. In: SAE Government Industry Meeting and Exposition. SAE International, Washington (USA). https://doi.org/10.4271/851246.

Prasad, P., Mertz, H.J., Dalmotas, D.J., Augenstein, J.S., Digges, K., 2010. Evaluation of the Field Relevance of Several Injury Risk Functions. In: Stapp Car Crash Conference. SAE International, Scottsdale (USA), pp. 1–24. https://doi.org/10.4271/2010-22-0004.

Puthan, P., Lubbe, N., Shaikh, J., Sui, B., Davidsson, J., 2021. Defining crash configurations for Powered Two-Wheelers: Comparing ISO 13232 to recent in-depth crash data from Germany, India and China. Accid Anal Prev 151 December 2020 , 13. doi:10.1016/j.aap.2020.105957.

Ran, A., Koch, M., Mellander, H., 1984. Fitting injury versus exposure data into a risk function. In: Conference Proceedings International Research Council on the Biomechanics of Injury. IRCOBI. IRCOBI, Delft, The Netherlands, pp. 301–312.

Richardson, J., Kim, K., Li, L., Nitz, L., 1996. Patterns of motor vehicle crash involvement by driver age and sex in Hawaii. J Safety Res 27 (2), 117–125. https://doi.org/10.1016/0022-4375(96)00006-0.

Rogers, N.M., Zellner, J.W., 1998. An overall evaluation of UKDS motorcyclist leg protectors based on ISO 13232, in: International Technical Conference on the Enhanced Safety of Vehicles (ESV). NHTSA, Windsor (Canada).

Rouhana, S.W., Jedrzejczak, E.A., McCleary, J.D., 1990. Assessing Submarining and Abdominal Injury Risk in the Hybrid III Family of Dummies: Part II -. In: Development of the Small Female Frangible Abdomen, in: Stapp Car Crash Conference. SAE International, Orlando (USA). https://doi.org/10.4271/902317.

Ryan, A., Tainter, F., Fitzpatrick, C., Gazzillo, J., Riessman, R., Knodler, M., 2022. The impact of sex on motor vehicle crash injury outcomes. Journal of Transportation Safety & Security 14 (5), 818–842. https://doi.org/10.1080/19439962.2020.1834478.

Schmidt, G., Kallieris, D., Barz, J., Mattern, R., 1974. Results of 49 Cadaver Tests Simulating Frontal Collision of Front Seat Passengers. doi:10.4271/741182.

Searle, J.A., Bethell, J., Baggaley, G., 1978. The Variation of Human Tolerance to Impact and Its Effect on the Design and Testing of Automotive Impact Performance. In: Stapp Car Crash Conference. SAE International. Ann Arbor (USA), pp. 3131–3143. https://doi.org/10.4271/780885.

Seber, G.S.F., Wild, C.J., 2003. Non-linear Regression. Wiley.

Shannon, C.E., 1948. A Mathematical Theory of Communication. Bell Syst. Tech. J. 27 (3), 379–423. https://doi.org/10.1002/j.1538-7305.1948.tb01338.x.

Tadokoro, H., Fukuda, S., Miyazaki, K., 1985. A study of motorcycle leg protection, in: International Technical Conference on Enhanced Safety of Vehicles (ESV). NHTSA, Oxford (England).

Versace, J., 1971. A Review of the Severity Index, in: Stapp Car Crash Conference. SAE International, Warrendale. doi:10.4271/710881.

Viano, D.C., 1988. Limits and challenges of crash protection. Accid Anal Prev 20 (6), 421–429. https://doi.org/10.1016/0001-4575(88)90040-1.

Walz, M.C., 2003. NCAP Test Improvements with Pretensioners and Load Limiters. Washington DC (USA).

Wang, L., Banglmaier, R., Prasad, P., 2003. In: Injury Risk Assessment of Several Crash Data Sets. International, Detroit (USA). https://doi.org/10.4271/2003-01-1214.

Yannis, G., Kopsacheili, A., Dragomanovits, A., Petraki, V., 2020. State-of-the-art review on multi-criteria decision-making in the transport sector. Journal of Traffic and Transportation Engineering (english Edition) 7 (4), 413–431. https://doi.org/10.1016/j.jtte.2020.05.005.