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Injury severity: Scales, incidence, hospitalization rate, mortality risk, economic costs, modeling considerations, and best practices

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ABSTRACT

Introduction: Injury assessment and modeling present several challenges. Methods are needed for evaluating the severity of injury, for quantifying impacts along those gradations (e.g., economic costs), and for comparing injuries to each other and to fatalities. While a variety of methods exist, there are limited comprehensive, direct, and collated information and models available for comparing them along various dimensions or to assess their fitness for a particular purpose. *Method*: Three common and widely applicable injury severity scales are reviewed: hospitalized/non-hospitalized dichotomy; Abbreviated Injury Scale (AIS); and Injury Severity Score (ISS). Their advantages, limitations, caveats, and risks are discussed, and data for each are summarized (incidence, hospitalization, mortality, and economic costs). Operations research and econometrics methods are used to enumerate the theoretical range of AIS levels at each ISS value, subset these to AIS-ISS pairs that can actually occur, develop a probabilistic AIS-ISS map, transfer AIS-based cost data onto the ISS scale, and cluster ranges of severity levels according to various data features. *Results*: Each ISS value links to at most two valid AIS levels. The cluster assignments are somewhat stable across data features (for a given number of clusters fit), although significant variability exists. When viewed over the entire ISS range, both the average AIS (power function) and mapped ISS costs are reasonably linear, and reduced-form ISS cost and AIS-ISS linkage models are presented. *Conclusions*: The methodology can be applied to any injury quantity (not just costs) and represents a new development in the understanding of the AIS-ISS relationship. *Practical Applications*: This improves the comparability of the scales, allows seemingly disparate AIS/ISS values to be better and more directly compared, facilitates the pooling of mixed AIS/ISS data in meta-analyses, and allows costs for the ISS scale to be quantified.

1. Introduction

1.1. Injury modeling challenges

Mortality and morbidity modeling is an important aspect of injury, health, and safety analysis, as well as in related economic and cost-effectiveness evaluations and risk management and policy decisions. Often, the focus is fatalities, and many analyses sidestep nonfatal injuries entirely by examining only fatal injuries. Nevertheless, nonfatal injuries can be important, perhaps even more so than fatalities.

Injury modeling presents several challenges. Nonfatal injuries are more prevalent that deaths, present along a spectrum of severity, and are multidimensional in their effects, particularly as it relates to disability and impairment, pain and suffering, and quality-of-life (Gennarelli & Wodzin, 2006; U.S. Department of Transportation, 2021; Asscheman et al., 2023). For sure, death is not entirely unidimensional or monolithic. For example, the *timing* of death is variable (relative to the event that precipitated it), and presents along a spectrum (e.g., immediate, in hospital, reduced life expectancy). However, death is far less variable in its presentation and effects than injuries.

This necessitates methods for evaluating injury severity, for quantifying impacts along those gradations (e.g., economic costs), and for systematically comparing nonfatal injuries to each other and to fatalities. A variety of such methods exist. Currently, this information is scattered, with limited comprehensive, direct, and collated information available to compare them (advantages, limitations, caveats, and risks), assess their fitness for a particular purpose (across diverse injury datasets), or provide best practices for applying them in safety analyses.

This article fills these voids by summarizing and extending various injury data and scales. In doing so, new insights are derived relating to the scales and their relationship to one another. This improves the comparability of the scales, allows seeming disparate severity values expressed using different scales to be better and more directly compared, facilitates the pooling of mixed data in *meta*-analyses, and allows any

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Table 1
Maximum Abbreviated Injury Scale.

Injury Severity		Example Injuries	General Prognosis
MAIS 1	Minor	Abrasion, laceration, strain, sprain, contusion	Treated and released (see also Section 1.4)
MAIS 2	Moderate	Simple broken bone, loss of consciousness, serious strain or sprain	Follow-up required, weeks to months to heal, but will heal
MAIS 3	Serious	Complicated fracture, serious joint injury, concussion, minor crush injury	Substantial follow-up needed, some minor disability likely
MAIS 4	Severe	Massive organ injury, heart laceration, loss of limb, crushed extremities	Hospitalization, substantial short-term and moderate long-term disability
MAIS 5	Critical	Spinal cord syndrome, crush syndrome with kidney failure	Extended hospitalization, significant long-term disability
MAIS 6	Maximum	Decapitation, massive destruction of head, spinal cord/column, brainstem, or torso, partial thickness burns to ≥ 90% of body area	Usually (though not invariably) fatal (see also Table 3)

MAIS = maximum Abbreviated Injury Scale. Sources: Association for the Advancement of Automotive Medicine (2018); MAIS 1–5 from Willis & LaTourrette (2008); MAIS 6 from Russell et al. (2004), Schellenberg et al. (2021), and Eidenbenz et al. (2025).

Table 2
Hospitalized and Non-Hospitalized Injuries – Incidence and Economic Costs.

Injury Severity	**Incidence** (distribution)		**Cost per Injury Incident** (2023$)	
	Finkelstein *et al.* (2006)	WISQARS (CDC, 2025)	Finkelstein *et al.* (2006) + QoL	WISQARS (CDC, 2025)
Non-hospitalized	96.3%	84.5%	$85,300	$88,000
Hospitalized	3.7%	15.5%	$247,000	$235,000

CDC = U.S. Centers for Disease Control and Prevention. QoL = quality-of-life.
Incidence of nonfatal injuries. Mortality rate zero for both groups.
Finkelstein et al. (2006) – 49,978,023 injuries (2000), medical and work costs, supplemented using WISQARS QoL costs (for better comparisons).
WISQARS (CDC, 2025) – 26,480,000 injuries (2023), medical and work costs and monetized QALYs (Section 1.2), using methods of Assistant Secretary for Planning and Evaluation (2016) and Miller et al. (2022).
Additional data available in Miller *et al.* (1985), but are more dated (1985).

quantity (e.g., economic costs) for one scale to be mapped (transferred or imputed) onto the other scale. Interesting sources of variation and counterintuitive results are identified and discussed. Throughout, relevant modeling considerations and best practice recommendations are offered.

1.2. Injury cost types

Three basic types of economic costs are used to describe injuries (Tolley et al., 1994; Miller et al., 1995; Lawrence et al., 2006; Robinson & Hammitt, 2011; Bishai & Bachani, 2012; Robinson & Hammitt, 2013; Assistant Secretary for Planning and Evaluation, 2016; Blincoe et al., 2023).

Cost of injury. Costs that are relatively easy to quantify in monetary terms (e.g., medical expenditures, lost work); can include both market productivity (formal employment) and household productivity (family and household responsibilities); generally regarded as a lower bound cost value.

Quality-of-life. Quality-related costs, or the more intangible and difficult-to-monetize costs of injuries, such as pain and suffering and disability and impairment (aside from their impacts on productivity); assessed using some quality measure or instrument; may also be translated into monetary terms, although the link between the quality metric and true economic value may be tenuous or uncertain.

Willingness-to-pay. Value that society actually places on injury risk reductions, considering all of the trade-offs involved, as evidenced by behavior of persons and firms in economic markets (*revealed preference*); often based on wage-risk studies.

The various cost types are illustrated using the example of an individual who is injured in a motor-vehicle accident. The person (or their insurer) may incur costs for medical treatment and recovery (e.g., hospital, rehabilitation, outpatient, pharmacy, caretakers). The individual, their household, and their employer may all experience losses stemming from the person's absence from or reduced participation in normal life activities. These *costs of injury* do not include more *quality-related costs*, such as pain and psychological anguish the person may also experience. These costs, alone or in aggregate, may or may not align with *willingness-to-pay* estimates.

Willingness-to-pay estimates are often based on wage-risk studies, analyzing wages that workers accept to perform riskier employment. These studies typically assume efficient economic markets, where workers (and employers) have accurate and complete information of job risks, and workers have multiple employment options available to them. Neither of these may be the case in actuality. Wage rates that are mutually acceptable to employees and employers ("micro") also may not be a good proxy for the societal value of injury risk reductions ("macro"). Many wage-risk studies also do not stratify results by injury severity, disproportionally represent injuries of the types that occur in workplace and occupational settings, and use injury metrics germane to those particular settings (e.g., overall injury rate, injuries resulting in a lost workday, total workdays lost; Viscusi & Aldy, 2003).

A common quality-related measure is the *quality-adjusted life year* (QALY),[1] which assesses the trade-offs between longevity and time spent in various health or injury states. One year of perfect health equals one QALY; death confers zero QALY; and myriad disutility states between these extrema. QALY values might be based on survey data, structured interviews or expert elicitations, time-to-recovery and functional limitations data, and so forth. And while useful for making comparisons, many authors caution against assigning monetary values to QALYs, as linking QALYs (or any quality measure) to economic value can be tenuous (because QALYs or similar goods are not traded in economic markets, and so their value in an economic sense is not directly observable; Tolley et al., 1994; Hammitt, 2002; Lawrence et al., 2006; Robinson & Hammitt, 2011; Robinson & Hammitt, 2013; Assistant Secretary for Planning and Evaluation, 2016).

Costs can also include losses and disutility incurred by family members or caregivers. Different cost components can sometimes be summed (e.g., cost-of-injury and quality costs), to generate a more complete cost picture or facilitate comparisons (being careful to avoid double counting). In this article, all costs are per injury incident (not population level), given in 2023 U.S. dollars (using the Consumer Price Index-CPI for inflation adjustments), and given to three significant digits.

1.3. Injury severity scales

Myriad injury severity scales have been developed and used (Champion, 2002; Chawda et al., 2004; Seguí-Gómez et al., 2012; Tohira

[1] Similar measures include the *disability-adjusted life year* (DALY) and *health-adjusted life year* (HALY). However, these are not discussed, as they apply also (and perhaps mostly) to disease or illness rather than injuries.

Table 3
Maximum Abbreviated Injury Scale – Incidence, Hospitalization, and Mortality.

Injury Severity Level	Incidence (distribution) Copes et al. (1990)	Finkelstein et al. (2006)	Blincoe et al. (2023)	Hospitali-zation Rate Blincoe et al. (2023)	Mortality Risk Copes et al. (1990)	Gennarelli et al. (1994)	Gennarelli & Wodzin (2006)
MAIS 1	12.4%	76.6%	86.0%	0.007	0.002	0.007	0.007
MAIS 2	34.9%	20.7%	9.5%	0.233	0.002	0.017	0.008
MAIS 3	35.6%	1.9%	3.1%	0.815	0.053	0.054	0.035
MAIS 4	13.0%	0.3%	0.4%	1	0.224	0.202	0.146
MAIS 5	3.9%	0.1%	0.2%	1	0.459	0.453	0.396
MAIS 6	0.1%	0.3%	0.8%	1	0.893	0.873	0.790

MAIS = maximum Abbreviated Injury Scale. Nonfatal incidence/hospitalization. Mortality risk pools fatal/nonfatal.
Copes et al. (1990) – 85,820 injuries/8,381 deaths (1982–1988).
Gennarelli et al. (1994) – 174,160 fatal/nonfatal (1982–1989).
Finkelstein et al. (2006) – circa 43,100,000 injuries (2000); excludes unknown MAIS (approx. 6,950,000).
Gennarelli & Wodzin (2006) – 181,707 fatal/nonfatal ("past several years"); all persons had only a single injury.
Blincoe et al. (2023) – 4,470,023 injuries/36,500 deaths (2019); motor-vehicle accidents (reported and estimated non-reported); aggregated over victim types (e.g., vehicle occupants, bicyclists, pedestrians); MAIS 6 fatal.
Additionally, Schellenberg et al. (2021) find a MAIS 6 mortality risk of 0.746 (19,247 fatal/nonfatal, 2007–2017).
Additional data (motor-vehicle accidents) available in Baker et al. (1974), but the study is smaller (1,840 injuries/247 deaths), more dated (1968–1969), and MAIS 6 was not used, and also in Clarke et al. (2004), but is smaller (5,333 injuries/201 deaths) and all persons had only a single injury.

Table 4
Maximum Abbreviated Injury Scale – Economic Costs.

Injury Severity Level	Cost per Injury Incident (2023$) Graham et al. (1997)	Finkelstein *et al.* (2006) + QoL	DOT (2021, 2025)	Blincoe *et al.* (2023)
MAIS 1	$0	$52,700	$39,600	$59,000
MAIS 2	$1,450,000	$490,000	$620,000	$551,000
MAIS 3	$2,110,000	$2,130,000	$1,390,000	$2,410,000
MAIS 4	$924,000	$3,590,000	$3,510,000	$4,270,000
MAIS 5	$10,700,000	$6,130,000	$7,830,000	$7,170,000
MAIS 6	$13,200,000	$11,200,000	$13,200,000	$11,800,000

CoI = cost of injury. DOT = U.S. Department of Transportation. MAIS = maximum Abbreviated Injury Scale. QoL = quality-of-life. VSL = value of a statistical life. WTP = willingness-to-pay.
VSL (DOT, 2025) - WTP measure; $13.2 million; from wage-risk studies (Section 1.2); applied to Graham et al. (1997) and DOT (2021) injury values.
Graham et al. (1997) – QoL/WTP measure; disutility fractions (0, 0.11, 0.16, 0.07, 0.81, 1); based on the Functional Capacity Index (MacKenzie et al., 1996); MAIS 1 excluded (relatively minor); MAIS 6 fatal.
Finkelstein et al. (2006) – CoI/QoL measure; medical and work lost costs, supplemented using QoL costs of Blincoe et al. (2023) (for better comparisons); excludes unknown MAIS (approx. 6,950,000).
Blincoe et al. (2023) – CoI/QoL measure; motor-vehicle accidents (2019); includes medical, EMS, productivity, workplace, insurance, legal costs, and monetized QALYs (Section 1.2); MAIS 6 estimated as weighted average of MAIS 5 (25%) and deaths (75%), on the basis that MAIS 6 resemble fatalities 75% of the time (Schellenberg et al., 2021).
DOT (2021, 2025) – QoL/WTP measure; quality-adjusted portions of remaining life lost (0.003, 0.047, 0.105, 0.266, 0.593, 1); MAIS 6 fatal.

et al., 2012). A review by Mehmood et al. (2019) identified 57 such scales. This article reviews and extends three of the most common and broadly applicable off-the-shelf injury severity scales. The focus is injury and safety analyses and related economic evaluations (not clinical settings). Only *anatomic* severity scales are included, or those describing *physical* injuries (not disease, illness, sickness, psychological ailments, etc.). In order of increasing complexity, the scales are:

- Hospitalized/non-hospitalized dichotomy (two-level)
- Abbreviated Injury Scale (AIS) (six-level)
- Injury Severity Score (ISS) (44-level)

1.4. Hospitalized and non-hospitalized injuries

This characterization splits injuries into two mutually exclusive categories (Miller et al., 1995; Finkelstein et al., 2006; U.S. Centers for Disease Control and Prevention, 2025).

- *Non-hospitalized*. Treated and released (e.g., at scene, hospital ED, outpatient, doctor's office).
- *Hospitalized*. Inpatient hospitalization, where the person survives at least until discharge.

Non-hospitalized injuries can also include injuries that were sufficiently mild that the person did not seek formal treatment. Hospitalized injuries are further stratified by their *length of stay* (LOS), which can be a reasonable surrogate for injury severity (Newgard et al., 2010). After the Boston Marathon bombing (2013, USA), LOS was used to allocate victim compensation funds, with payments for hospitalized persons increasing in their LOS value (City of Boston Massachusetts, 2013). Data on cost per hospital inpatient day by U.S. state are available from the Kaiser Family Foundation (2025), and on average LOS and total cost per stay from Freeman et al. (2018). However, not all inpatient days may be equivalent (from a cost or other standpoint). And while often useful, the hospitalized/non-hospitalized bifurcation can be a somewhat blunt instrument, often unable to differentiate the many gradations of injury.

1.5. Abbreviated injury scale (AIS)

A more elaborate instrument is the *Abbreviated Injury Scale* (AIS), ranging from 1 to 6 (integer-valued). The AIS was developed as a systematic and standardized way of characterizing injuries from motor-vehicle accidents, by the Association for the Advancement of Automotive Medicine (AAAM). It is usable across many kinds of injuries, and often regarded as a good compromise between clinical detail and ease of practical application. Based on expert deliberation and consensus, AIS scoring methods and injuries covered are periodically revised and expanded (Chawda et al., 2004; Gennarelli & Wodzin, 2006; Seguí-Gómez et al., 2012; Loftis et al., 2018), most recently with the 2015 version (Association for the Advancement of Automotive Medicine, 2018).

For multiple injuries, the *maximum AIS* (MAIS) is the most severe injury (highest AIS). This discards all injury information other than the most severe, potentially limiting its ability to capture the full landscape of injury (Asscheman et al., 2023) (Section 1.1). In this article, the AIS

Table 5
Injury Severity Score – Incidence and Mortality.

ISS	Incidence (distribution)		Mortality Risk		ISS (cont.)	Incidence (cont.)		Mortality Risk (cont.)	
	Copes *et al.* (1988)	Kilgo *et al.* (2004)	Copes *et al.* (1988)	Kilgo *et al.* (2004)		Copes *et al.* (1988)	Kilgo *et al.* (2004)	Copes *et al.* (1988)	Kilgo *et al.* (2004)
1	13.28%	14.69%	0.003	0.007	**26**	0.83%	0.78%	0.237	0.276
2	1.49%	3.09%	0	0.003	**27**	0.39%	0.50%	0.191	0.144
3	0.11%	0.40%	0	0.006	**29**	1.18%	1.11%	0.226	0.175
4	18.79%	19.64%	0.003	0.006	**30**	0.14%	0.20%	0.208	0.318
5	8.85%	8.25%	0.005	0.004	**32**	0.16%	0.06%	0.290	0.288
6	0.83%	1.26%	0	0.004	**33**	0.17%	0.18%	0.324	0.292
8	3.57%	2.17%	0.008	0.008	**34**	0.85%	0.66%	0.331	0.300
9	19.80%	20.84%	0.025	0.023	**35**	0.11%	0.15%	0.407	0.387
10	6.60%	5.62%	0.020	0.020	**36**	0.10%	0.13%	0.440	0.192
11	0.37%	0.75%	0	0.012	**38**	0.21%	0.30%	0.356	0.376
12	0.80%	0.71%	0	0.009	**41**	0.27%	0.20%	0.449	0.393
13	3.65%	2.89%	0.029	0.025	**42**	0.02%	0.04%	0.727	0.498
14	2.33%	2.66%	0.024	0.020	**43**	0.11%	0.19%	0.385	0.413
16	3.91%	2.41%	0.146	0.128	**45**	0.07%	0.09%	0.583	0.478
17	3.03%	3.01%	0.104	0.047	**48**	0%	0.02%	1	0.462
18	1.11%	1.11%	0.088	0.074	**50**	0.12%	0.15%	0.564	0.546
19	0.64%	0.79%	0.063	0.052	**51**	0.01%	0.01%	0.667	0.694
20	1.14%	0.68%	0.141	0.087	**54**	0.01%	0.02%	0.800	0.611
21	0.72%	0.68%	0.123	0.063	**57**	0%	0.03%	1	0.602
22	1.13%	1.42%	0.087	0.055	**59**	0.01%	0.02%	0.667	0.694
24	0.59%	0.51%	0.099	0.074	**66**	0%	0.01%	1	0.773
25	2.46%	1.48%	0.382	0.438	**75**	0.03%	0.08%	0.926	0.812

Incidence of nonfatal injuries. Mortality risk uses pooled fatal/nonfatal data.
Copes et al. (1988) – 13,925 injuries/951 deaths (1982–1985); aggregated over age groups and injury types.
Kilgo et al. (2004) – 342,319 injuries/19,057 deaths (1994–2002).

and MAIS are used interchangeably. The MAIS levels are perhaps best understood using the examples in Willis and LaTourrette (2008) (Table 1). Injury researchers and investigators often consider the most severe level (MAIS 6) as being equivalent to fatalities (Gennarelli et al., 1994; Graham et al., 1997; Willis & LaTourrette, 2008; U.S. Department of Transportation, 2021; Blincoe et al., 2023), although some MAIS 6 are survivable in some circumstances (Copes et al., 1990; Gennarelli et al., 1994; Russell et al., 2004; Aharonson-Daniel et al., 2006; Gennarelli & Wodzin, 2006; Seguí-Gómez et al., 2012; Peng et al., 2015; Schellenberg et al., 2021; Eidenbenz et al., 2025) (see also Table 3). Nevertheless, theoretical justification does exist for considering MAIS 6 overall as being indistinguishable from fatalities (Section 4.3).

The basic goal of the AIS is to divide the vast, diverse, complex, and multifaceted landscape of injuries (Section 1.1) into a handful of manageable levels – to facilitate categorization, analysis, research, communication, and discussion. In this way, the AIS is similar to many other scales, such as the:

- Enhanced Fujita scale (tornadoes)
- Saffir-Simpson scale (hurricanes)
- Modified Mercalli Intensity (earthquakes)
- Volcanic Explosivity Index (volcanic eruptions)
- International Nuclear and Radiological Event Scale (radiation disasters)
- Air Quality Index (air pollution hazards)
- Carnegie Classification (higher education institutions)
- Insurance Institute for Highway Safety crash ratings (vehicle safety)

Rigorous AIS scoring requires specialized clinical knowledge and training. However, if injury descriptions are available, AIS scores can sometimes be estimated with sufficient accuracy (see also the clustered injury values, Section 4.1). Semi-structured approaches are also available, such as Eidenbenz et al. (2025). If injury diagnosis codes are at-hand, in the form of International Classification of Diseases (ICD) codes, AIS (and ISS) values can also be estimated using the R software's 'ICDPICR' package (R Foundation for Statistical Computing, 2025). While the severity scores it outputs are estimates, the results have shown good alignment with other methods (Wan et al., 2022).

The AIS was developed to describe injuries in motor-vehicle accidents, which consist mainly of blunt trauma types of injuries (push/pull/impact). Caution should be exercised when applying it to fundamentally different kinds of injuries, such as penetrating injuries (e.g., gunshot wounds; Beverland & Rutherford, 1983; Copes et al., 1988; Champion, 2002; Tohira et al., 2012). Nevertheless, the AIS has been used to characterize a wide array of injuries occurring in diverse settings, including: transportation accidents (its original purpose; Graham et al., 1997; Chatterjee & Abkowitz, 2009; U.S. Department of Transportation, 2021; Blincoe et al., 2023), tornados (Niederkrotenthaler et al., 2023), earthquakes (Porter et al., 2006), hurricanes (Ramírez-Martínez et al., 2020), firearms (Beverland & Rutherford, 1983), terrorist attacks (Brismar & Bergenwald, 1982; Willis & LaTourrette, 2008; Chatterjee & Abkowitz, 2011), and war (Wallsten & Kosec, 2005).

1.6. *Injury severity Score (ISS)*

A more information-rich alternative to the MAIS (previous subsection), one that can be especially useful in cases of multiple injuries, is the *Injury Severity Score* (ISS) (Baker et al., 1974),[2] which is based on the AIS. First, the most severe (highest AIS) injury in each of six pre-defined body regions is noted (head/neck, face, chest, abdomen, extremities, and external). The ISS is then the sum of squares of the three highest of these AIS values

$$ISS = (AIS_1)^2 + (AIS_2)^2 + (AIS_3)^2 \quad (1)$$

each representing an injury in a different body region. The ISS ranges

[2] Similar measures include the *ICD-9 Injury Severity Score* (ICISS), *New Injury Severity Score* (NISS), and *Trauma and Injury Severity Score* (TRISS). However, these are not discussed in this article, as the NISS is not as ubiquitous as the ISS, and the ICISS and TRISS are most useful in clinical settings (not safety analyses).

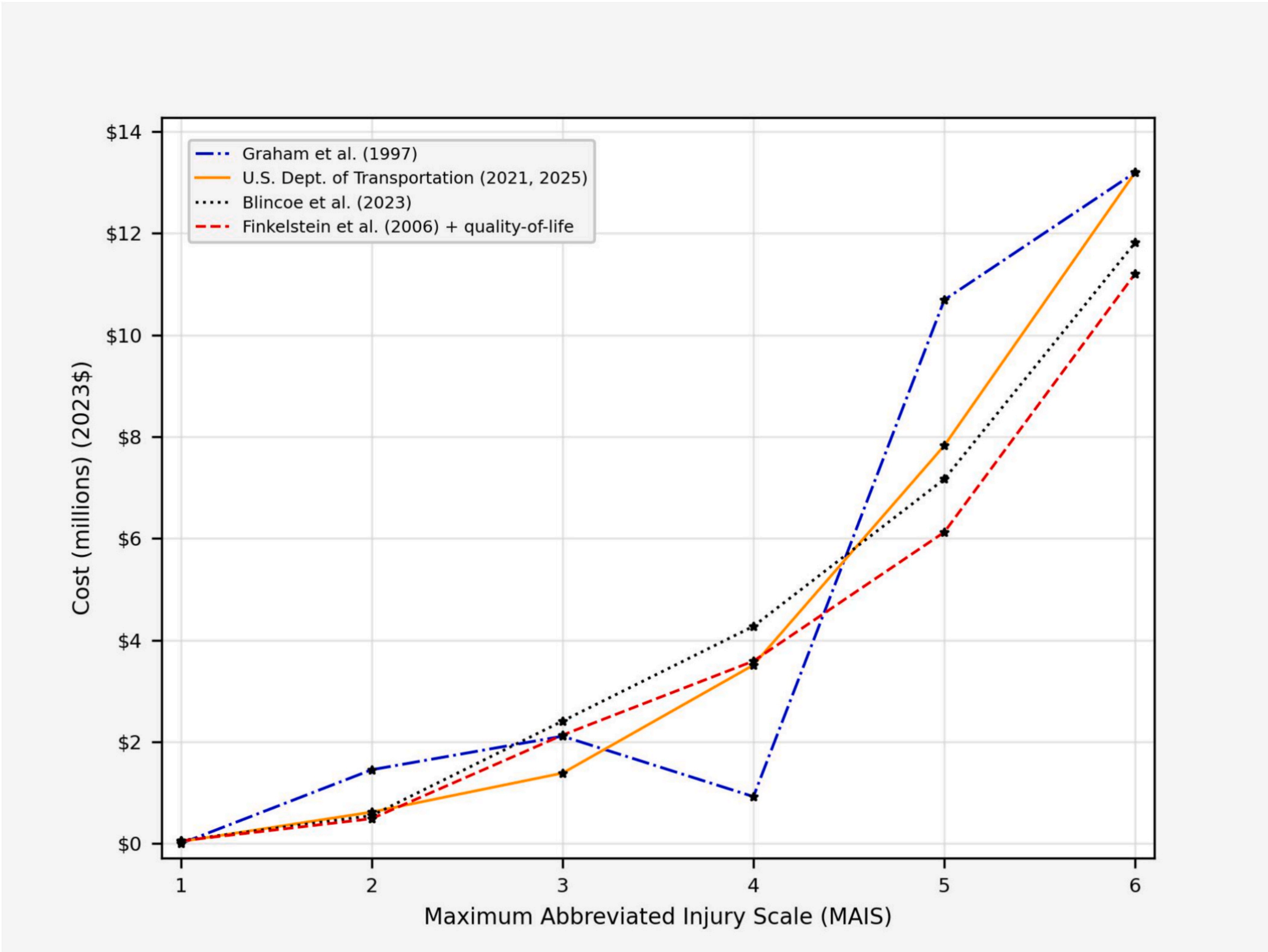

Fig. 1. Maximum Abbreviated Injury Scale – Economic Costs.

from 1 (for a single AIS 1) to 75 (for a trio of AIS 5 or any number of AIS 6), taking on 44 possible integer values (with varying distance between adjacent ISS values). The ISS developers cite its linearity (as it relates to mortality risk) as a primary benefit relative to the MAIS (previous subsection). The ISS is used mostly to control for injury severity or patient mix in injury and trauma studies, and to correlate it to various injury outcomes of interest (Copes et al., 1988; Stevenson et al., 2001; Chawda et al., 2004; Kilgo et al., 2004; Russell et al., 2004; Aharonson-Daniel et al., 2006; Tohira et al., 2012; Rozenfeld et al., 2014; Kuo et al., 2017). The ISS has proven enormously useful to researchers: *Google Scholar* reveals > 11,900 citations of the original ISS article (Sept. 2025) (see also the discussion in Kilgo et al., 2004).

The ISS is based on the AIS (Section 1.5), and so inherits many of its limitations. Like the MAIS, the ISS effectively discards much injury information. The ISS considers only the most severe injury in each body region, potentially biasing it for multiple injuries in a single body region. The ISS also sometimes overlooks more severe injuries in favor of less severe ones occurring in a different body region. It also includes only the three most severely injured body regions (Osler et al., 1997). However, this could also be a benefit of the ISS, or taking a more “holistic” approach, rather than “overfitting” to injuries in a single body region. Kilgo et al. (2004) find that when the body regions assumption is relaxed, and the three most severe injuries are used (regardless of where in the body they occur), the ISS value is unchanged in the majority (56%) of cases.

1.7. *Statistical perspective*

The ISS has three parameters, whereas the MAIS has only one. Even if one or two of its component AIS values are zero-valued (Equation (1), the ISS still has three parameters, as the zeros nonetheless contain statistical information. Specifically, it conveys the information that the parameter does *not* take on any of the values one through six, and also that the ISS body region associated with it was not injured.

From a statistical standpoint, justifying these additional parameters requires that the model fit improve. This idea is incorporated in statistics such as the *Akaike information criterion* (AIC) (Akaike, 1974) and *Bayesian information criterion* (BIC) (Schwarz, 1978), which penalize models that have more parameters (while rewarding models with better fits). Whether or not sufficiently improved predictive power is achieved (as assessed using these or other statistics) will depend on the nature and structure of the model and data, but should be considered when making MAIS/ISS comparisons.

2. Methods

2.1. *Literature searches*

Data related to these three scales are collated, summarized, and compared (incidence, hospitalization, mortality, and economic costs). Mortality risk data can be used to remove deaths from mixed (fatal/nonfatal) data, or to adjust injury-only incidence estimates to gauge the

Table 6
Injury Severity Score (ISS) – Maximum Abbreviated Injury Scale (MAIS) Map.

ISS	MAIS Theory	MAIS Valid	AIS Triplet #1	AIS Triplet #2	Shares #1	Shares #2	Total	Body Regions	Avg. MAIS
1	[1]	[1]	(1, 0, 0)	–	100%	–	–	[1]	1.00
2	[1]	[1]	(1, 1, 0)	–	100%	–	–	[2]	1.00
3	[1]	[1]	(1, 1, 1)	–	100%	–	–	[3]	1.00
4	[2]	[2]	(2, 0, 0)	–	100%	–	–	[1]	2.00
5	[2]	[2]	(2, 1, 0)	–	100%	–	–	[2]	2.00
6	[2]	[2]	(2, 1, 1)	–	100%	–	–	[3]	2.00
8	[2]	[2]	(2, 2, 0)	–	100%	–	–	[2]	2.00
9	[2, 3]	[2, 3]	(2, 2, 1)	(3, 0, 0)	8.03%	91.97%	101,267	[1, 3]	2.92
10	[2, 3]	[3]	(3, 1, 0)	–	100%	–	–	[2]	3.00
11	[2, 3]	[3]	(3, 1, 1)	–	100%	–	–	[3]	3.00
12	[2, 3]	[2]	(2, 2, 2)	–	100%	–	–	[3]	2.00
13	[3]	[3]	(3, 2, 0)	–	100%	–	–	[2]	3.00
14	[3]	[3]	(3, 2, 1)	–	100%	–	–	[3]	3.00
16	[3, 4]	[4]	(4, 0, 0)	–	100%	–	–	[1]	4.00
17	[3, 4]	[3, 4]	(3, 2, 2)	(4, 1, 0)	57.06%	42.94%	11,590	[2, 3]	3.43
18	[3, 4]	[3, 4]	(3, 3, 0)	(4, 1, 1)	84.68%	15.32%	4,550	[2, 3]	3.15
19	[3, 4]	[3]	(3, 1, 1)	–	100%	–	–	[3]	3.00
20	[3, 4]	[4]	(4, 2, 0)	–	100%	–	–	[2]	4.00
21	[3, 4]	[4]	(4, 2, 1)	–	100%	–	–	[3]	4.00
22	[3, 4]	[3]	(3, 3, 2)	–	100%	–	–	[3]	3.00
24	[3, 4]	[4]	(4, 2, 2)	–	100%	–	–	[3]	4.00
25	[3, 4, 5]	[4, 5]	(4, 3, 0)	(5, 0, 0)	30.08%	69.92%	6,751	[1, 2]	4.70
26	[3, 4, 5]	[4, 5]	(4, 3, 1)	(5, 1, 0)	50.94%	49.06%	3,031	[2, 3]	4.49
27	[3, 4, 5]	[3, 5]	(3, 3, 3)	(5, 1, 1)	89.80%	10.20%	1,942	[3]	3.20
29	[4, 5]	[4, 5]	(4, 3, 2)*	(5, 2, 0)	75.48%	24.52%	4,588	[2, 3]	4.25
30	[4, 5]	[5]	(5, 2, 1)	–	100%	–	–	[3]	5.00
32	[4, 5]	[4]	(4, 4, 0)	–	100%	–	–	[2]	4.00
33	[4, 5]	[4, 5]	(4, 4, 1)	(5, 2, 2)*	19.05%	80.95%	735	[3]	4.81
34	[4, 5]	[4, 5]	(4, 3, 3)	(5, 3, 0)	66.46%	33.54%	2,701	[2, 3]	4.34
35	[4, 5]	[5]	(5, 3, 1)	–	100%	–	–	[3]	5.00
36	[4, 5]	[4]	(4, 4, 2)	–	100%	–	–	[3]	4.00
38	[4, 5]	[5]	(5, 3, 2)	–	100%	–	–	[3]	5.00
41	[4, 5]	[4, 5]	(4, 4, 3)*	(5, 4, 0)	72.73%	27.27%	880	[2, 3]	4.27
42	[4, 5]	[5]	(5, 4, 1)	–	100%	–	–	[3]	5.00
43	[4, 5]	[5]	(5, 3, 3)	–	100%	–	–	[3]	5.00
45	[4, 5]	[5]	(5, 4, 2)	–	100%	–	–	[3]	5.00
48	[4, 5]	[4]	(4, 4, 4)	–	100%	–	–	[3]	4.00
50	[5]	[5]	(5, 4, 3)	(5, 5, 0)	87.84%	12.16%	633	[2, 3]	5.00
51	[5]	[5]	(5, 5, 1)	–	100%	–	–	[3]	5.00
54	[5]	[5]	(5, 5, 2)	–	100%	–	–	[3]	5.00
57	[5]	[5]	(5, 4, 4)	–	100%	–	–	[3]	5.00
59	[5]	[5]	(5, 5, 3)	–	100%	–	–	[3]	5.00
66	[5]	[5]	(5, 5, 4)	–	100%	–	–	[3]	5.00
75	[5, 6]	[5, 6]	(5, 5, 5)	(6, 0, 0)	0.48%	99.52%	1,467	[1, 3]	6.00

AIS triplets from: Kilgo et al. (2004), Russell et al. (2004), Aharonson-Daniel et al. (2006), and Peng et al. (2015). Total is sum of study sizes. Triplets with asterisks are not given in Stevenson et al. (2001). "Theory" is all theoretical MAIS-ISS pairs. "Valid" is MAIS-ISS pairs that can actually occur. Shares and average MAIS based on empirical prevalence by AIS triplet. Body regions is total non-zero elements in the AIS triplet. Dashes indicate not applicable.

total number of persons impacted. Unless otherwise noted, all data are for nonfatal injuries only.

Only the *severity of injury* dimension is varied. Uncertainty and variability are discussed in Section 4.3. Literature reviews included all works in English, examining injuries overall (not narrow subsets), and in U.S. populations. Motor-vehicle accident injuries are included, as these are very prevalent and well-studied. Only studies where data are articulated for each level of the scale are included (not in the form of ranges, distributions, or summary statistics). When comparing data quality across studies, both recency (years covered) and abundancy (study size) were considered. All studies meeting the inclusion criteria are noted, although data from some older and smaller studies are not presented.

2.2. MAIS-ISS map

Operations research and econometrics methods are used to enumerate the theoretical range of MAIS levels at each ISS value, subset to MAIS-ISS pairs that can actually occur, develop a probabilistic AIS-ISS map, and transfer AIS-based cost data onto the ISS scale. All modeling and visualizations were performed using Python (Python Software Foundation, 2024).

First, bounding analysis is used to assess the extremities of the theoretical MAIS-ISS space. By design (Equation (1), at each MAIS level, the ISS value necessarily falls between

$$ISS_{min} = (MAIS)^2 \tag{2}$$

$$ISS_{max} = 3 \bullet (MAIS)^2 \tag{3}$$

reflecting the AIS triplets (*MAIS*, 0, 0) and (*MAIS*, *MAIS*, *MAIS*), respectively. MAIS 6 is automatically assigned ISS 75 (Section 1.6). As such, the region encompasses ISS 1–66 and MAIS 1–5 (along with ISS 75).

However, this does not consider that some theoretical MAIS-ISS pairs may not actually occur, nor the relative likelihood of those pairs that remain. The conditional MAIS distribution (shares) is specified using data on the empirical prevalence of different AIS triplets at each ISS value. This forms the basis of the probabilistic MAIS-ISS map, which is used to link and transfer costs between the scales. This assumes that empirical injury incidence is the only relevant factor when allocating MAIS shares (see also Section 4.4). The average MAIS curve (computed using these shares) is well-modeled by power function best fits (OLS

Table 7
Logistic Regression Models Predicting MAIS Level from ISS.

Model Type	MAIS-ISS	Y Var.	X Var.	Regression Coefficients Constant	Slope
Multinomial Logistic Regression	Theoretical ($n = 71$)	MAIS 3	*ISS*	−7.46 ($p = 0.044$)	0.705 ($p = 0.040$)
		MAIS 4		−12.5 ($p = 0.002$)	0.940 ($p = 0.008$)
		MAIS 5		−16.2 ($p < 0.001$)	1.04 ($p = 0.003$)
	Valid only ($n = 50$)	MAIS 3	*ISS*	−6.78 ($p = 0.075$)	0.687 ($p = 0.069$)
		MAIS 4		−12.0 ($p = 0.006$)	0.956 ($p = 0.016$)
		MAIS 5		−15.9 ($p = 0.001$)	1.08 ($p = 0.007$)
Likelihood Ratio Test	**MAIS-ISS**	**Y**	**X**	**Regression Statistics Log-Likelihood**	**Chi-Squared**
	Theoretical ($n = 71$)	*MAIS*	*ISS*	LL-full = -52.5 LL-simpler = -59.5	$\chi 2 = 14.0$ ($p = 0.001$, dof = 2)
	Valid only ($n = 50$)	*MAIS*	*ISS*	LL-full = –33.6 LL-simpler = -38.2	$\chi 2 = 9.08$ ($p = 0.011$, dof = 2)

ISS = Injury Severity Score. MAIS = maximum Abbreviated Injury Scale. "Theoretical" is all MAIS-ISS pairs that could occur in theory. "Valid" is only MAIS-ISS pairs that can actually occur. MAIS 2 is reference level for multinomial regressions. ISS 1–3 and ISS 75 (five valid MAIS-ISS pairs) excluded from the training data (Section 3.2). Caveats regarding using these equations and probability recoding procedures are described in Section 3.2. Ordinal logistic regression results (not shown) are the basis of comparison for the likelihood ratio tests. Chi-squared statistic is equal to twice the difference between the log-likelihood (LL) of the "full" model (multinomial) and that of the simpler model (ordinal). Degrees of freedom (dof) is number of additional parameters in the "full" model versus that in the simpler model.

regression, log–log). This provides a simple link between the scales, allowing more direct comparisons of even seemingly disparate MAIS and ISS values.

Restricting to valid MAIS-ISS pairs eliminates a sizeable portion of the theoretical space. These impacts are investigated formally using *logistic regression*, which is an extension of linear regression that is used to model a categorical quantity (rather than a linear relationship). It uses the logistic function (s-curve) to estimate probabilities across levels of the dependent variable. If the categories have a natural "order" or monotonicity (e.g., MAIS), *ordinal logistic regression*[3] is available, which assumes the slopes are invariant across levels ("proportional odds"), with the categories (MAIS) being differentiated only through their intercepts. Otherwise, *multinomial logistic regression*[4] relaxes this assumption, allowing the regression to select differential slopes across levels.

Logistic regression is used because relative to many other statistical classification methods (e.g., random forest, Bayes classifier), its functional form is easier to comprehend and its parameter values are easier to interpret. It therefore represents a more "controlled" modeling environment, making the impacts of changes more apparent. The *training data* are MAIS-ISS pairs. Although technically integer-valued, the ISS is modeled as a continuous quantity (as it is often treated in analyses). The logistic regression data excludes ISS 1–3, because they are associated with MAIS 1 only (and conversely, MAIS 1 associated with ISS 1–3 only), and also ISS 75, which is essentially MAIS 6 only (Table 6).

[3] Python, OrderedModel() function, statsmodels library.
[4] Python, MNLogit() function, statsmodels library.

2.3. ISS economic costs

The probabilistic map (previous subsection) is demonstrated by using it to transfer AIS-based economic costs onto the ISS scale. The underlying AIS costs are assumed invariant, both within and across ISS values. Data are lacking on how the costs might vary along these dimensions. Even if the maximum potential bounds of variation are known or could be specified (Section 4.3), the functional form is also important, yet difficult to specify (i.e., may be non-uniform).

Although the methodology is used to transfer cost data from one scale to the other, it can be applied to any injury quantity (incidence, hospitalization, LOS, ICU admission, mortality, work lost, disability, etc.). As such, it represents a new development in the understanding of the AIS-ISS relationship, improving the comparability of the scales and facilitating the pooling of mixed AIS/ISS data in *meta*-analyses.

Reduced-form models are presented, fitting linear (OLS)[5] regression models to the average MAIS (preceding subsection) and the mapped ISS costs. Both unrestricted and constrained model forms are examined. *Unrestricted models* have no restrictions on their parameter values, and are statistically fit. *Constrained models* have parameter values that are selected so as to hit certain benchmarks (or to align with known boundary conditions) and are algebraically fit (simultaneous equation solving).

A *reduced-form model* is a streamlined version of some more complex model, system, or process. Their potential benefits are primarily threefold (Heatwole & Rose, 2013; Rose et al., 2017):

- *Transparency*. Equations using a minimum of predictors and without complicated inputs.
- *Flexibility*. Applicable to many different circumstances and useable by non-experts.
- *Rapidity*. Capable of generating results quickly with rapid turnarounds.

These benefits are typically achieved by sacrificing some level of accuracy or granularity (levels that could potentially be achieved using more convoluted models and techniques). Navigating these trade-offs represents the fundamental art and science of reduced-form modeling: creating models that are sufficiently accurate, yet also simple and broadly applicable.

2.4. Clustered injury values

A clustering algorithm is used to group ranges of MAIS/ISS values according to various data features, including the newly-generated ISS costs (previous subsection). Mortality risk, while describing likelihood of *death*, may nonetheless correlate with injury severity (or aspects of it), and so is included. These clusters can be especially useful for practitioners facing coarse injury severity information, or where specific MAIS/ISS values are unknown, but severity *ranges* can be specified. *K-means clustering* is used, which is an iterative routine that assigns observations to the cluster with the nearest centroid (hence, "means"), minimizing variance about the cluster centroids, and maximizing within-cluster homogeneity.

The lone model *hyperparameter*, *k*, is the number of clusters to fit. For MAIS, two and three clusters are examined. Any more than this would cause the expected number of MAIS levels per cluster to fall below two, which is deemed to be too thin a partitioning. Studies use a variety of ISS total cohorts and partitions, complicating the ability to systematically compare. Based on literature reviews, and using a classification and regression tree (CART) based algorithm (focused on mortality), Rozenfeld et al. (2014) suggest using four ISS groups for most samples, and at most six groups. The ISS is also grounded in the AIS, which has six levels

[5] Python, OLS() function, statsmodels library.

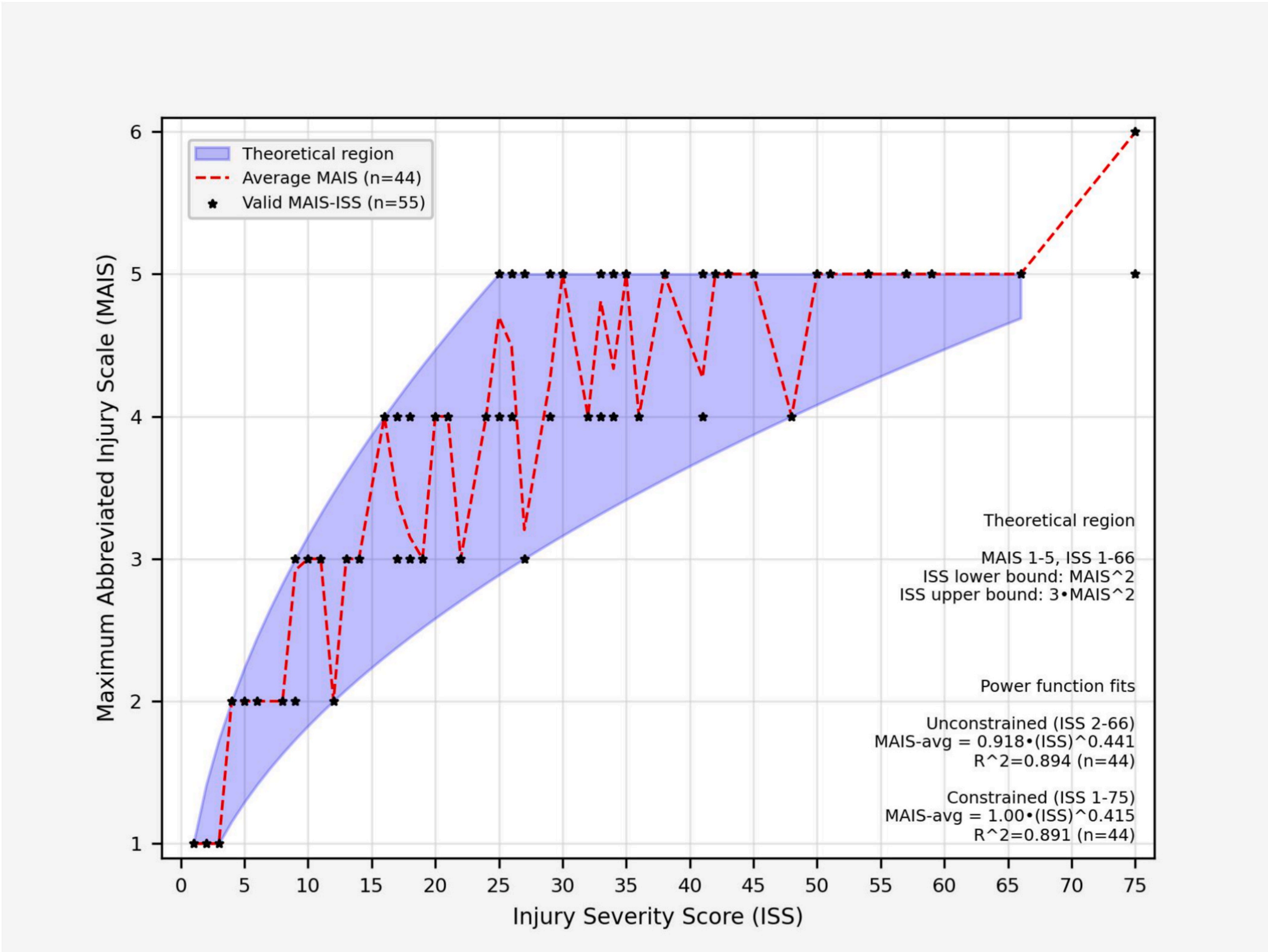

Fig. 2. MAIS-ISS Theoretical Region and Empirical Map.

(one of which, MAIS 6, occurs only at ISS 75), and so using more than five or six ISS groups may be unwise, given this underlying structure of the scale. Additionally, given the relative empirical scarcity of some ISS values (Table 5), further augmenting the number of clusters increases the risk that some cohorts will contain small populations and complicate meaningful statistical analyses. Given all of this, a maximum of six ISS clusters are fitted.

The severity scales (MAIS/ISS) are discrete, and so there are effectively a finite number of potential cluster boundaries (one less than the number of scale levels). The possible cluster boundaries are set midway between adjacent MAIS/ISS values. A k-means clustering algorithm was created from scratch. For the MAIS, and for the ISS when the number of clusters is four or less, a "brute force" approach is taken, where literally all potential sets of cluster boundaries are enumerated and the best among them is selected. When the number of ISS clusters exceeds four, the size of the sample space is considerably larger, and so a "random-iterative" approach is used, examining many different sets (100 total) of randomly generated cluster boundaries. Within each set, one-dimensional parametric optimization is performed, going through the clusters once from first to last, and selecting the best boundary for each (given the current values all of the other boundaries). This approach covers the sample space in tractable computational time.

2.5. Average injury costs

Finally, while the primary goal of this article is to stratify injuries by severity, it can also be useful and informative to have some injury costs that are severity-neutral. These can be applied by injury researchers seeking some off-the-shelf injury values that they can use, without having to devote significant resources to injury modeling. These average injury costs, formed by combining the incidence and cost data in various ways, are presented and compared.

3. Results

3.1. Literature data

Data for hospitalized and non-hospitalized injuries are presented in Table 2. While the Finkelstein et al. (2006) study size is larger, WISQARS data (U.S. Centers for Disease Control and Prevention, 2025) are more recent. However, WISQARS may represent a somewhat more severely injured population (hospitalization rate). Regardless, the costs are similar between the two sources.

MAIS injury data are summarized in Table 3. These studies differ in their data, methods, manner of AIS coding, and so forth, and exhibit some variability (see also Section 4.2). For example, the samples in Copes et al. (1990), Gennarelli et al. (1994), and Gennarelli and Wodzin (2006) consist of persons treated at hospital trauma centers (theoretical 100% hospitalization rate), potentially representing more severely injured populations than those of Finkelstein et al. (2006) and Blincoe et al. (2023). Hospitalization rate by MAIS level blends the hospitalized/non-hospitalized distinction (Section 1.4) and the MAIS. Beginning at

Table 8
Reduced-Form Injury Severity Score Linear Regression Models.

Model Type	Dependent Var. (Y)	X Var.	Model Form	Regression Coefficients Constant	Slope	R^2
MAIS-ISS Link	ln(*MAIS-avg*)	ln (*ISS*)	U	−0.0854 ($p = 0.254$)	0.441 ($p < 0.001$)	0.894
			C1	0	0.415	0.891
ISS Costs	Graham et al. (1997)	*ISS*	U	−0.474 ($p = 0.515$)	0.187 ($p < 0.001$)	0.643
	Finkelstein et al. (2006) + QoL			0.483 ($p = 0.105$)	0.116 ($p < 0.001$)	0.808
	DOT (2021, 2025)			−0.125 ($p = 0.755$)	0.154 ($p < 0.001$)	0.800
	Blincoe et al. (2023)			0.622 ($p = 0.067$)	0.132 ($p < 0.001$)	0.810
	Graham et al. (1997)	*ISS*	C2	0	0.176	0.640
	Finkelstein et al. (2006) + QoL			0	0.149	0.701
	DOT (2021, 2025)			0	0.176	0.729
	Blincoe et al. (2023)			0	0.158	0.779
	Graham et al. (1997)	*ISS*	C3	−0.178	0.178	0.642
	Finkelstein et al. (2006) + QoL			−0.0980	0.151	0.705
	DOT (2021, 2025)			−0.138	0.178	0.739
	Blincoe et al. (2023)			−0.0999	0.159	0.777

DOT = U.S. Department of Transportation. ISS = Injury Severity Score. MAIS = maximum Abbreviated Injury Scale. QoL = quality-of-life. All costs in million 2023$ ($n = 44$ for all models).
Additional details regarding the specification of the various cost values are given in Table 4.
U – Unrestricted (no parameter restrictions). Some predictions of these models are out-of-range (Section 3.3).
C1 – Constrained to intersect: MAIS 1 at ISS 1, and MAIS 6 at ISS 75.
C2 – Constrained to intersect: $0 at (non-existent) ISS 0, and MAIS 6 cost at ISS 75.
C3 – Constrained to intersect: MAIS 1 cost at ISS 1, and MAIS 6 cost at ISS 75.
Average MAIS is incidence-weighted by ISS value (Table 6), and is modeled using a power function (log–log linear).
p-values and residuals analysis not examined for the constrained models (because they are algebraically rather than statistically fit). R^2 values *are* presented, to facilitate comparisons with the other models.
Normality of the residuals is assessed using the correlation between the residuals: (1) empirical cumulative distribution function; and (2) fitted cumulative normal distribution. Values for all models are ≥ 0.986 (greater values are sought).

MAIS 4, all injuries require hospitalization (motor-vehicle accidents).

Cost data by MAIS level are summarized in Table 4. The U.S. Department of Transportation (2021) injury values are based on the concept of *quality-adjusted portion of remaining life lost*, which is similar to the QALY (Section 1.2).[6] DOT uses this approach for injury valuation because it could not locate willingness-to-pay studies and estimates (Section 1.2) across a sufficient range of injury severities. The Graham et al. (1997) costs exhibit non-monotonicity (MAIS 4), and the MAIS cost have a generally exponential nature (Fig. 1).

[6] Similar measures include *years of potential life lost* (YPLL) and *value of a statistical life year* (VSLY).

Table 5 presents the ISS injury data. Note that the study size in Kilgo et al. (2004) is much larger and the data more recent than in Copes et al. (1988). However, both study populations consist of persons treated at hospital trauma centers (potential 100% hospitalization rate), and may be skewed towards more severe injuries (rather than being representative of injuries more generally). Mortality risk is not always monotonic in the ISS. This is partly because different AIS triplets with the same ISS value (Table 6) can have very different mortality rates (Copes et al., 1988; Kilgo et al., 2004; Russell et al., 2004; Aharonson-Daniel et al., 2006). Injury incidence also varies enormously across ISS values, potentially contributing to variability at the less-populated ISS values, and the majority of injured persons exist at only three ISS values: 1, 4, or 9.

3.2. MAIS-ISS map

The special AIS-ISS relationship (Equation (1) allows the MAIS to be linked (mapped) to the ISS – either perfectly or within a small range of MAIS values. Theoretically, the total number of MAIS-ISS pairs is 76 (not to be confused with the maximum ISS scale value of 75). However, many of these MAIS-ISS pairs cannot actually occur. Subsetting to valid MAIS-ISS pairs eliminates over a quarter of these, leaving 55 pairs (Table 6). Each ISS value links to at most two valid MAIS-ISS pairs. Among valid pairs, 12 link to more than one AIS triplet, although only 11 of these link to more than one MAIS level (ISS 50 has two triplets, but MAIS 5 only). ISS 27 links to MAIS 3 and 5, but not MAIS 4. ISS 9 can occur with one or three body regions impacted, but not two body regions. Among valid MAIS-ISS pairs, MAIS 2–5 begin at ISS (4, 9, 16, 25), respectively, and MAIS 1–4 cease at ISS (3, 12, 27, 48), respectively.

The impacts of subsetting to valid MAIS-ISS pairs are investigated formally using logistic regression, by examining the changes in the coefficient values (Table 7). Likelihood ratio tests are used to assess the proportional odds assumption (Section 2.2), indicating that the more flexible multinomial logistic regression model offers a significant increase in model fit ($\alpha = 0.05$ level), and is therefore deemed worthwhile relative to the simpler ordinal logistic regression model. Regardless, the coefficient values do not vary drastically between the two MAIS-ISS scenarios (theoretical, valid only). The logistic regression models in Table 7 are presented to show the impacts of including different sets of MAIS-ISS pairs, but are not otherwise used in the modeling. If used to predict probabilities across MAIS levels, the outputs for all non-sensical MAIS-ISS pairs should be recoded to zero, and the remaining probabilities renormalized to sum to one (by ISS).[7]

The plot of the MAIS-ISS theoretical region (Fig. 2) exhibits a cantilever-like structure, increasing slower-than-linearly in the ISS. At each ISS value, the average MAIS value is computed using the AIS triplets that can occur at that ISS value, based on their empirical prevalence (Table 6). The average MAIS value is quite non-monotonic in the ISS – "pinballing" around the theoretical region, often vacillating from one extremity to the other, and then reversing (quasi-cyclically), with multiple instances of changes of one MAIS level between adjacent ISS values. The extent to which the average MAIS curve "paints" the entire theoretical region so thoroughly is notable, and could have implications for sensitivity analyses (see also Section 4.3). Fig. 2 also shows the results of power function equation best fits to the average MAIS, which are further elaborated in Table 8.

[7] Logistic regression, unmodified, always predicts non-zero probabilities across all levels of the dependent variable for any arbitrary input value (because the logistic function's domain spans the entire x-axis).

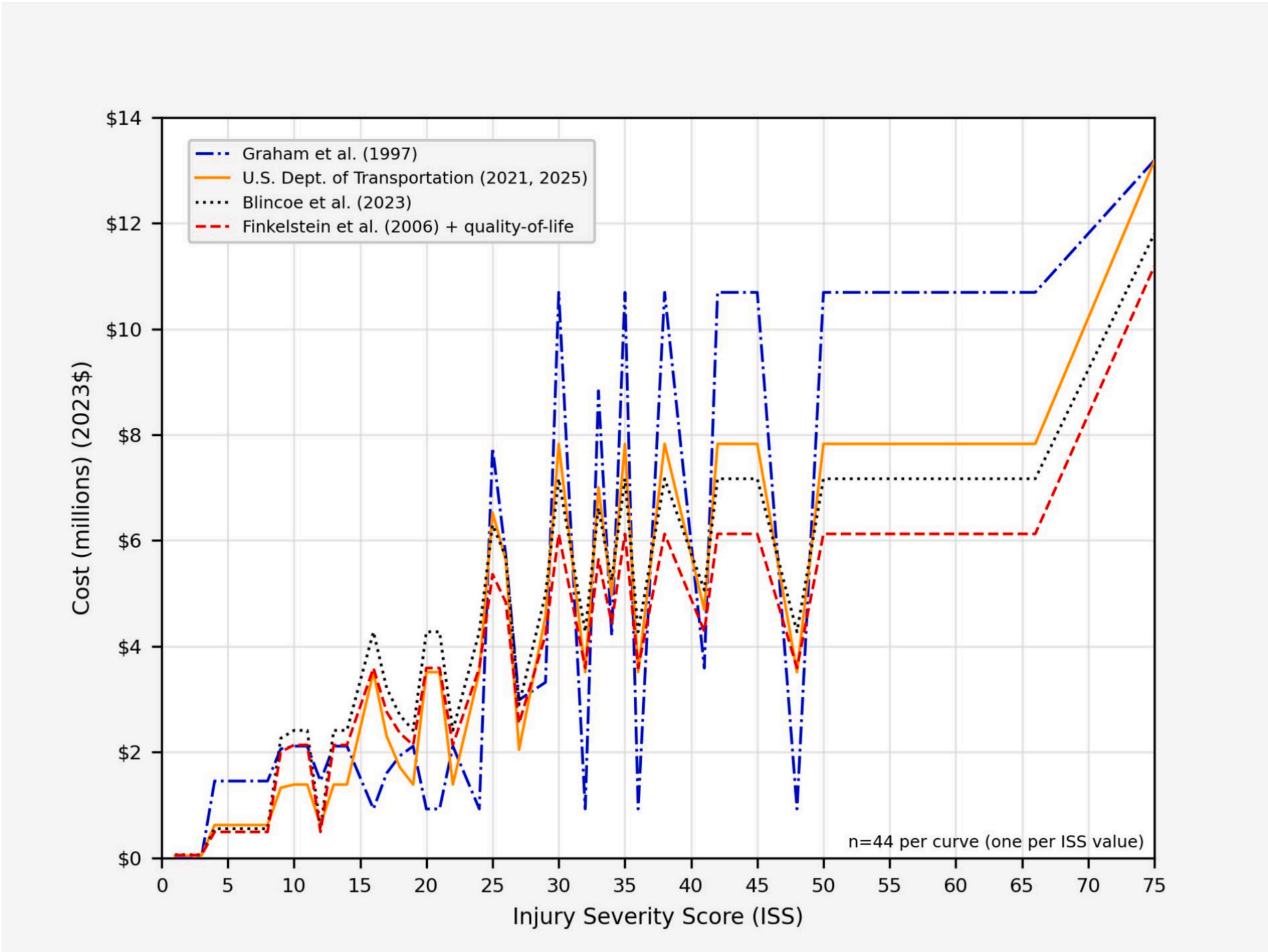

Fig. 3. Maximum Abbreviated Injury Scale (MAIS) Economic Costs Mapped to the ISS.

3.3. ISS economic costs

Literature searches did not reveal any cost data for the ISS scale that are anyway near as comprehensive as exists for the MAIS.[8] Nevertheless, the probabilistic map (Section 3.2) can be used to transfer MAIS-based costs onto the ISS scale, by fusing MAIS costs (Table 4) and ISS-MAIS shares (Table 6).

The mapped ISS costs (Fig. 3) exhibit considerable variation, especially in the midrange values (ISS 25–50). This is a consequence of the variability and non-monotonicity in the average MAIS value (Fig. 2). The Graham et al. (1997) costs are particularly erratic, repeatedly swinging over an order-of-magnitude between adjacent ISS values ($1 to $10 million), reducing the model fit (R^2). Despite this variation, when viewed over the entire ISS range, the mapped ISS costs are reasonably linear. This result is the confluence of the MAIS costs increasing faster-than-linearly (Fig. 1) and the MAIS-ISS theoretical region (and average MAIS) increasing slower-than-linearly (Fig. 2). Recall also that the developers of the ISS cite its linearity as a primary benefit (Section 1.6).

Additional support for these linearities is given in Table 8, which presents a series of reduced-form ISS cost and MAIS-ISS linkage models. This encompasses both constrained models, which are designed around specific boundary conditions, and unrestricted models, with no parameter restrictions. Formal regression diagnostics and robustness checks are also included. Note that these models use cost in *millions* of dollars. The unrestricted version of the Graham et al. (1997) cost model predicts negative cost values at ISS 1 and 2. The constrained model forms resolve this, by intersecting either zero dollars at the (non-existent) ISS 0, or the MAIS 1 cost at ISS 1 (and MAIS 6 cost at ISS 75 in both cases). However, this comes at the expense of some model fit (R^2). The reduced-form ISS cost models are not otherwise used in the modeling or analysis.

Table 8 also presents power functions modeling the average MAIS as a function of the ISS (both variables log-transformed). The predictions of the unrestricted power function extend slightly below MAIS 1 at ISS 1 and slightly above MAIS 6 at ISS 75. The constrained version of the model resolves this, with parameter values set so as to hit these boundary points exactly, and with minimal reduction in model fit (R^2). Analysis of residuals data (Table 8) and residual plots (not shown) indicate the regressions do not have any significant heteroscedasticity, and with residuals that are reasonably normally distributed.

The power functions provide a method for converting severity values coded on one scale into their analogues on the other scale. The relationship is simple, direct, consistent, smooth, and monotonic, and improves comparisons of seeming disparate MAIS/ISS values (e.g., MAIS 2 versus ISS 25). While variation about the power function best-fit lines exist, they can nonetheless be used to control for injury severity in analyses and facilitate the pooling of mixed MAIS/ISS data in *meta*-analyses. This is what is currently done using the ISS (Section 1.6), even

[8] For example, Kuo et al. (2017) correlate the ISS to medical costs, with generally linear relationships (see also Section 1.6).

Table 9
Maximum Abbreviated Injury Scale – Clusters.

Total Clusters Fit	Feature Type	Data Source	Cluster Assignments (MAIS ranges) C1	C2	C3
$k = 2$	Incidence	Copes et al. (1990)	1–3	4–6	–
		Finkelstein et al. (2006)	1	2–6	–
		Blincoe et al. (2023)	1	2–6	–
	Hospitalization	Blincoe et al. (2023)	1–2	3–6	–
	Mortality	Copes et al. (1990)	1–4	5–6	–
		Gennarelli et al. (1994)	1–4	5–6	–
		Gennarelli & Wodzin (2006)	1–4	5–6	–
	Costs	Graham et al. (1997)	1–4	5–6	–
		Finkelstein et al. (2006) + QoL	1–4	5–6	–
		DOT (2021, 2025)	1–4	5–6	–
		Blincoe et al. (2023)	1–4	5–6	–
$k = 3$	Incidence	Copes et al. (1990)	1	2–3	4–6
		Finkelstein et al. (2006)	1	2	3–6
		Blincoe et al. (2023)	1	2	3–6
	Hospitalization	Blincoe et al. (2023)	1–2	3	4–6
	Mortality	Copes et al. (1990)	1–3	4–5	6
		Gennarelli et al. (1994)	1–4	5	6
		Gennarelli & Wodzin (2006)	1–4	5	6
	Costs	Graham et al. (1997)	1–4	5	6
		Finkelstein et al. (2006) + QoL	1–3	4–5	6
		DOT (2021, 2025)	1–4	5	6
		Blincoe et al. (2023)	1–3	4–5	6

DOT = U.S. Department of Transportation. MAIS = maximum Abbreviated Injury Scale. QoL = quality-of-life. K-means clustering (*k* in total). Ranges are inclusive. Incidence of nonfatal injuries. Mortality risk uses pooled fatal/nonfatal data. Dashes indicate not applicable. Additional details regarding the specification of the various cost values are given in Table 4.

though many injury quantities are non-monotonic in the ISS (Tables 5 and 6).

4. Discussion

4.1. Clustered injury values

In addition to stratifying injury values by severity, it can also be useful to go in the other direction – "condensing" ranges of severity values (MAIS/ISS), grouping them according to various data features. This can be especially useful in cases where only limited or coarse severity information is available. These cluster assignments are summarized in Table 9 (MAIS) and Table 10 (ISS).

For the MAIS clusters, MAIS 6 is sometimes in its own cluster, emphasizing the special nature of MAIS 6 (Section 1.5). The first and second clusters cease at median MAIS values of 3.5 and 5, respectively (excluding clusters that end at MAIS 6). For the ISS, as with MAIS 6, ISS 75 is sometimes segregated (Section 1.6). ISS 9 too is often by itself, as this is the plurality of the ISS incidence distribution (Table 5). Clusters one through five cease at median ISS values of (11.5, 24, 34, 44, 49), respectively (excluding clusters that end at ISS 75). Overall, the cluster assignments are somewhat stable across data features (for a given number of clusters fit), although significant variability exists.

ISS 15 is frequently used to classify major trauma or serious injury (Palmer, 2007). This is where MAIS 4 emerges (Table 6), and where mortality risk departs from the ISS-axis (Table 5). Among the four-level ISS clusters, none selected this as the first cluster (note that ISS 15 itself cannot occur). The National Trauma Data Bank (NTDB) (American College of Surgeons, 2016) ISS categorization is fourfold: 1–8 / 9–15 / 16–24 / 25–75. These are the same cohorts recommended by Rozenfeld et al. (2014) for use with most injury data samples (Section 2.4). However, none of the four-level ISS clusters align particularly well with these divisions. Of course, the thresholds most useful in clinical settings may be quite different from those selected by a clustering algorithm.

4.2. Average injury costs

In addition to stratifying injury costs by severity, it can also be useful and informative to generate severity-neutral injury cost values ("snapshot" costs). These can be applied in analyses where the focus may not be injuries, but there is still a desire to incorporate some injury cost information (without doing any detailed modeling). Additionally, this improves the comparability of the various injury data sources used, which vary considerably in the average severity levels they represent.

Average severities across studies and severity scales are summarized in Table 11, and average costs in Table 12. Among the MAIS/ISS results, the study populations in Copes et al. (1988), Copes et al. (1990), and Kilgo et al. (2004) consist of persons treated at hospital trauma centers (possible 100% hospitalization rate), and may represent generally more severely injured populations than those in Finkelstein et al. (2006) and Blincoe et al. (2023). For the MAIS/ISS, Table 12 also presents the corresponding severity values on the other scale, computed using the power functions (Table 8). Among the ISS studies, the average severities (ISS 9 to 9.5) correspond to about MAIS 2.4 or 2.5, which is much more closely aligned with the average value in Copes et al. (1990) (MAIS 2.6) than those in Finkelstein et al. (2006) and Blincoe et al. (2023) (MAIS 1.2 to 1.3).

Average costs (Table 12) are formed by meshing injury incidence (Tables 3 and 5) and injury costs (Table 4, Fig. 3) together in various permutations. The hospitalized/non-hospitalized costs are considerably below the MAIS/ISS costs, possibly because of differential severity levels involved. Additional research is needed to better compare hospitalized/non-hospitalized injuries to those coded on the MAIS/ISS scales. Among the MAIS/ISS costs, those for Finkelstein et al. (2006) and Blincoe et al. (2023) are considerably below those of the other sources, in line with the fact that their study populations were, on balance, less severely injured (Table 11).

When specifying cost values for injuries that are of generally unknown severity, Chatterjee and Abkowitz (2011) suggest averaging costs across all MAIS levels. However, given the generally exponentially nature of the MAIS costs (Fig. 1), a better choice may be the *geometric mean* (non-zero values only), so as to put greater emphasis on *lower* values (rather than more catastrophic injuries).

4.3. Uncertainty and variability

All of the injury data presented are average or expected values. This neglects the considerable variation that exists about these central values (see also Section 1.1). Dimensions along which injury values can vary include (Miller et al., 1995; Finkelstein et al., 2006; Seguí-Gómez et al., 2012; U.S. Centers for Disease Control and Prevention, 2025):

- Injury characteristics (e.g., mechanism/cause, body region, polyinjury).
- Individual impacted (e.g., age, co-morbidities).
- Treatment characteristics (e.g., promptness, quality, availability/cost).

Uncertainty analysis is therefore an important aspect of injury and safety analysis and related risk management activities and policymaking (Morgan et al., 1990; Lawrence et al., 2006; Assistant Secretary for Planning and Evaluation, 2016; U.S. Department of Transportation, 2021).

Significant variation may exist *within* MAIS levels (see also the discussion in next subsection). Based on literature reviews, DOT (2021) recommends parametric variation of 40% about the central or base injury values. If left unbounded, this can cause the value of injury to exceed that of fatalities (base value), as is the case with the Graham et al.

Table 10
Injury Severity Score – Clusters.

Total Clusters Fit	Feature Type	Data Source	Cluster Assignments (ISS ranges) C1	C2	C3	C4	C5	C6
$k = 2$	Incidence	Copes et al. (1988)	1–10	11–75	–	–	–	–
		Kilgo et al. (2004)	1–10	11–75	–	–	–	–
	Mortality	Copes et al. (1988)	1–38	41–75	–	–	–	–
		Kilgo et al. (2004)	1–36	38–75	–	–	–	–
	Costs	Graham et al. (1997)	1–24	25–75	–	–	–	–
		Finkelstein et al. (2006) + QoL	1–24	25–75	–	–	–	–
		DOT (2021, 2025)	1–24	25–75	–	–	–	–
		Blincoe et al. (2023)	1–22	24–75	–	–	–	–
$k = 3$	Incidence	Copes et al. (1988)	1–8	9	10–75	–	–	–
		Kilgo et al. (2004)	1–8	9	10–75	–	–	–
	Mortality	Copes et al. (1988)	1–24	25–45	48–75	–	–	–
		Kilgo et al. (2004)	1–24	25–48	50–75	–	–	–
	Costs	Graham et al. (1997)	1–24	25–48	50–75	–	–	–
		Finkelstein et al. (2006) + QoL	1–22	24–66	75	–	–	–
		DOT (2021, 2025)	1–24	25–66	75	–	–	–
		Blincoe et al. (2023)	1–22	24–66	75	–	–	–
$k = 4$	Incidence	Copes et al. (1988)	1–5	6–8	9	10–75	–	–
		Kilgo et al. (2004)	1–5	6–8	9	10–75	–	–
	Mortality	Copes et al. (1988)	1–24	25–34	35–45	48–75	–	–
		Kilgo et al. (2004)	1–24	25–36	38–50	51–75	–	–
	Costs	Graham et al. (1997)	1–24	25–45	48	50–75	–	–
		Finkelstein et al. (2006) + QoL	1–8	9–24	25–66	75	–	–
		DOT (2021, 2025)	1–22	24–41	42–66	75	–	–
		Blincoe et al. (2023)	1–8	9–24	25–66	75	–	–
$k = 5$	Incidence	Copes et al. (1988)	1–8	9	10	11–35	36–75	–
		Kilgo et al. (2004)	1–8	9	10–18	19–22	24–75	–
	Mortality	Copes et al. (1988)	1–24	25–29	30–42	43–45	48–75	–
		Kilgo et al. (2004)	1–13	14	16–24	25–50	51–75	–
	Costs	Graham et al. (1997)	1–24	25–27	29–38	41–50	51–75	–
		Finkelstein et al. (2006) + QoL	1–3	4–8	9–24	25–66	75	–
		DOT (2021, 2025)	1–8	9–24	25–41	42–66	75	–
		Blincoe et al. (2023)	1–8	9–25	26–38	41–66	75	–
$k = 6$	Incidence	Copes et al. (1988)	1–5	6–8	9	10–29	30–38	41–75
		Kilgo et al. (2004)	1	2–10	11–12	13–17	18–42	43–75
	Mortality	Copes et al. (1988)	1–5	6–24	25–38	41–43	45	48–75
		Kilgo et al. (2004)	1–22	24	25–29	30–41	42–50	51–75
	Costs	Graham et al. (1997)	1–9	10–22	24–27	29–45	48	50–75
		Finkelstein et al. (2006) + QoL	1–9	10–17	18–32	33–57	59–66	75
		DOT (2021, 2025)	1–8	9–27	29–36	38–43	45–66	75
		Blincoe et al. (2023)	1–8	9–24	25–30	32–42	43–66	75

DOT = U.S. Department of Transportation. ISS = Injury Severity Score. QoL = quality-of-life. K-means clustering (k in total). Ranges are inclusive. Incidence of nonfatal injuries. Mortality risk uses pooled fatal/nonfatal data. Dashes indicate not applicable. Additional details regarding the specification of the various cost values in Table 4.

Table 11
Average Injury Severity – Variation Across Studies and Severity Scales.

Injury Severity Scale	Injury Incidence Data Source	Avg. Severity	MAIS Analogue Unrestricted	MAIS Analogue Constrained	ISS Analogue Unrestricted	ISS Analogue Constrained
HOSP	Finkelstein et al. (2006)	3.7%	–	–	–	–
	WISQARS (CDC, 2025)	15.5%	–	–	–	–
MAIS	Copes et al. (1990)	2.61	–	–	10.7	10.1
	Finkelstein et al. (2006)	1.28	–	–	2.11	1.80
	Blincoe *et al.* (2023)	1.22	–	–	1.90	1.61
ISS	Copes et al. (1988)	9.48	2.47	2.54	–	–
	Kilgo et al. (2004)	9.01	2.42	2.49	–	–

CDC = U.S. Centers for Disease Control and Prevention. HOSP = hospitalized/non-hospitalized. ISS = Injury Severity Score. MAIS = maximum Abbreviated Injury Scale. Analogue values computed using MAIS power functions (Table 8). "Unrestricted" models do not have any parameter restrictions. "Constrained" models are fit so as to intersect two points: MAIS 1 at ISS 1, and MAIS 6 at ISS 75. Average severity value for HOSP is percent hospitalized. Dashes indicate not applicable or not specified.

(1997) cost values (MAIS 5). The implication of this in cost-effectiveness analyses is that preventing some injuries may be deemed more cost-efficient than preventing fatalities (all else equivalent). This result is counterintuitive, but not necessarily nonsensical.

Miller et al. (1995) note that while death entails the cessation of physical functioning and loss of all future life years, it also squelches pain and suffering and the costs of medical treatment. They suggest three general categories of injuries – quadriplegia, severe head trauma, and catastrophic burns – cause comparable or greater losses than death. The worst fate possible, they posit, is severe burns, with a total loss almost 40% greater than death (1982 treatment capabilities). This also provides a rationale for considering MAIS 6 overall as being indistinguishable from fatalities (Section 1.5), because while some MAIS 6 are survivable, others may entail costs exceeding those of fatalities.

Table 12
Average Injury Costs – Variation Across Studies and Severity Scales.

Injury Severity Scale	Injury Incidence Data Source	Cost per Injury Incident (2023$)				
		Graham *et al.* (1997)	Finkelstein et al. (2006) + QoL	DOT (2021, 2025)	Blincoe *et al.* (2023)	WISQARS (CDC, 2025)
HOSP	Finkelstein et al. (2006)	–	$91,400	–	–	$93,500
	WISQARS (CDC, 2025)	–	$110,000	–	–	$111,000
MAIS	Copes et al. (1990)	$1,810,000	$1,650,000	$1,490,000	$1,900,000	–
	Finkelstein et al. (2006)	$402,000	$240,000	$252,000	$268,000	–
	Blincoe et al. (2023)	$332,000	$275,000	$271,000	$304,000	–
ISS	Copes et al. (1988)	$1,770,000	$1,570,000	$1,400,000	$1,810,000	–
	Kilgo et al. (2004)	$1,710,000	$1,460,000	$1,290,000	$1,680,000	–

CDC = U.S. Centers for Disease Control and Prevention. DOT = U.S. Department of Transportation. HOSP = hospitalized/non-hospitalized. ISS = Injury Severity Score. MAIS = maximum Abbreviated Injury Scale. QoL = quality-of-life. Finkelstein et al. (2006) costs supplemented using QoL costs from either WISQARS (CDC, 2025) (HOSP) or Blincoe et al. (2023) (MAIS/ISS) (for better comparisons). Dashes indicate not applicable or not specified. Additional details regarding the specification of the various cost values in Table 4.

Conversely, and paradoxically, at the other extreme, there may be justification for considering some injuries as having zero or even *negative* cost (i.e., benefits). In a study of severe burn survivors, Pindus et al. (1993) found that some study participants rated their quality-of-life as *improved*. Some of the positive impacts cited included greater appreciation of life, increased family closeness, being more goal-oriented, improved health behaviors, and enhanced sensitivity to disabled persons.

4.4. Limitations and generalizability

Two assumptions are central to the analysis. The first is that MAIS prevalence (incidence) is a good way of combining disparate MAIS levels at each ISS value. In actuality, some MAIS levels may be more/less influential than their empirical prevalence would suggest. The second assumption is that the MAIS cost values (Table 4) are invariant, both across and within ISS values. However, these costs may vary, just as many other injury elements are variable at this level (Table 6).

The AIS-ISS mapping inherits artifacts of these assumptions, and additional research is needed to assess their veracity and usefulness. The ideal data structure would consist of *both* AIS and ISS scores (and all of their component information), coded on the same population (scored in a consistent and repeatable manner), and representing a broad cross-section of persons, injuries, and settings (and also including data elements that would allow for these factors to be controlled for in analyses).

Only U.S. injury data are used. The inclusion of non-U.S. datasets and cross-country comparisons is problematic, for two main reasons: (1) different relative frequencies of injuries, treatment characteristics, and injury outcomes across countries; and (2) the U.S. medical system, and its corollary systems of health insurance and medical financing, is different from the structures that exist in many other countries. One of the most extensive non-U.S. data sources may be Israel, and its national trauma registry, which has been used by many injury researchers (e.g., Rozenfeld et al., 2014).

The analysis is also somewhat centric to motor-vehicle accident injuries. This represents much of the input data, and the AIS/ISS scales were originally developed to describe injuries from motor-vehicle accidents. It is unknown how well the results might generalize to other types of injuries, especially those that are very different from the kinds sustained in motor-vehicle accidents. The MAIS/ISS analyses are also necessarily limited to cases where AIS/ISS values have been assigned (or estimated), and it is unknown how representative this subset may be of injuries overall.

5. Practical applications

This article brings together, reviews, and extends three of the most common and broadly applicable injury severity scales that are useful in injury and safety analyses. It collates, summarizes, and compares data for these scales, clusters ranges of severity values according to various data features, and develops reduced-form ISS cost models and MAIS-ISS linkage functions. Interesting boundary cases and sources of variation are identified. Throughout, relevant modeling considerations are discussed and best practice recommendations offered.

The data and models presented can be readily applied in injury analyses. The methodology for transferring AIS-based costs onto the ISS scale can be applied to any injury quantity, not just costs (incidence, hospitalization, LOS, ICU admission, mortality, work days lost, disability, etc.). It therefore represents a new development in the understanding of the AIS-ISS relationship, improves the comparability of the scales, allows seeming disparate AIS/ISS values to be better and more directly compared, facilitates the pooling of mixed AIS/ISS data in *meta*-analyses, and allows cost values for the ISS scale to be quantified. Previously, such comparisons either had to be made informally (e.g., using heuristics), or data for the scales analyzed separately, or data for one scale discarded. AIS-ISS comparisons can now be made more directly, and reduced-form ISS cost models are available.

CRediT authorship contribution statement

Nathaniel Heatwole: Writing – review & editing, Writing – original draft, Visualization, Validation, Software, Methodology, Investigation, Formal analysis, Data curation, Conceptualization.

Declaration of competing interest

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

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