H. W. Heinrich and the Biggest Fallacy in Road Safety Research History

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Abstract

H. W. Heinrich was an influential 20th century industrial safety engineer who never studied road crashes. His theory of "identical causal mechanisms" for accidents of different severities led to Behavior-Based Safety (BBS) and its road safety applications. It was also the explicit basis for today's Naturalistic Driving (ND) Mixed-Safety Critical Event (SCE) method, a prominent research paradigm in recent decades. This paper recognizes the general success of BBS while debunking the theory of identical causal mechanisms and the ND Mixed-SCE method. The theory is easily discredited by both crash and ND statistics. Non-crash SCEs are not causally similar to crashes. Even all-crash ND datasets are dissimilar to major datasets of harmful crashes. Societally important crashes are causally heterogeneous both horizontally by scenario type and vertically by severity. "Risk" can be quantified only in relation to a referent crash population, not as an abstract generality.

Résumé

H. W. Heinrich fût un ingénieur du 20e siècle, influentiel en matière de sécurité industrielle, qui n'étudia jamais les collisions routières. Sa théorie de "mécanismes causatifs identiques" pour les accidents de sévérité variée donna lieu aux principes de Sécurité Basée sur le Comportment (SBC) et leurs applications à la sécurité routière. Elle

fût également la base explicite pour la méthode actuelle de Conduite Naturaliste (CN)/ Incident Critique - Sécurité Mixte (ICSM), un éminent modèle de recherche de ces dernières décades. Cette étude reconnaît le succès de SBC en général, tout en rejettant aussi bien la théorie de mécanismes causatifs identiques que la méthode CN/ICSM. La théorie est facilement mise en cause par les statistiques de collisions routières ainsi que celles de CN. Les incidents critiques de sécurité non liés aux collisions ne sont pas causalement semblables aux collisions. Même les bases de données de Conduite Naturaliste limitées aux collisions diffèrent des principales bases de données de collisions nocives. Les collisions importantes au niveau social sont causalement hétérogènes aussi bien en axe horizontal par type de scénario qu'en axe vertical par sévérité. Le "risque" ne peut se quantifier qu'en relation à une population de référence pour les collisions, pas en tant que généralité abstraite.

BACKGROUND: H. W. HEINRICH & HIS LEGACY

H. W. Heinrich [1] was an influential mid-20th century industrial safety engineer. Based on studies of industrial and military operations (but not traffic crashes!), Heinrich formulated seminal concepts about industrial accident causation and prevention. Most familiar is the "Heinrich Triangle" schematic showing the common "pyramid" relationship between accident severity and frequency. He made two iconic assertions, perhaps perceived as logical corollaries of each other:

1. "Identical Causal Mechanisms," whereby serious accidents, minor ones, and even no-injury operator errors all have identical or highly similar causes.
2. Operator errors, even if inconsequential, should be the prime targets of safety interventions because reducing them concordantly reduces errors causing important consequences.

Each of the above assertions became foundational in schools of safety research and accident mitigation. The *second* assertion is addressed first, below. Examination of the first assertion follows, and is the principal topic of this paper.

Behavior-Based Safety

Behavior-Based Safety (BBS) is the application of behavioral principles and methods to modify safety-related behaviors to thereby reduce accidents and injuries [2]. Behaviorism, articulated most persuasively by psychologist B. F. Skinner, espoused that human and animal behavior is driven mostly by positive and negative feedback in the form of rewards and punishments. Heinrich's focus on operator behaviors was sympatico with Skinner's concepts of animal and human behavior. Heinrich [1] pronounced that, "In a workplace, for every accident that causes a major injury, there are 29 accidents that cause minor injuries and 300 that cause no injuries." Reducing behavioral errors will concurrently reduce adverse consequences all the way to the top of the triangle.

BBS has been successful in manual work settings. In a review of 53 occupational safety interventions of various types, BBS was found most effective with an average 60% reduction in injury rates [2]. Today's innovative work fleets employ advance telematics to monitor and record driver behaviors indicative of risk. Supervisors provide objective, quantitative feedback to drivers. Research demonstrates its effectiveness. Model safety plans provided to fleets by their insurance carriers espouse this technique [3].

Current thinking in industry settings, however, seems to be that focusing on minor operator mistakes and misbehaviors will reduce those behaviors but not reduce major injuries proportionately. F. A. Manuele [4], a leading industrial safety critic of Heinrich, has argued that BBS reduces minor consequences proportionately far more than it has reduced major events. In one cited example [5], worker small injury claims were reduced by 34% versus just 7% for large claims. A reason for this [4, P.62] is, "Causal factors for low-probability, high-consequence events are rarely represented in the analytical data on frequent incidents."

Ironically, 50 years into his career, Heinrich himself disclaimed identical mechanisms. As quoted in [6, P.2], in 1980 Heinrich wrote, "It [the accident triangle with its identical mechanisms] does not mean, as we have too often interpreted it to mean, that the causes of frequency are the same as the causes of severe injury. Different things cause severe injuries than the things that cause minor injuries . . . we have only been partially successful in reducing severity by attacking frequency."

Naturalistic Driving "Safety-Critical Events"

Though safety engineers have equivocated on Heinrich's identical mechanisms, a paradigm of crash research has embraced his original theory. The Naturalistic Driving (ND) Mixed-Safety-Critical Event (SCE) method instruments the vehicles of volunteer drivers to capture a variety of mostly non-crash events. This includes avoidance maneuvers and other kinematic events (e.g., lane drifts). Researchers aggregate them across dynamic triggers and event scenarios to form a dependent variable dataset ostensibly representative of important and harmful crashes.

Unlike "traditional" empirical scientific datasets, Mixed-SCE datasets are not drawn from a target population sampling frame. ND researchers themselves decide on the types of triggers (e.g., swerves, lane breaks) to be included, and they control event type proportions by adjusting dynamic thresholds for each type. The commingled dataset's generalizability to important real-world consequences depends on the truth of Heinrich's identical causal mechanisms. This was expressed in a validation study [7] of the *100-Car Naturalistic Driving Study*:

- "The underlying assumption of Heinrich's Triangle is that the unsafe acts, minor injuries, and major injuries all share the same underlying causal mechanism." (P.4)
- "One key requirement for using near-crashes as a surrogate measure is that they possess the same causal mechanism as crashes (the only difference between a crash and an appropriate near crash surrogate is the severity of the safety outputs)." (P.16)

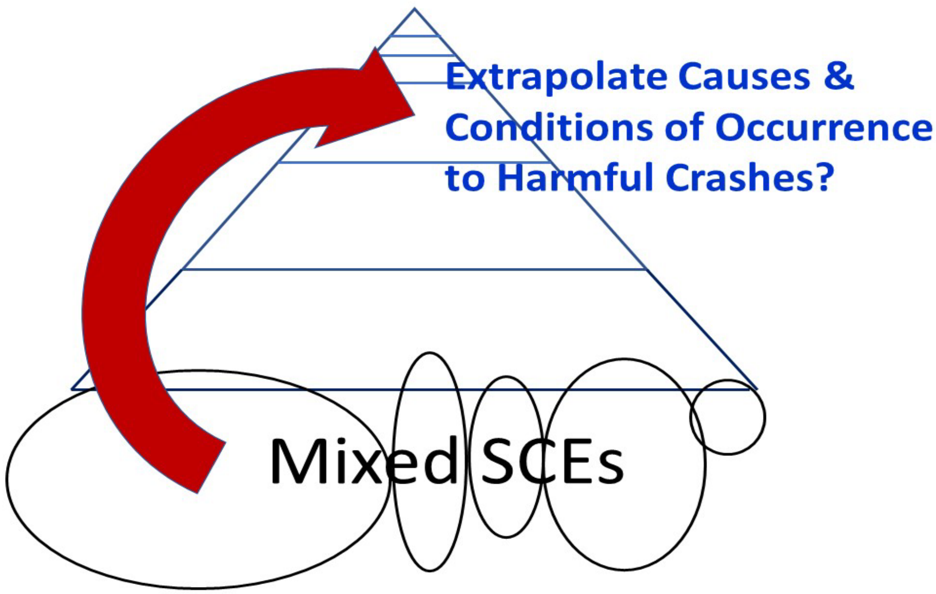


Figure 1 – Schematic of Crash Triangle, Mixed-SCEs (mostly non-crashes or minor crashes), and a question asked in this paper.

The study [7] presented evidence of crash-near crash similarities by comparing attribute percentages for different coding variables. Specifically, it compared *100-Car* crashes (1% of its dataset) to near-crashes (8%). There were no comparisons to the lowest-intensity SCEs termed "incidents" (91%), nor to crashes in public records. For most fully reported event characteristics (e.g., weather, lighting condition, driver age), crash vs. near-crash correlations were near +1.00. These correlations were said to, "indicate that there is a strong linear relationship between the frequency of crashes and near-crashes" (P.50). Further, the study claimed to have found "no evidence suggesting that the causal mechanism[s] for crash and near-crash are different" (Pp. viii and 50).

Yet a re-examination undertaken by the current lead author [8,9] found sharp crash/near-crash differences within the validation study's data. For example, the *Conflict Type* variable described how crashes/ SCEs occurred using 15 attributes like "single-vehicle" and "conflict with lead vehicle." From attribute percentages shown in the validation report, this author calculated that crash and near-crash attribute profiles correlated only +0.44 (R^2 = .20). Thus, crash/near-crash conflict scenario profiles were distinctly different. Similarly, the *100-Car* variable *Precipitating Factor* had 54 attributes for critical events initiating a crash/event scenario. Examples were “pedestrian in roadway” and “vehicle ahead decelerating.” The crash vs. near-crash correlation post-calculated [8,9] from validation report [7] data was R = +0.18, R^2 = +0.03. One might ask how ND crashes and near-crashes can have an “identical mechanism” when they are so different in their scenario types and triggering events [8].

For more than a decade, the U.S. Federal Motor Carrier Safety Administration (FMCSA) has sponsored large ND Mixed-SCE studies on truck driver Hours-of-Service (HOS) rules. Their objective has been “to collect ND data . . . related to . . . crash risk” [10, P.viii]. Though not usually stated explicitly, the theory of identical mechanisms has been at their theoretical core. This is apparent in statements such as, “The non-crash events [SCEs] were operationally defined for this study as having elements identical to a crash scenario, with the exception that a successful evasive maneuver was also present” [10, P.184]. Thus the implicit ND assumption is that crashes *avoided* (i.e., non-crash SCEs) are representative of crashes *which actually occur* [8]. Success represents failure!

A Transportation Research Board (TRB) Truck & Bus Safety Committee research needs statement [11] asks, “ND SCE Datasets: What Exactly Do They Represent?” The question exists because SCE datasets are researcher-chosen mixtures of event types, not samples of a target crash population. The TRB statement suggests exploratory analyses to identify the most valid referent(s) of these surrogates. Hypothesized referents included crash risk, serious/fatal crash risk, crash harm risk, driver fatigue, driver “performance deterioration,” at-fault crash involvements, single-vehicle crashes, crashes with avoidance maneuvers, traffic-related crashes, and “safety impacts.” None appeared to meet validity criteria such as similarities in attribute profiles between Mixed-SCEs and hypothesized referents. Perhaps reflecting the conundrum, FMCSA has employed the indefinite phrase “safety impacts” or simply “risk” to characterize the safety relevance of Mixed-SCEs.

Three kinds of scientific validity threats have been identified in HOS ND Mixed-SCE studies [12]. *External* validity is the generalizability of data to important real-world events. *Construct* validity is the extent to which surrogate events represent a psychological construct like “fatigue.” *Internal* validity is the demonstration of a true cause-effect relation in a study; e.g., reflective of controls on confounding factors. The first two criticisms centered on the truth or non-truth of Heinrich’s identical mechanisms.

Adding to previous work, this paper will present new evidence of the causal heterogeneity of crashes, casting doubt on most causal extrapolations across different categories. It will also identify external validity concerns about minor sensor-detected ND crashes. A further question is whether ND crashes described as "severe" are similarly "severe" in their medically scaled injury outcomes. An ultimate question is whether generalized driving "risk" can be accurately discerned. Or must risk always be stated in relation to a specified category of outcomes?

METHOD

We reviewed crash causation literature and analyzed statistics from several major U.S. National Highway Traffic Safety Administration (NHTSA] databases. All of these crash datasets have significant damage/injury reporting thresholds. Cases are sampled and weighted to be representative of U.S. target harmful crash populations. New here are statistics from the NHTSA Crash Investigation Sampling System (CISS). CISS [13] is a nationally representative sample of light passenger vehicle (car, light truck, SUV, or van) crashes where at least one vehicle is towed from the scene. Once a crash has been sampled, investigators document crash scenes, inspect involved vehicles, conduct confidential interviews, and review victim medical records. Severity is scaled as the single highest injury level for an occupant of an involved towed vehicle. The variable CAIS is based on Abbreviated Injury Scale (AIS) values discerned from medical injury records or specific injuries documented in investigations. Levels include Not Injured (0), Minor Injury (1), Moderate (2), Serious (3), Severe (4), Critical (5), and Maximum/ Untreatable (6). NHTSA provided, per author specifications, four aggregated years representing 10.7 million U.S. crashes occurring during 2017-2020.

Other statistics were retrieved from the second Strategic Highway Research Program (SHRP2; [14]), the largest ND study ever conducted. Its instrumented vehicles monitored nearly 3,600 drivers for up to three years at six U.S. sites. As with other ND studies, SHRP2 captured non-crash SCEs. Researchers decided which types of anomalies to include and controlled proportions by adjusting thresholds for each type. Any detected and verified contact was included as a crash, with higher severity classifications requiring more damage and/or collision force. Three SHRP2 crash categories addressed here are:

- Minor: Physical contact with object or road departure, not including tire strikes.
- Moderate: Police-reportable; >$1,500 in damage as approximated from video, or >1.3g acceleration/deceleration.
- "Severe": Airbag deployment, rollover, injury, or Delta V > 20mph.

No statistical tests were performed in this analysis. Reasons include: (a) All crash and SCE statistics cited are from large datasets; and (b) The large statistical differences and strong trends highlighted far exceed statistical significance criteria. Most percentages are stated to two significant digits.

HORIZONTAL HETEROGENEITY

Horizontal heterogeneity refers to the variety of types and roles seen pervasively within almost any population of crashes or involvements. Causal attribute percentage profiles vary accordingly [8,9]. A basic causal schism is seen between single-vehicle (SV) and multi-vehicle (MV) crash involvements. The National Motor Vehicle Crash Causation Study (NMVCCS; passenger car crashes) and Large Truck Crash Causation Study (LTCCS) were two U.S. in-depth crash investigation studies. Knipling [8] disaggregated at-fault SV and MV involvements from these two studies into nine Critical Reason (CR) categories. The CR represents the final error or failure triggering a crash scenario. The nine CR categories were: (1) non-performance (e.g., asleep); (2) inadequate surveillance; (3) other recognition failure; (4) too fast; (5) other decision failure; (6) maneuver execution error; (7) vehicle failure; (8) environmental/ roadway; and (9) miscellaneous other. Below are the four Pearson **r** correlations comparing the CR profiles of each crash category within each study:

- NMVCCS SV × NMVCCS MV: **-0.35**
- LTCCS SV × LTCCS MV: **-0.15**
- NMVCCS SV × LTCCS SV: **+0.67**
- NMVCCS MV × LTCCS MV: **+0.75**.

The two negative correlations show that, for both cars and trucks, SV and MV involvements were more dissimilar than similar in their proximal cause profiles. The two positive correlations suggest causal robustness within each crash category, even across two studies with different vehicle types, driver types, and data collection years. CISS statistics also reveal causal differences between SV and MV involvements (Table 1).

Crash Category: Factor:	Single-Vehicle	Multi-Vehicle	All
Alcohol Involvement	**13.3%**	**3.5%**	**7.1%**
Drug Involvement	**4.7%**	**1.6%**	**2.7%**
Dark (Unlighted + Lighted)	**50.6%**	**23.4%**	**33.3%**
“Looked But Did Not See”	**0.2%**	**8.0%**	**5.2%**
Sleepy/Asleep Driver	**6.7%**	**1.0%**	**3.1%**
Vehicle Out-of-Control Pre-Impact	**27.2%**	**3.1%**	**10.3%**

Table 1 – Single-Vehicle vs. Multi-Vehicle factor involvement in 2017-2020 Crash Investigation Sampling System (CISS) crashes, 2017-2020.

In a 2016 FMCSA ND fatigue/HOS report [10], 81% of the SCEs involved only the truck. For police-reported truck crash involvements nationally, the SV percentage was 21% [11]. Based on SV vs. MV causal differences cited here and previously, it's doubtful that such disparate SCE data in [10] can be causally representative of police-reported crashes.

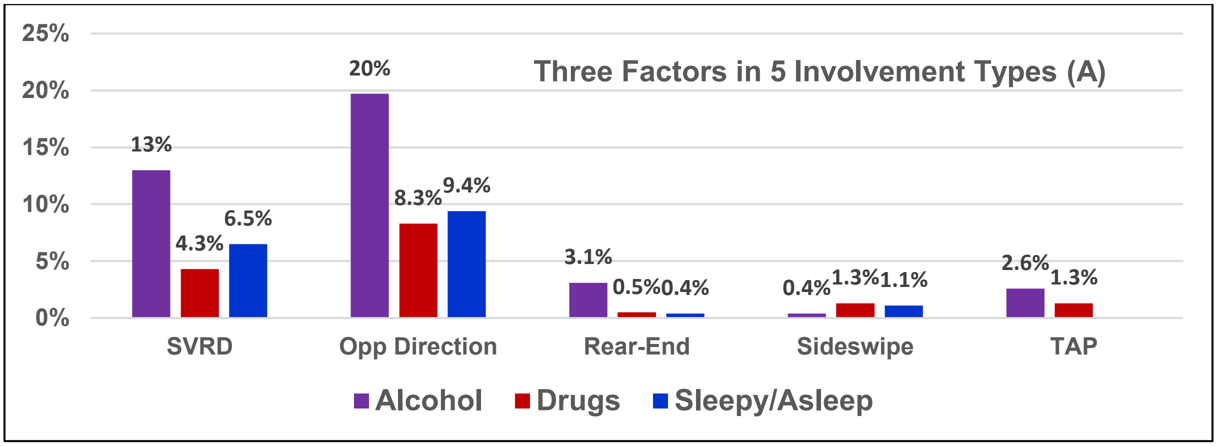
Embedded within MV involvements is another causal schism: at-fault vs. not-at-fault. Critical Reason assignment in the LTCCS and NMVCCS essentially denoted fault, since CRs were assigned to just one vehicle in a crash. This expands events to three categories, nicknamed "The Good, the Bad, and the Ugly" [8]. Allowing that no crash involvement is actually "Good," the three vehicle involvement categories may be defined as "Good" (MV, no CR assigned), "Bad" (MV, CR assigned), and "Ugly" (Single-Vehicle). Table 2 presents LTCCS attribute comparisons across the three categories in the order "Ugly," "Bad," "Good." Large category differences are seen. This breakout further highlights SV vs. MV causal differences and reinforces the common sense difference between at-fault and not-at-fault MV involvements. Studies aggregating at-fault and not-at-fault ignore the obvious reality that most MV crashes involve a critical error/failure of one driver/vehicle with little significant contribution from the other drivers/vehicles [15]. Yet 40% of MV involvements treated as fatigue surrogates in the 2016 fatigue/HOS study [10] were not-at-fault; i.e., the truck driver made no cited error contributing to causation.

LTCCS Variable	Attribute (or Aggregation)	"Ugly" (SV)	"Bad" (MV, CR)	"Good" (MV, No CR)
Driver Seat Belt Use	**None used or not indicated***	**23%**	**8%**	**6%**
Driver Roadway Familiarity	**Truck driver rarely/never drove road before***	**38%**	**29%**	**17%**
Vehicle Factor (Truck)	**Present (any inspection deficiency)**	**62%**	**50%**	**21%**
Driver Fatigue Present	**Truck driver fatigued***	**30%**	**14%**	**3%**
Hours of Last Sleep	**< 6 hours last main sleep***	**29%**	**15%**	**10%**
Traffic Factor	**Ambient traffic, time of crash**	**6%**	**42%**	**31%**

* % of knowns. Table percentages are LTCCS estimates for all U.S. large trucks (combination- plus single-unit) involved in serious (KAB) crashes.

Table 2 - "Good-Bad-Ugly" Attribute Percentages of LTCCS Crash-Involved Trucks [8]

Horizontal causal heterogeneity extends to individual crash involvement types. CISS statistics corroborate this. Figures 2-A and 2-B show the frequencies of six attributes in five crash involvement types. MV types are specific to the encroaching or turning (for turning across path) vehicle. The single-vehicle road departure (SVRD) percentages differ most from the three MV involvement types on the right. However, MV oppositive direction involvements are much like SV involvements in their profiles, perhaps reflecting that both types usually involve lane departures.



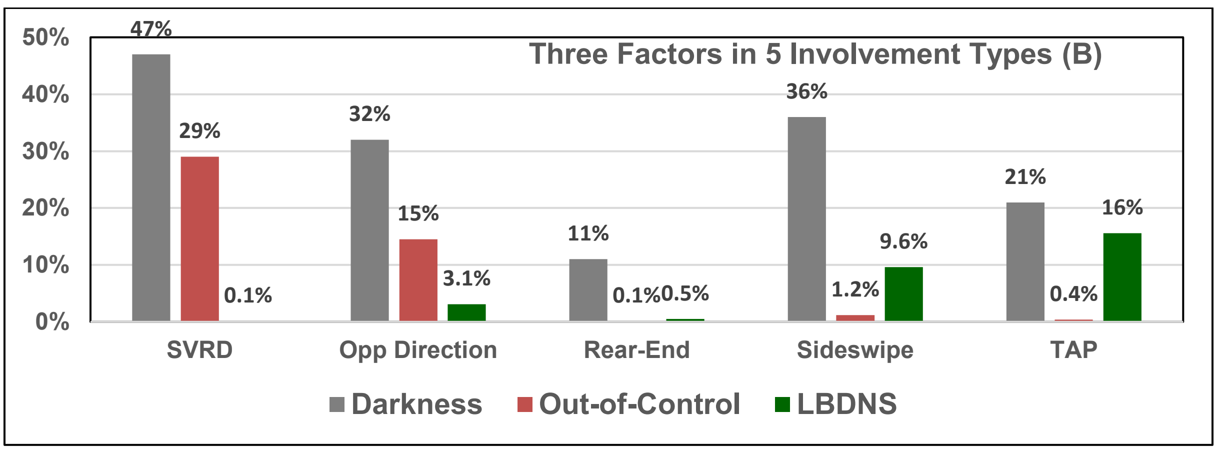


Figure 2 (A&B) – Incidence of six factors in 2017-2020 crash involvements of Single-Vehicle Road Departures (SVRDs), Opposite Direction (encroaching), Rear-End (striking), Same Direction Sideswipes (encroaching), and Turn Across Path (TAP; turning vehicle).

VERTICAL HETEROGENEITY

Vertical heterogeneity refers to scenario and causal changes seen as one ascends or descends the crash severity triangle. For example, the AAA Safety Foundation [16] estimated that passenger vehicle drivers were drowsy/fatigued in 3% of crashes with no injuries, 8% of injury crashes, and in 15% of fatal crashes. New CISS statistics again demonstrate this crash phenomenon, here for three forms of driver impairment. These same CISS statistics further attest to SV vs. MV causal profile differences.

CAIS: Category & Factor:	0	1	2	3	4	5	6
SV Alcohol	14%	12%	14%	15%	23%	18%	21%
MV Alcohol	2.4%	4.2%	5.9%	7.8%	6.8%	33%	41%
All Crash Alcohol	6.7%	6.7%	8.5%	11%	12%	27%	31%
SV Drugs	2.4%	5.7%	21%	30%	37%	50%	58%
MV Drugs	0.5%	1.7%	5.4%	16%	15%	24%	40%
All Crash Drugs	1.2%	3.0%	11%	22%	22%	35%	49%
SV Sleepy/Asleep	6.0%	9.8%	11%	11%	20%*	*CAIS 4-6 Aggregated for Sleepy	
MV Sleepy/Asleep	0.5%	1.5%	3.1%	3.3%	1.9%*		
All Crash Sleepy/Asleep	2.6%	4.1%	5.9%	6.7%	9.0%*		

Table 3 – Three driver impairments as a function of category and CAIS level distribution for 2017-2020 CISS crash involvements.

The ostensible purpose of road safety research is to formulate ways to reduce the harmful consequences of crashes, most of which occur at the highest levels of severity. Table 4 shows a bivariate breakout of three crash severity categories and three magnitude metrics: crash numbers, economic cost, and total societal harm. Economic cost elements include damage, traffic congestion, medical, legal, insurance, and lost income. Total societal harm adds monetary valuations of lost quality-of-life. In 2010, 22.1% of police-reported crashes resulted in fatalities or other injuries, but they accounted for 70.5% of economic cost and 91.4% of total societal loss. We see that crash harm is “top-heavy” in the crash triangle. This suggests that the true external validity of crash causation-related data is primarily the extent to which it represents causality at the top strata of severity.

Metric: Severity:	Number of Crashes	Total Economic Cost	Total Societal Harm
Fatal	0.2%	19.1%	36.1%
Injury	21.9%	51.4%	55.4%
Property Damage Only	77.9%	29.5%	8.6%

Table 4 Severity Percent Distributions of 2010 U.S. Crash Numbers, Economic Cost, and Total Societal Harm [17].

SHRP2 EVENT ANOMALIES

This paper has strengthened the conclusions of past work [8, 9, 12]. Crashes are pervasively heterogeneous in regard to when, where, how, and why they happen. Crash epidemiology is complex and rich. It cannot be ignored. Direct cause-related extrapolations vertically by severity and horizontally by involvement type are likely to be spurious. Further, human harm resides predominantly at the top severity levels. The external validity of any kind of crash/event data depends on how it relates to harm. The creation and analytic characteristics of any crash-related dataset should be examined for its likely external validity. This section examines SHRP2 from this perspective.

SHRP2 crash/event statistics are dissimilar to conventional crash statistics in key ways. Table 5 presents newly retrieved "Good-Bad-Ugly" distributions of four levels of SHRP2 events. The numbers in three cells are underlined for discussion. First, notice that minor crash "Ugly" involvements (i.e., minor SV at-fault) are the majority of all crash involvements. They far outnumber minor "Bad" and "Good" involvements in the category. In contrast, the opposite is true of the two higher severity levels. Given the heterogeneity of crashes, it appears that the numbers in this one cell could distort inferences about the higher categories and about crashes as a whole. The Ugly-Bad-Good total crash percentages are 58%, 21%, 22%. In NMVCCS, they were 17%, 39%, 44% [8]. Secondly, looking at near-crashes, the small number of "Ugly" and large number of "Bad" events suggests that near-crashes are not simpatico with crashes. This should not be surprising since ND crashes and ND non-crashes are collected in qualitatively different ways. Thus, SHRP2's own crash/near-crash discrepancies further refute "Identical Mechanisms."

SHRP2 Crash/Event Severity	"Ugly" (SV, At-Fault)	"Bad" (MV, At-Fault)	"Good" (MV, Not-At-Fault)	Total
"Most Severe" Crash	20/1.9%	48/4.6%	44/4.3%	112/11%
Police-Reportable Crash	30/2.9%	71/6.8%	81/7.9%	182/17%
Minor Crash	<u>552/53%</u>	97/9.3%	99/9.7%	748/72%
Crash Total (of above)	602/58%	216/21%	224/22%	1042/100%
Near-Crash	<u>256/3.9%</u>	<u>3,944/60%</u>	2,341/36%	6541/100%

Table 5 - Percent Distributions of SHRP2 events by category and severity.

Discontinuities are also seen in the SHRP2 severity distributions of specific crash involvement types. Statistics from a 2018 report [18] are post-analyzed here in regard to the prevalence of two different crash/event involvement types across three event severity categories (Figure 3). The two involvement types are rear-end striking and road departures. One sees no similarities in the breakouts of these two common involvement types. Near-crashes are dominated by rear-end striking and minor crashes by road departures. This suggests that vertical extrapolations from neither of those two datasets would be representative of reportable crashes.

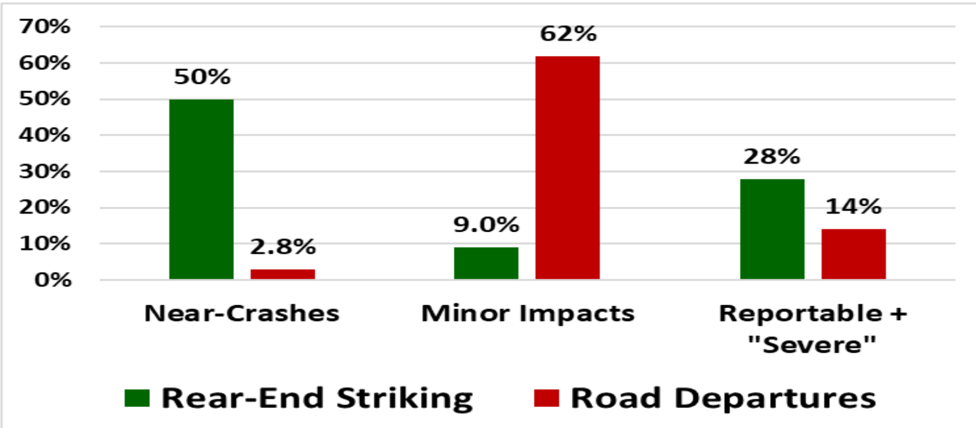


Figure 3 – Prevalence of two scenario types by 3 SHRP2 severity levels [18].

ND studies consider a "crash" to be any sensor-detected contact. In Table 5, just 28% of SHRP2 crashes meet conventional reporting thresholds. The ratio of non-reportable to all reportable crashes is 748:(112+182) = 748:294 = 2.5. A 2010 NHTSA survey [19] estimated unreported crashes vis-à-vis police-reported crashes. It asked respondents if they had been involved in a damage or injury-producing crash in the prior 12 months and, if so, whether it was police-reported or not. The ratio of unreported to reported crashes was 692:1,545 = 0.45. The ND crash criterion of any detectable contact results in proportionately 2.5:0.45 = 5.6 more non-reported crashes than found per NHTSA's "unreported" crash criteria. Because of vertical heterogeneity, the disproportionate number of ND minor crashes challenges the representativeness of ND crash datasets in relation to conventional crash datasets.

The highest SHRP2 crash severity level is "severe," with the primary threshold being airbag deployment [14]. An established standard in crash medicine is the Abbreviated Injury Scale [13]. AIS scales severity on a 0-6 scale, as follows: (0) no injury, (1) minor, (2) moderate, (3) serious, (4) severe, (5) critical, and (6) maximum/ untreatable. CISS is the largest crash database to base its crash severity scaling on medical scaling of specific injuries. CAIS is the single highest injury level for any occupant of an involved towed vehicle One may ask how "severe" crashes in SHRP2 are actually manifested in crash injuries scaled by CAIS. The authors know of no follow-up studies of SHRP2 "severe" crash victims, but CISS statistics do tell us the injury severities of crashes meeting the principal SHRP2 "severe" criterion of airbag deployment. The 2017-2020

CAIS distribution of such crashes was (0) no injury: 45%; (1) minor: 41%; (2) moderate: 8.9%; (3) serious: 4.3%; (4) severe: 0.8%; (5) critical: 0.4%; (6) maximum/untreatable: 0.2% Per CISS, fully 85% of airbag deployment crashes result in no injury, or just a minor one. Just 1.3% result in severe, critical, or maximum injuries. Thus, SHRP2 “severe” crashes encompass a range of medical outcomes probably dominated by low severities as defined medically. Recall the vertical causal heterogeneity findings explored above. Driver impairment percentages rise sharply in the mid CAIS injury levels. It is at those higher severities where most human crash harm resides.

CONCLUSIONS

This paper has stated its main conclusion in its title. H.W. Heinrich contributed to industrial injury reduction and, via onboard monitoring technology, to motor vehicle crash reduction. These applications to individual behavior don’t require identical causal mechanisms across accident types and severities. Partial similarity seems to suffice.

Direct extrapolations of accident causes do require identical mechanisms across accident severities and types, however. Yet, arguably, the concept of identical mechanisms is fallacious. ND non-crashes don’t causally represent crashes. ND minor crashes don’t represent minor crashes as society perceives them. Few ND “severe” crashes are severe by medical standards. SV crashes do not represent MV crashes, and vice versa. The authors know of no other road safety research paradigm with such an unsubstantiated foundation, or with such spurious applications; e.g., to determining truck driver HOS rules affecting millions and with billions of dollars in economic impacts. A new analytic foundation, the *Heterogeneity Principle*, has been verified across major road crash and other event datasets. Crash characteristics and causes are pervasively heterogeneous both horizontally by scenario type and vertically by severity. Most direct extrapolations of characteristics and causal profiles are spurious. Quantifying factors in serious crashes is most important because that is where most human harm is found.

As apparent from the cited TRB research needs statement [11], Mixed-SCE rate seems to be a surrogate measure looking for a valid referent. This is scientifically backwards. The Mixed-SCE method was never based on empirical science -- the systematic observation of target external phenomena. Surrogate metrics are valid in relation to target phenomena only if proven to be so. In science, the onus to prove validity rests on those espousing a theory or method.

A revelatory insight from crash heterogeneity is that the *generalized* road risk associated with any scenario (e.g., rear-end striking, road departure) or factor (e.g., distraction, speeding, night driving, hours-of-driving) *cannot be quantified*. One must always specify a crash population referent. One must answer the question, “Risk of what?”

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