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Evaluation of Crash Contributing Factors

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Abstract

Understanding crash contributing factors is essential in safety management and improvement. These factors drive investment decisions, policies, regulations, and other safety-related initiatives. This paper analyzes factors that contribute to crash occurrence based on two national datasets in the United States (CISS and NASS-CDS) for the years 2017-2022 and 2010-2015, respectively. Three taxonomies were applied to enhance understanding of the various crash contributing factors. These taxonomies were developed based on previous research and practice and involved different groupings of human factors, vehicle factors, and roadway and environmental factors. Statistics for grouping the different types of factors and statistics for specific factors are provided. The results indicate that human factors are present in over 95% of crashes, roadway and environmental factors are present in over 45% of crashes, and vehicle factors are present in less than 2% of crashes. Regarding factors related to human error and vehicle maintenance, speeding is involved in over 25% of crashes, distraction is involved in over 20% of crashes, alcohol and drugs are involved in over 9% of crashes, and vehicle maintenance is involved in approximately 0.45% of crashes. Approximately 4.4% of crashes involve a driver who "looked but did not see." Weather is involved in over 13% of crashes. *Conclusions*: The findings indicate that, consistent with previous research, human factors or human error are present in around 95% of crashes. Infrastructure and environmental factors contribute to about 45% of crashes. Vehicle factors contribute to only 1.67% - 1.71% of crashes. The results from this study could potentially be used to inform future safety management and improvement activities, including policy-making, regulation development, safe systems and systemic safety approaches to safety management, and other engineering, education, emergency response, enforcement, evaluation, and encouragement activities. The findings could also be used in the development of future Driver Assistance Technologies (DAT) systems and in enhancing existing technologies.

Keywords

Contributing Factors, Human Factors, Vehicle Factors, Environmental Factors, Crash Data, Vision Zero

1. Introduction and Literature Review

Traffic safety is a basic measure of effectiveness for transportation systems and is closely linked to human health and economic development. According to the Centers for Disease Control and Prevention (CDC), roadway traffic crashes are the leading cause of death for people aged 1 to 54 in the United States [1]. An estimated 6,756,000 traffic crashes occurred in the United States in 2019, including 33,244 fatal motor vehicle crashes and 36,096 deaths in these crashes [2]. Since 2010, the number of traffic crashes has increased, revealing the need to prevent traffic crashes. To improve traffic safety and prevent crashes, countermeasures should be based on a detailed analysis of the contributing factors associated with crashes.

Crash contributing factor is a term frequently used in traffic safety management to refer to an element or condition that potentially influences or contributes to the occurrence of a crash or the severity of a crash. The term contributing factor is often confused with the term causal factor. The latter refers to the primary cause or factor directly responsible for a crash and reveals the root cause of the crash; the crash would have been avoided if this causal factor had been mitigated. In contrast, a crash contributing factor may not be the root cause of a crash but may still influence the sequence of events before, during, and after the crash (*i.e.*, removing the factor may or may not have prevented the crash from occurring) [3]. In safety management, the identification of a crash casual factor is valuable for addressing the main issues within transportation system that led to the crash, yet this is typically impossible to do in practice. Thus, identification and use of crash contributing factors for use in safety analysis, management, and other activities can enhance the overall safety of the transportation system by reducing crash risks associated with those factors through targeted interventions.

An example of the identification of crash contributing factors is the widely cited statistics that 94% of vehicle collisions are due to driver-related factors [4] or that 93% are related to human factors (which broadly includes both human factors and aberrant driver behaviors) [5]. These statistics are based on the 2005 National Motor Vehicle Crash Causation Survey (NMVCCS), where the "critical" factor was assigned to the driver if there were any potential driver-related contributing factors, regardless of other factors [4], or on data collected from a few counties across the United States in the 1970s [5]. Over time, changes in driving behaviors (e.g., the rise of distracted driving due to the use of smartphones or other entertainment devices), improvements in automobile technologies (e.g., advanced driver-assistance systems), and improvements in the roadway network and driving environment are likely to affect the distribution of crash types and contributing factors.

By understanding the factors involved in crashes, crash occurrence and crash severity can be reduced through the implementation of specific measures to target specific contributing factors. In particular, understanding the relative contribution of various factors to crashes can assist with the determination of how best to allocate resources to minimize crash frequency and severity. A detailed analysis of crash contributing factors would also help in the identification, development, and evaluation of current and emerging safety countermeasures such as improved geometric design, improved planning and maintenance of transportation systems, enhanced training for drivers and engineers, the development of policies and legislation to enhance safety, targeted enforcement activities, and the development of advanced vehicle technologies.

Numerous studies have evaluated various contributing factors to crashes. Most of these studies focused on a small number of factors and attempted to link these factors to crash frequency or crash severity. This paper focuses on factors that contribute to crash occurrence; therefore, the literature review does not summarize literature specific to crash severity[1].

Some previous studies evaluated contributing factors for specific crash types or infrastructure types (e.g., intersections, different functional classes). For instance, the Volpe National Transportation Systems Center conducted an analysis using the National Automotive Sampling System (NASS) General Estimates System (GES) that examined contributing factors for different crash-imminent scenarios with a focus on alcohol and drug use, impaired and distracted driving, speeding, and hit-and-run behaviors [6]. Another study used the NMVCCS to analyze intersection crashes and found that 96% of critical factors contributing to crashes were related to the driver [7] [8]. Additional studies estimated that driver errors are involved in 99% of crashes [9] and 94% of crashes [4] [10] [11] and that inattention contributes to more than 40% of crashes [12].

A recent study used data from the Fatality Analysis Reporting System (FARS) and Highway Safety Information System (HSIS) to stratify the analysis of contributing factors based on crash type, area type, roadway type, location type, intersection type, traffic control type, light conditions, road alignment type, and severity [13]. The factors that were considered focused mainly on the infrastructure but also accounted for weather and other environmental variables. Given the reliance on police-reported data and roadway inventory data in crash analysis, the factors found to be associated with higher crash frequencies included higher traffic vol-

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[1] Factors that directly influence crash severity are factors that change the forces from the crash on the bodies of the people in the crash [55] [53], factors that influence the body's of those involved to withstand the forces [54], and the timeliness and quality of medical care [55] [56]. This is a fundamental principle used in developing crash testing programs such as the US New Car Assessment Program (NCAP) [57]. While factors that influence crash frequency may change the number of different types of crashes, they may or may not directly influence the severity (after accounting for changes in crash types, etc.).

umes, steeper grades, sharper horizontal curves, narrower lanes and shoulders, unpaved shoulders or the absence of shoulders, the presence of mountainous terrain, higher speed limits, wider crossings at intersections, and the absence of left- and right-turn channelization at intersections.

Furthermore, since most traffic crashes are related to human factors, detailed assessments of the impact of driver behaviors on the risk of crash involvement have been discussed in previous studies. Most previous assessments have been conducted using self-reported driver behavior data collected through a survey named the Manchester Driver Behavior Questionnaire (DBQ) and have emphasized the need for extensive data collection and analysis to effectively capture the complexities of driver behaviors [14]-[18]. Reason *et al.* initially identified the distinction between errors and violations based on a 50-item version of the DBQ [15]. Errors were defined as planned actions that failed to achieve their intended consequences, such as driving behaviors involving a failure of observation, a misjudgment, or wrong operation of the vehicle. In the version of the DBQ used in that study, behaviors like misreading road signs, misjudging oncoming vehicle speeds, and turning the wrong devices on or off were classified as errors and lapses. Violations were identified as deliberate deviations from established practices deemed essential for the safe operation of a vehicle, including behaviors like speeding and impaired driving due to alcohol and drug use. The main difference between these two terms is that errors and lapses are unintentional while violations are deliberate. Errors and lapses are always associated with the information-processing characteristics of the individual driver. Violations can arise with various social and motivational factors, including drivers' attitudes, beliefs, and acceptance of social norms.

2. Objective

The purpose of this research was to use multiple detailed datasets from recent years that include police-reported crash information, crash reconstructions, hospital data, and interviews with people involved in the collisions documented in the datasets to evaluate factors that contribute to the occurrence of vehicle-related crashes. To this end, multiple taxonomies were applied to the data in order to yield results, including potential interactions, that would enhance understanding of potential crash contributing factors for use in future crash reduction and other safety management efforts, including Vision Zero [19]. This is similar in concept to research that utilized video and GPS data to evaluate contributing factors [20], but utilizes existing National-level datasets that include details unavailable from video or GPS data. It also includes all severity levels as opposed to focusing on fatal crashes only [21], specific groups of drivers [22] [23], or specific crash types [24].

3. Data

The traffic crash data used in this research are from two national crash datasets collected and maintained by the National Highway Traffic Safety Administration (NHTSA): the Crash Investigation Sampling System (CISS) and the National Automotive Sampling System Crashworthiness Data System (NASS-CDS, hereafter referred to as CDS). The National Automotive Sampling System was established in the 1970s and was comprised of multiple datasets, including the CDS. The purpose of the CDS dataset after 1988 was to enhance knowledge related to vehicle crashworthiness by capturing detailed data, including the following [25] [26]:

1) Vehicle crash profiles
2) Restraint system performance
3) Injury mechanisms

Due to changes in the data needs of the highway safety community, the NHTSA undertook a data modernization effort in 2012 [27]. This included an update of the purpose of each dataset, the variables collected, where data were collected, and the focus of in-depth investigations. In this update, the CDS was replaced by the CISS, which is based on data from 32 geographical areas across the United States (the CDS was based on data from 24 geographical areas across the United States). The stated purpose of the CISS dataset in terms of the NHTSA's efforts to meet the updated data needs of the highway safety community, and thus the focus of the data collection efforts for the CISS dataset, includes the following [25]:

1) Identification of emerging issues in traffic safety
2) Evaluation of vehicle designs and safety systems
3) Examination of the detailed crash performance of vehicles
4) Evaluation of the effectiveness of motor vehicle and traffic safety program standards
5) Design of future crash avoidance and mitigation technologies
6) Improvement in the knowledge of crash-related injuries and mechanisms

Both systems (CDS and CISS) are comprised of detailed data collected by expert teams. The data collected include police-reported crash data, data from hospital and medical records, crash reconstruction data, and data from interviews with people involved in the crashes documented in the datasets (when possible). It should be noted that both systems require a vehicle to be towed in order for a crash to be eligible for inclusion in the dataset, although the CDS imposes additional restrictions. For each crash that has been selected and sampled, trained crash technicians collect data from the crash site by recording scene evidence that helps users understand the nature and outcome of the crash. Given that the data collection team is not at the crash site in an enforcement role, it is possible that the people interviewed provide more accurate information regarding what happened than the information they reported to the responding police officers (e.g., distracted driving and other behaviors). Advanced technologies and methods are utilized by the data collection team to ensure that the resulting high-quality data can be queried by end users. The CDS and CISS are both intended to be nationally representative and therefore use sampling strategies that result in nationally representative weighted data for the United States (with raw counts of up to 5,000 crashes per year). For details regarding the sampling design and weighting procedures, see [25] [26].

Given the detailed nature of the CDS and CISS data, these datasets were selected for the analysis of crash contributing factors in this research. At the time the research was conducted, CISS data for 2017-2022 were available. (A limited number of data observations had been collected for 2016, and a full dataset was not published by the NHTSA for that year.) The final year in which data were collected for the CDS was 2015. Therefore, to yield the most relevant results based on an adequate sample size of recent data, CDS data for the years 2010-2015 and CISS data for the years 2017-2022 were used. This resulted in a total of 17,447 crashes in the CISS data and 21,629 crashes in the CDS data.

The codebooks for the CDS and CISS were reviewed to identify variables that could be used to identify factors that potentially contribute to crash occurrence. (Factors that potentially influence crash severity were not considered in the analysis.) Care was taken to ensure that each factor used could be considered a precipitating factor to a crash occurring. Various factors related to human factors, human errors (*i.e.*, aberrant driver behaviors), vehicle issues, environmental factors, and infrastructure factors were considered and included. It should be noted that while the data include factors that potentially contributed to crash occurrence, it is not known for certain which of the factors present in individual crashes contributed to the crash occurring. Therefore, the presence of a factor should not be assumed to indicate that it is a causal factor. This applies to all factors, including human errors and human factors.

4. Methods

Given that the objective of this project was to evaluate the factors that potentially contribute to the occurrence of vehicle-related crashes and to apply multiple taxonomies for classifying contributing factors, taxonomies were developed as shown in **Figure 1**. The first taxonomy, identified in **Figure 1** as Taxonomy 1, is based on previous research and the taxonomy used in the *Highway Safety Manual* [28]. Additional taxonomies were created to disaggregate the factors in order to better understand the various factors that potentially contribute to crash occurrence. Each of the three taxonomies has similarities, though Taxonomies 2 and 3 both stratify into more specific groupings than Taxonomy 1. Human Factors and Driver Errors in Taxonomy 2 and Distraction, Fatigued Driving, Alcohol and Drug, Other Behavior and Decision Factors, and Speeding in Taxonomy 3 are all related to Human Factors in Taxonomy 1. Vehicle Factors and Vehicle Maintenance in Taxonomy 2 and Vehicle-Specific Factors in Taxonomy 3 are all grouped into Vehicle Factors in Taxonomy 1. Environmental Factors and Infrastructure Factors in Taxonomy 2 and Driving Environment, Roadway Surface Conditions, and Weather in Taxonomy 3 are grouped into Environment Factors in Taxonomy 1.

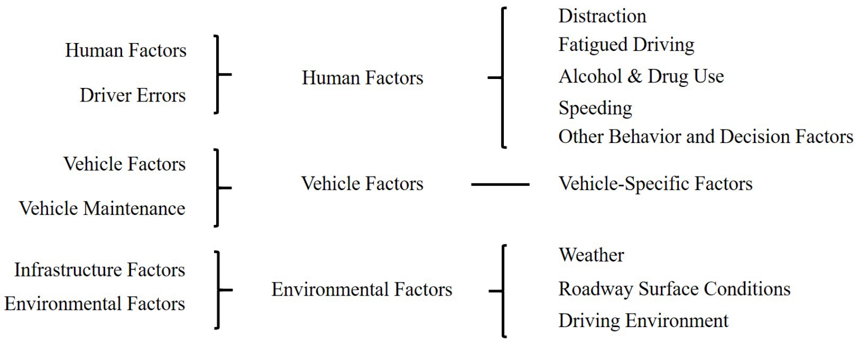


Figure 1. Taxonomies applied to categorize contributing factors.

There are key differences in some similar factors and groupings across the taxonomies, yet each is categorized differently. The human factors in Taxonomy 1 include the contributing factors related to drivers' age, judgement, driving skill, attention, fatigue, experience, and sobriety. The vehicle factors in Taxonomy 1 include all vehicle-related issues that could potentially cause a crash, including factors associated with maintenance issues (e.g., bald tires). In Taxonomy 1, the environmental factors include both the natural or built environment, aspects of roadway design, and land use.

In Taxonomy 2, human factors only represent the crash contributing factors related to drivers' physical limitations, such as reaction time. These are factors that influence policies such as stopping sight distance requirements, which include conservative values for driver reaction time and deceleration rates based on distributions from driver performance data measured by researchers [29] [30]. Driver errors in Taxonomy 2 include factors associated with driver decisions such as distracted driving, impaired driving due to alcohol and drug use, speeding, and inappropriate driving decisions. This grouping provides a high-level (aggregate) breakdown of how often these factors are present in crashes. Environmental factors in Taxonomy 2 emphasize natural environmental factors such as weather or the presence of animals on the road and separate factors related to infrastructure and the built environment into their own category.

Taxonomy 3 considers distraction, fatigued driving, alcohol and drug use, and speeding as individual categories, with all other behavioral and decision-related factors grouped into a single category. This is done to provide specific details related to these factors, as they are some of the most common driver-related factors. The vehicle factors are no different between Taxonomies 1 and 3 due to there being too few vehicle-specific factors to provide additional detail beyond what is provided in the first two taxonomies. The environmental factors in Taxonomy 3 separate weather into its own category, which represents the occurrence of crashes related to poor weather conditions, like rain, snow, and fog. The roadway surface condition category in Taxonomy 3 contains the crash contributing factors related to non-dry roadway surfaces. This category has some overlap with the weather category but also includes some other factors related to low-friction roadway surfaces (e.g., oily surface, sandy surface, gravelly surface, and muddy surface). The driving environment category in Taxonomy 3 captures the possible physical objects (fixed or moving) that drivers faced before a vehicle crash occurred, such as the animals, roadway elements, and other fixed objects surrounding the road.

According to these classifications, a review of the variables from the CISS and CDS datasets was conducted. Based on the definitions of the variables, each value for variables that could potentially be a precipitating factor in a crash was labeled appropriately for each of the taxonomies. Python was then used to obtain weighted statistics (*i.e.*, percentages) using the sample weights in the datasets. It should be noted that the categories and subcategories for Taxonomies 2 and 3 are not mutually exclusive (*i.e.*, the sums of percentages do not necessarily add up to 100%). Additionally, most crashes have multiple factors that potentially precipitated the collision. The percentages reported in the results are based on crashes with one or more observed factors within each category. Care was taken to ensure that no crash was counted more than once for a single category, even if multiple factors were observed within a single category for an individual crash. The Python code used to process the data is available from the authors on request.

The weighted percentages are based on indicator variables and are computed using Equation (1), as shown below.

$$P = \frac{\sum_{i=1}^{n} x_i w_i}{\sum_{i=1}^{n} w_i} \cdot 100 \tag{1}$$

where $P =$ the weighted percentage, $x_i =$ the indicator variable value for observation *i*, $w_i =$ the sample weight for observation *i*, and $n =$ the number of observations.

Given that the data are based on weighted samples, the effective sample size (n^*) can be estimated using Equation (2), known as Kish's effective sample size ([31], pp. 183-200).

$$n^* = \frac{\left(\sum_{i=1}^{n} w_i\right)^2}{\sum_{i=1}^{n} w_i^2} \tag{2}$$

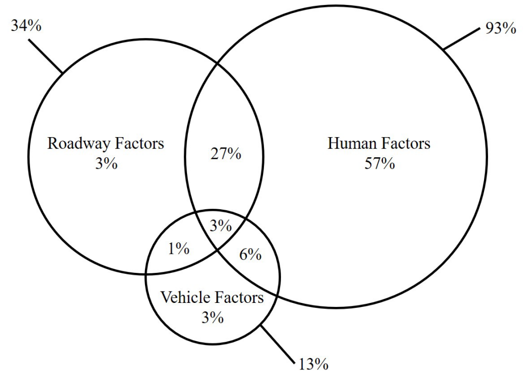
The confidence intervals for proportions can be computed using a Wald interval with the effective sample size, as shown in Equation (3).

$$CI = p \pm z_{\alpha/2} \sqrt{\frac{p(1-p)}{n^*}} \tag{3}$$

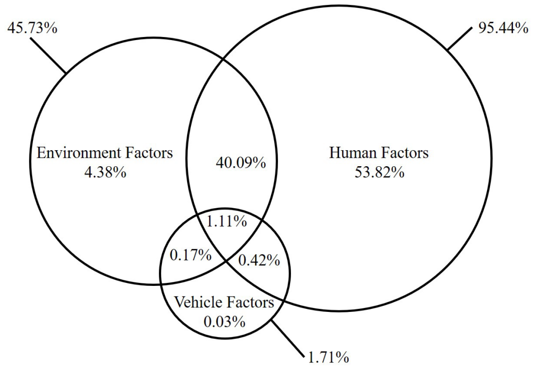
where $CI =$ the confidence interval, $p =$ the weighted proportion (*i.e.*, $p = P/100$), $z_{\alpha/2} =$ the two-tail p-score value for the desired confidence level, and $n^* =$ the effective sample size.

5. Results

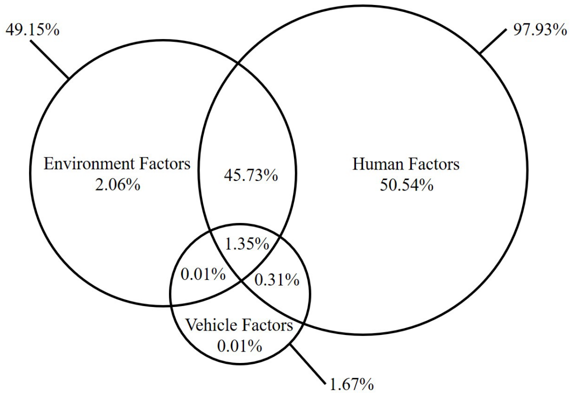
The results of the analysis for Taxonomy 1 are shown as Venn diagrams in **Figure 2** for both the CDS and CISS datasets, along with the corresponding Venn diagram based on the *Highway Safety Manual* (HSM) [28] [32]. The structure of Taxonomy 1 is the same as that of the Venn diagram in the HSM, making comparisons straightforward. **Figure 2(a)** indicates that, in the HSM, vehicle factors contribute to 13% of all crashes. However, **Figure 2(b)** and **Figure 2(c)** indicate that vehicle factors only contribute to 1.71% and 1.67% of crashes based on the 2017-2022 (CISS) and 2010-2015 (CDS) data, respectively. This is not surprising given the improvements in vehicle design and federal regulations that have improved both the quality and safety performance of vehicles. However, the reduction in crashes resulting from vehicle factors makes it more likely that the crashes that occur will have human and roadway/environmental factors as contributing factors. Therefore, it is not a surprise that contribution of human factors has increased from 93% in the HSM to 95.44% (CISS) and 97.93% (CDS) or that the contribution of roadway/environmental factors has increased from 34% in the HSM to 45.73% (CISS) and 49.15% (CDS). This is also consistent with NHTSA research (NHTSA, 2015). It should be noted that these factors are a product of the NHTSA data collection process. Human factors often represent behaviors that can be influenced by infrastructure design, policies, and training [33] [34]. Therefore, the fact that 53.82% of crashes in the CISS data and 50.54% of crashes in the CDS data only had human factors as contributing factors should not be interpreted to mean that engineers cannot influence or do anything about over half of all crashes. Rather, it can be used to inform strategies for crash countermeasures and policy development.



(a)



(b)



(c)

Figure 2. (a) Venn diagram of contributing factors from the highway safety manual; (b) Venn diagram of contributing factors using the CISS dataset; (c) Venn diagram of contributing factors using the CDS dataset.

The minimal changes in percentages for human factor contributions, even with changes in driver assistance technologies and changes in the potential sources of distractions and other human factors, are potentially due to risk compensation and behavioral adaptation. Risk compensation occurs when behaviors change based on perceived differences in risk. Therefore, it is important to evaluate contributing factors in greater detail. Detailed analysis is provided below for Taxonomies 2 and 3 and regarding specific factors.

The results for Taxonomies 2 and 3 provide an additional breakdown of factor groupings, as shown in Table 1. Due to the presence of more than three groupings in Taxonomies 2 and 3, overlaps between the groups are not provided. As shown in Taxonomy 2, driver errors are present in nearly all crashes, while human factors are present in 16.31% and 16.79% of all crashes based on the CISS and CDS datasets, respectively. The Taxonomy 3 results for human factors indicate that distraction plays a role in 19.06% - 20.92% of crashes, fatigued driving is related to 2.93% - 2.71% of vehicle crashes, alcohol and drugs are present in 8.99% - 9.62% of crashes, and speeding is a factor in 25.23% - 33.38% of crashes. This breakdown presents an opportunity for comparison with fatal crashes. For example, FARS data queries for 2010-2020 indicated that 99,084 of fatal crashes (27.8%) involved speeding, 39,828 (11.2%) involved distracted or drowsy drivers, and 169,159 (47.5%) involved drivers with a blood alcohol concentration (BAC) of over 0.08 g/dL. (Note that this is the percentage of crashes involving a driver with a BAC at this level, not the number of people killed with a BAC at this level.) This indicates the CISS results for speeding are representative of the percentage of fatal crashes that involve speeding. (It should be noted that speeding is based on the posted speed, not on the overall speed of the vehicles involved or the impact speed.) It also indicates that distracted driving, fatigued driving, and alcohol/drug use are underrepresented in fatal crashes. Higher fidelity analysis of specific human factors is provided in Section 5.1.

Table 1. Results of contributing factors for each taxonomy with 95% confidence intervals.

Taxonomy 1			Taxonomy 2			Taxonomy 3		
Classification	**% CISS**	**% CDS**	**Classification**	**% CISS**	**% CDS**	**Classification**	**% CISS**	**% CDS**
Human Factors	95.44 [94.67, 96.21]	97.73 [97.42, 98.04]	Human Factors	16.31 [14.94, 17.68]	16.79 [16.02, 17.56]	Distraction	19.06 [17.60, 20.52]	20.92 [20.08, 21.76]
						Fatigued Driving	2.93 [2.30, 3.56]	2.71 [2.38, 3.04]
			Driver Errors	95.40 [94.63, 96.18]	97.88 [97.58, 98.17]	Alcohol & Drugs	8.99 [7.93, 10.05]	9.62 [9.01, 10.23]
						Speeding	25.23 [23.62, 26.84]	33.38 [32.41, 34.35]
						Other Behavioral and Decision Factors	87.81 [86.60, 89.02]	89.81 [89.19, 90.43]
Vehicle Factors	1.71 [1.23, 2.19]	1.67 [1.41, 1.93]	Vehicle Factors	1.20 [0.80, 1.60]	1.22 [1.00, 1.45]	Vehicle Factors	1.71 [1.23, 2.19]	1.67 [1.41, 1.93]
			Vehicle Maintenance	0.51 [0.24 0.77]	0.45 [0.31, 0.58]			
Environmental Factors	45.73 [43.88, 47.57]	49.15 [48.12, 50.18]	Infrastructure Factors	31.63 [29.91, 33.36]	34.32 [33.33, 35.28]	Roadway Surface Conditions	18.92 [17.47, 20.37]	23.94 [22.67, 24.41]
			Environmental Factors	27.45 [25.79, 29.10]	30.46 [29.50, 31.40]	Weather	13.52 [12.25, 14.79]	16.95 [16.18, 17.72]
						Driving Environment	36.53 [34.74, 38.32]	36.56 [35.57, 37.55]

The Taxonomy 2 results for vehicle-related factors indicate that for the CISS and CDS datasets, vehicle maintenance issues (which could be considered an indirect human factor/error) contribute to approximately 0.51% and 0.45% of all crashes while other vehicle factors are present in 1.20% and 1.22% of all crashes, respectively. Further details on vehicle factors and vehicle maintenance factors are provided in the Vehicle Factors section of this paper.

Infrastructure and environmental factors contribute to a significant proportion of crashes and overlap in some cases. Based on Taxonomy 2, 13.35% of CISS crashes and 15.63% of CDS crashes involve both infrastructure and environmental factors. Based on Taxonomy 3, the driving environment is a factor in approximately 36.5% of all crashes, weather contributes to 13.52% - 16.95% of crashes, and roadway surface conditions contribute to 18.92% - 23.94% of all crashes. These results are limited to CISS and CDS variables that indicate specific related factors that could potentially directly contribute to crash occurrence. The results do not include any of the potential influence of the roadway environment, driving environment, or weather on human factors or driver errors. Further discussion is provided in the Roadway and Environmental Factors section of this paper.

5.1. Human Factors

As shown in Figure 2 and Table 1, human factors contribute significantly to crashes. The key human factors and human errors from the CISS and CDS data, with associated weighted percentages, are provided in Table 2. The factors are grouped based on Distraction, Fatigued Driving, Alcohol and Drugs, Speed Related, and Other Behavior and Decision Factors. Distraction is classified slightly differently between the CISS and CDS data, which is why there are missing values in Table 2.

Table 2. Detailed statistics for human factors with 95% confidence intervals.

Grouping	Factor	% CISS	% CDS
Distraction	Looked But Did Not See	4.45 [3.68, 5.21]	6.76 [6.24, 7.28]
	Distraction Outside Vehicle	3.16 [2.51, 3.80]	2.91 [2.56, 3.26]
	Other Distraction	-	3.07 [2.72, 3.42]
	Other Inside Vehicle	2.44 [1.87, 3.01]	-
	Unknown Distraction	1.64 [1.17, 2.11]	0.69 [0.52, 0.86]
	Manually Operating an Electronic Communication Device	1.20 [0.79, 1.60]	-
	Device/Control Integral to Vehicle	1.01 [0.64, 1.38]	0.86 [0.67, 1.05]
	Talking on Hand-Held Electronic Device	0.58 [0.30, 0.87]	-
	Other Device Brought into Vehicle	0.71 [0.40, 1.03]	0.97 [0.77, 1.17]
	Inattentive or Lost in Thought	0.88 [0.53, 1.23]	-
	Cell Phone	-	0.79 [0.61, 0.97]
	Passenger	0.61 [0.32, 0.89]	1.45 [1.20, 1.70]
	Smoking Related	-	0.12% [0.05, 0.19]
	Talking on Hands-Free Electronic Device	0.07 [0.00, 0.16]	-
Fatigued Driving	Sleepy	2.93 [2.31, 3.56]	2.71 [2.38, 3.04]
Alcohol & Drugs	Alcohol Involvement	6.94 [5.99, 7.88]	7.74 [7.19, 8.29]
	Drug Involvement	2.84 [2.22, 3.54]	2.86 [2.52, 3.20]

Continued

Speed Related	Driving Too Fast for Conditions	5.17 [4.35, 5.99]	6.58 [6.07, 7.09]
	Other Speed-Related	23.40 [21.48, 25.32]	26.53 [25.62, 27.44]
Other Behavior and Decision Factors		87.81 [86.60, 89.52]	89.81 [89.19, 90.43]

As shown in **Table 2**, some of the most prominent human factors that contribute to crash occurrence (excluding factors grouped under Other Behavior and Decision Factors) include the following:

1) Other Speed-Related (23.40% CISS, 26.53% CDS)
2) Alcohol Involvement (6.94% CISS, 7.74% CDS)
3) Looked But Did Not See (4.45% CISS, 6.76% CDS)
4) Driving Too Fast for Conditions (5.17% CISS, 6.58% CDS)
5) Distraction Outside Vehicle (3.16% CISS, 2.91% CDS)
6) Sleepy (2.93% CISS, 2.71% CDS)

It is interesting to note that these prominent factors are all related to social acceptance of speeding behavior, distraction, alcohol use, and fatigued driving. Previous research has evaluated driver characteristics and other factors that contribute to each of these. For instance, the proportion of US drivers that drive within the speed limit has been evaluated as a function of age (with younger drivers more likely to speed), income (with drivers having higher income drivers less likely to speed), gender (with female drivers less likely to speed), and education level (with drivers having a high school education or beyond more likely to speed) [35]. It has been shown that a driver's intention to speed is determined primarily by the driver's attitude toward speeding, while little influence comes from the driver's attitude towards the speed limit [36]. Additionally, it is often socially acceptable to speed, provided the speeding is within a specific range over the posted speed. Countermeasures for speeding are numerous. Examples include intelligent speed adaptation and intelligent speed assistance systems (in-vehicle systems) [37]; education of drivers on the effects of speeding on crash involvement, crash severity, and vehicle control [34]; and automated enforcement [38]. Speeding can also potentially be influenced by the roadway design [39], work zone layouts [40], and other infrastructure-related factors (e.g., pavement markings and signage) [41]-[43].

Previous studies have found that 10% to nearly 40% of drivers had reported falling asleep at the wheel at least once in the previous year [34]. Socioeconomics may require drivers to travel at times when they are fatigued, leading to drowsy driving. This phenomenon could also be due to numerous other reasons, yet it highlights the need for awareness and countermeasures related to drowsy driving. Countermeasures for drowsy driving could include advanced driver assistance systems (ADAS) such as driver alert (for alerting the driver to fatigue) [44], graduated driver's licensing (GDL) [38], and educating drivers on how to recognize drowsiness early and methods for coping or dealing with fatigue [34].

Alcohol and drug use has long been understood as a factor contributing to crash occurrence and severity [45]. Countermeasures used in the United States that have been shown to be effective are primarily deterrence laws and enforcement such as administrative license revocation or suspension programs, high-visibility saturation patrols, and alcohol ignition interlocks (for reducing recidivism) [34] [38].

Included in the category of Other Behavior and Decision Factors are specific crash contributing factors involved in pre-crash critical driving events, such as turning behavior, lane changing behavior, driving decisions when crossing an intersection or roadway, and vehicle location after a critical event. The most highly weighted contributing factors in this category are shown in **Table 3**. Among the almost 45 factors grouped under Other Behavior and Decision Factors from both datasets, vehicle departure from the roadway is a contributing factor in 32.70% - 30.38% of crashes, and a vehicle leaving the original lane, which indicates lane departure behavior, is a contributing factor in around 13% of crashes. Left turning movements, another highly weighted contributing factor, are involved in about 16% of vehicle crashes. A vehicle crossing an intersection is a factor in 12% of vehicle crashes, and the stopping of another vehicle potentially contributes to 11.64% - 16.28% of crashes. Several highway design strategies for reducing roadway departure crashes are identified by the American Association of State Highway and Transportation Officials (AASHTO), including installation of pavement edge lines, improvements to traffic barrier design, and improvements to the design of skid-resistant pavements on horizontal curves [45]. Previous research has also evaluated the effectiveness of lane departure warning (LDW) systems for run-off road crashes [46]. Left-turning vehicle crashes always involve misjudgment of the speed of oncoming vehicles and inappropriate gap selection, both of which could be improved by driver training and education [47].

Table 3. Top 5 Contributing Factors in the Category of Other Behavior and Decision Factors

Factor	% CISS	% CDS
Departed roadway	32.70 [30.96, 34.44]	30.38 [28.51, 32.25]
Turning left	15.97 [14.61, 17.33]	16.13 [14.64, 17.62]
Stayed on roadway, but left the original lane	12.24 [11.02, 13.45]	12.99 [11.62, 14.36]
Cross over intersection	12.32 [11.10, 13.53]	12.10 [10.78, 13.42]
Other vehicle stopped	11.64 [10.45, 12.83]	16.28 [14.78, 17.78]

Aberrant driver behaviors are an important part of the human-related factors that contribute to vehicle crashes. **Table 4** shows how human factors and aberrant driver behaviors interact with other categories of contributing factors. The statistics shown in the table indicate the percentage of crashes that occur only in the presence of corresponding contributing factors. For example, approximately 50.54% to 53.82% of vehicle crashes only involve potential human factors, and the corresponding weighted percentage of crashes only involving aberrant driver behaviors is around 28%. Both potential human factors and vehicle factors are present at the same time in 0.31% - 0.42% of crashes (with no environmental factors present).

Table 4. Detailed statistics of corresponding contributing factors.

Factors	% CISS	% CDS	Factors	% CISS	% CDS
Human Factors	53.82	50.54	Aberrant Driver Behaviors	28.26	28.49
Vehicle Factors	0.03	0.01	Vehicle Factors	0.28	0.22
Environmental Factors	4.38	2.06	Environmental Factors	26.74	23.59
Human &Vehicle Factors	0.42	0.31	Aberrant Driver Behaviors & Vehicle Factors	0.17	0.10
Human & Environmental Factors	40.09	45.73	Aberrant Driver Behaviors & Environmental Factors	17.74	24.20
Vehicle & Environmental Factors	0.14	0.01	Vehicle & Environmental Factors	0.92	1.15
Human & Vehicle & Environmental Factors	1.11	1.35	Aberrant Driver Behaviors & Vehicle & Environmental Factors	0.33	0.21
No Factors	0.00	0.00	No Factors	25.56	22.05

According to Table 4, the percentage of crashes solely associated with aberrant driver behaviors factors is nearly half of that solely associated with potential human factors. Compared to crashes involving potential human factors, crashes involving aberrant driver behaviors are less likely to involve vehicle or environmental factors at the same time. These comparisons illustrate the distinction between human factors and aberrant driver behaviors. The human factors discussed above encompass a broad range of factors that involve human actions or conditions contributing to crashes, including not only direct driving actions (like reaction time, distracted driving, fatigued driving) but also other factors that may impact driving performance (misreading of road signs, misjudgment of another vehicle's speed). These potential human factors may not necessarily imply intentional inappropriate driving behaviors, but the interactions between human factors, vehicle factors, and environmental factors may contribute to crash occurrence. However, aberrant driver behaviors focus specifically on driver actions or behaviors that deviate from accepted norms or safe driving practices and directly lead to a crash. Unlike human factors, aberrant driver behaviors imply a deliberate disregard for traffic laws or safety regulations and may occur independently of concurrent vehicle or environmental factors. This distinction suggests that understanding the difference between potential human factors and aberrant driver behaviors is crucial for identifying applicable countermeasures to reduce crashes involving human-related factors.

The detailed review of human-related factors above indicates that most factors relate to drivers' senses or perceptions, predictions, decision-making, execution of driving tasks, and incapacitation [48]. It is widely anticipated that the use of autonomous vehicles (especially for vehicles in level 4 or 5) could reduce crashes involving human-related factors. It is obvious that autonomous vehicles could reduce crashes caused by human physical limitations (like reaction time), distracted driving, and driving under the influence of alcohol or drugs. For crashes caused by driving behaviors (habits) and decision-making, the effectiveness of autonomous vehicles in improving safety requires further research. Since the driving behaviors and decision-making methods of autonomous vehicles are programmed by humans, autonomous vehicles could also introduce safety risks based on the assumptions made and limitations encountered during system development.

5.2. Vehicle Factors

Vehicle safety is critical to the prevention of crashes. Under the National Traffic and Motor Vehicle Safety Act of 1966 [49], the NHTSA has the authority to obtain information on vehicle crashes and other safety data in order to conduct safety recalls and ensure that vehicles comply with laws and regulations. Due to the development of legal requirements and improvements in vehicle design, the percentage of crashes to which vehicle issues contribute has been significantly reduced over the last several decades (as indicated in **Figure 2**). The vehicle-related factors that contribute to collisions were identified in the CISS and CDS datasets and are provided in **Table 5**. As indicated, blowouts or flat tires are factors in 0.51% and 0.45% of crashes based on the CISS and CDS datasets, respectively. Blowouts and flat tires have numerous potential causes, including wear, low pressure, damage due to potholes or other objects in the roadway, and so on. Many of the other factors shown in **Table 5** are potentially related to maintenance but could have other causal sources that are not indicated in the datasets. Therefore, countermeasures for these factors are difficult to determine beyond driver education and inspection-related activities.

Table 5. Detailed statistics for vehicle factors with 95% confidence intervals.

Factor	% CISS	% CDS
Disabling vehicle failure	0.42 [0.18, 0.67]	0.26 [0.16, 0.36]
Non-disabling vehicle problem	0.12 [0.00, 0.25]	0.35 [0.23, 0.47]
Trailer, disconnected in transport	0.05 [0.00, 0.13]	0.06 [0.01, 0.11]
Other cause of control loss	0.61 [0.32, 0.90]	0.52 [0.37, 0.67]
Blowout/flat tire	0.51 [0.24, 0.77]	0.45 [0.31, 0.59]

5.3. Roadway and Environmental Factors

The grouping of factors that infrastructure owners, engineers, and planners have the most direct control over are roadway and environmental factors. Statistics for key roadways and other infrastructure-specific factors are provided in Table 6. As shown, many of the factors are related to objects that can be struck by a moving vehicle. The most common factor is trees with a diameter greater than 10 centimeters, which are a factor in 5.57% and 5.67% of crashes according to the CISS and CDS datasets, respectively. Trees and bushes, combined, contribute to 7.76% (CISS dataset) and 8.68% (CDS dataset) of crashes. The other factors in Table 6 are typically manmade objects (though some objects found in the road may not be manmade and poor road conditions may not have human causes). Many of the factors are specific to roadside design. The *Highway Safety Manual*, *A Policy on Geometric Design of Highways and Streets* (Green Book), and *Roadside Design Guide* are excellent tools for identifying countermeasures to address these factors [28] [50] [51].

Table 6. Detailed statistics for roadway and infrastructure-related factors with 95% confidence intervals.

Factor	% CISS	% CDS
Tree (>10 cm diameter)	5.57 [4.72, 6.42]	5.67 [5.19, 6.15]
Concrete traffic barrier	3.79 [3.09, 4.50]	4.57 [4.14, 5.00]
Curb	5.01 [4.20, 5.82]	4.25 [3.84, 4.66]
Guardrail face or end	3.34 [2.67, 4.01]	4.22 [3.81, 4.63]
Poor road conditions	2.17 [1.63, 2.71]	2.94 [2.59, 3.29]
Other fixed objects	3.13 [2.48, 3.77]	3.66 [3.27, 4.05]
Non breakaway pole or post (>10 cm diameter and ≤30 cm diameter)	3.09 [2.45, 3.73]	4.51 [4.08, 4.94]
Ditch or culvert	2.16 [1.62, 2.70]	2.63 [2.30, 2.96]
Embankment	1.95 [1.44, 2.47]	2.04 [1.75, 2.33]
Fence	2.66 [2.07, 3.26]	1.91 [1.63, 2.19]
Non breakaway pole or post (≤10 cm diameter)	2.86 [2.25, 3.48]	3.75 [3.36, 4.14]
Wall or building	1.91 [1.22, 2.77]	1.68 [1.42, 1.94]
Cable barrier	0.98 [0.62, 1.35]	0.48 [0.34, 0.62]
Non breakaway pole or post (>30 cm diameter)	1.30 [0.88, 1.72]	1.85 [1.27, 2.13]

Continued

Object in road	0.80 [0.47, 1.13]	1.12 [0.90, 1.34]
Breakaway pole or post	1.18 [0.78, 1.59]	1.31 [1.08, 1.54]
Tree (≤10 cm in diameter)	1.41 [0.97, 1.85]	1.58 [1.32, 1.84]
Shrubbery or bush	0.78 [0.45, 1.11]	1.43 [1.19, 1.67]

Statistics for environmental and weather-related factors that contribute to crashes are provided in Table 7. Among these factors, the most common is wet pavement (14.64% and 15.29% according to the CISS and CDS datasets, respectively) followed by rain (10.45% and 9.92% according to the CISS and CDS datasets, respectively). For wet pavement and rain, potential countermeasures are limited (e.g., providing adequate drainage and friction). Snow and snow on pavement are also key factors, although the percentages shown in Table 7 are national averages and may not be applicable to specific regions within the United States. Snow management and removal is often considered as a countermeasure by roadway owners in regions that see significant snowfall each year. Other environmental and weather-related factors also contribute to crashes, but countermeasures for each factor are either difficult to evaluate (*i.e.*, their effectiveness is unknown) or highly specific to local conditions (e.g., snow fences provided in geographical areas with significant snowfall and crosswinds to prevent blindness caused by blowing snow).

Table 7. Detailed statistics for environment and weather-related factors with 95% confidence intervals.

Factor	% CISS	% CDS
Wet Pavement	14.64 [13.33, 15.95]	15.29 [14.55, 16.03]
Raining	10.45 [9.32, 11.58]	9.92 [9.31, 10.53]
Animal	5.11 [4.29, 5.93]	3.21 [2.85, 3.57]
Snowing	2.05 [1.53, 2.58]	2.23 [1.93, 2.53]
Snow on Pavement	1.82 [1.32, 2.31]	2.16 [1.86, 2.46]
Ice/Frost on Pavement	1.86 [1.36, 2.36]	2.52 [2.20, 2.84]
Fog, Smog, or Smoke	0.44 [0.20, 0.69]	0.51 [0.36, 0.66]
Slush on Pavement	0.36 [0.14, 0.58]	0.59 [0.43, 0.75]
Severe Crosswinds	0.14 [0.00, 0.27]	0.09 [0.03, 0.15]
Sleet or Hail	0.14 [0.00, 0.28]	0.35 [0.23, 0.47]

Continued

Freezing Rain/Drizzle	0.21 [0.04, 0.38]	0.06 [0.00, 0.11]
Mud, Dirt, Gravel on Pavement	0.11 [0.00, 0.24]	0.08 [0.02, 0.14]
Blowing Snow	0.06 [0.00, 0.14]	0.93 [0.73, 1.13]
Water on Pavement	0.14 [0.00, 0.28]	0.13 [0.06, 0.20]
Blowing Sand, Dirt, or Soil	0.02 [0.00, 0.08]	0.03 [0.00, 0.07]
Sand on Pavement	0.01 [0.00, 0.03]	0.02 [0.00, 0.05]
Oil on Pavement	0.01 [0.00, 0.03]	0.01 [0.00, 0.03]

6. Conclusions and Recommendations

This study applied multiple taxonomies to two national datasets (CISS and CDS) in order to evaluate factors that potentially contribute to crash occurrence. The datasets are highly detailed and involve police-reported crash information, crash reconstructions, hospital data, and interviews with people involved in the collisions documented in the datasets. The datasets are collected and maintained by the NHTSA, with the CISS data used in this paper covering the years 2017-2022 and the CDS data covering the years 2010-2015. The crashes included in the datasets have weights assigned by the NHTSA based on a sampling scheme intended to ensure that the data are nationally representative. Using the definitions of the variables included in the datasets, factors that are likely to contribute to crash occurrence were extracted. Weighted statistics were then used to determine overall percentages for each factor based on how often they contribute to crashes in the United States. It is important to note that the mere presence of a factor does not ensure that it precipitated (*i.e.*, caused) the crash.

The findings indicate that, consistent with previous research, human factors or human errors are present in more than 95% of crashes. Infrastructure and environmental factors contribute to more than 45% of crashes. Vehicle factors, including issues related to maintenance (e.g., bald or worn tires), contribute to only 1.67% - 1.71% of all crashes. The percentage of crashes involving vehicle factors is significantly lower in the HSM, which is not a surprise given that the data on which the HSM are based were collected in the 1970s and vehicle regulations have become more stringent over time. The percentage of crashes involving human factors in the HSM is similar to the percentages in the CISS and CDC datasets. The percentage of crashes involving roadway and environmental factors is larger in the CISS and CDC datasets than in the HSM. It is noted in this paper that human factors often represent behaviors that can be influenced by infrastructure design, policies, and training [33] [34], and numerous countermeasures exist for specific human factors and errors. The HSM, *Roadway Design Guide*, and other resources are available for determining appropriate countermeasures for roadway and environmental factors. Detailed breakdowns of specific factors in each category are provided in this paper.

The contributing factors highlighted in this study are often widely acknowledged as critical for reducing crashes. However, few studies have presented how common these contributing factors are in actual crashes, which is essential for comprehending the full potential effectiveness of specific safety countermeasures or crash prevention programs. For instance, fatigued driving, specifically drowsiness, is present in approximately 3% of crashes. Therefore, interventions targeting fatigued driving (such as driver fatigue monitoring systems on newer cars), even if 100% successful at preventing crashes where fatigued driving is a factor, would have maximum effectiveness of reducing all crashes by 3%. Realistically, the overall crash reduction is not likely to be significant in this case.

Although this study provides a detailed evaluation of crash contributing factors based on recent national datasets, there are limitations. First, the sample size is limited to any individual year. The CISS and CDS datasets each record up to approximately 5,000 crashes per year, which are then scaled using weighting factors to represent the United States. Due to the sampling locations and sample sizes involved, however, the analysis is limited to representing the United States at the national level (*i.e.*, some factors may not be representative of specific geographical areas, such as snow and ice in southern states). This lack of region-specific analysis may limit the applicability of the results for local policy development. Future research should explore regional differences. Additionally, the contributing factors assigned to crashes in this project are based on the variables available in the CISS and CDS datasets. It is difficult to record all of the factors that likely contribute to crash occurrence due to the data collection method used and the complexity of crash events.

Future research should consider advanced data collection methods and technologies for large-scale data collection within specific geographical regions. Additionally, the interrelationships between factors that influence crash frequency and crash severity should be evaluated. Finally, detailed investigation of interactions between human behavior, road and environmental conditions, and vehicle technologies should be explored to determine important interactions that are associated with crash occurrence.

7. Practical Applications

It is anticipated that the results of this study could potentially be used to shape comprehensive strategies for enhancing transportation safety. Engineers, policymakers, and other stakeholders should utilize the results to identify effective targeted safety interventions and improvements, such as educational campaigns, policy development, infrastructure improvements, and law enforcement strategies. Additionally, engineers and transportation agencies should use the results to inform the design and maintenance of road infrastructure. Automotive companies and government agencies should use the results to guide the development of advanced safety technologies for vehicles. Moreover, public awareness campaigns and public health initiatives benefit from a nuanced understanding of the factors that influence crashes, allowing for the creation of impactful educational programs and policies.

Conflicts of Interest

The authors declare no conflicts of interest regarding the publication of this paper.

References

[1] Centers for Disease Control and Prevention (n.d.) Leading Causes of Death and Injury. https://www.cdc.gov/injury/wisqars/LeadingCauses.html

[2] Reish and Leah (2021) Traffic Safety Facts 2019: A Compilation of Motor Vehicle Crash Data. https://crashstats.nhtsa.dot.gov/.

[3] AASHTO (2010) Highway Safety Manual, Vol. 1.

[4] Highway Traffic Safety Administration and Department of Transportation (2015) Critical Reasons for Crashes Investigated in the National Motor Vehicle Crash Causation Survey.

[5] Treat, J.R., Tumbas, N.S., McDonald, S.T., Shinar, D., Hume, R.D., Mayer, R.E., *et al.* (1979) Tri-Level Study of the Causes of Traffic Accidents Executive Summary. DOT HS 805-099. Transportation Research Institute (UMTRI).

[6] Najm, W., Koopmann, J., Boyle, L. and Smith, D. (2002) Development of Test Scenarios for Off-Roadway Crash Countermeasures Based on Crash Statistics. United States Department of Transportation.

[7] Sayed, T., Abdelwahab, W. and Navin, F. (1995) Identifying Accident-Prone Locations Using Fuzzy Pattern Recognition. *Journal of Transportation Engineering*, **121**, 352-358. https://doi.org/10.1061/(asce)0733-947x(1995)121:4(352)

[8] Choi, E.-H. (2010) Crash Factors in Intersection-Related Crashes: An On-Scene Perspective. http://www-nrd.nhtsa.dot.gov/Pubs/811366.pdf

[9] Hendricks, D.L., *et al.* (2001) The Relative Frequency of Unsafe Driving Acts Summary Technical Report. U.S. Department of Transportation.

[10] National Highway Traffic Safety Administration and Department of Transportation (2018) Critical Reasons for Crashes Investigated in the National Motor Vehicle Crash Causation Survey.

[11] National Highway Traffic Safety Administration (2008) National Motor Vehicle Crash Causation Survey: Report to Congress.

[12] Bucsuházy, K., Matuchová, E., Zůvala, R., Moravcová, P., Kostíková, M. and Mikulec, R. (2020) Human Factors Contributing to the Road Traffic Accident Occurrence. *Transportation Research Procedia*, **45**, 555-561. https://doi.org/10.1016/j.trpro.2020.03.057

[13] Saleem, T., Porter, R., Srinivasan, R., Carter, D., Himes, S. and Le, T. (2020) Contributing Factors for Focus Crash and Facility Types. https://rosap.ntl.bts.gov/view/dot/54786/dot_54786_DS1.pdf

[14] Shi, J., Bai, Y., Ying, X. and Atchley, P. (2010) Aberrant Driving Behaviors: A Study of Drivers in Beijing. *Accident Analysis & Prevention*, **42**, 1031-1040. https://doi.org/10.1016/j.aap.2009.12.010

[15] Reason, J., Manstead, A., Stradling, S., Baxter, J. and Campbell, K. (1990) Errors and Violations on the Roads: A Real Distinction? *Ergonomics*, **33**, 1315-1332. https://doi.org/10.1080/00140139008925335

[16] Beanland, V., Sellbom, M. and Johnson, A.K. (2014) Personality Domains and Traits That Predict Self-Reported Aberrant Driving Behaviours in a Southeastern US University Sample. *Accident Analysis & Prevention*, **72**, 184-192. https://doi.org/10.1016/j.aap.2014.06.023

[17] Haghi, A., Ketabi, D., Ghanbari, M. and Rajabi, H. (2014) Assessment of Human Errors in Driving Accidents; Analysis of the Causes Based on Aberrant Behaviors. *Life Science Journal*, **11**, 414-420.

[18] Sullman, M.J.M., Stephens, A.N. and Taylor, J.E. (2019) Dimensions of Aberrant Driving Behaviour and Their Relation to Crash Involvement for Drivers in New Zealand. *Transportation Research Part F: Traffic Psychology and Behaviour*, **66**, 111-121. https://doi.org/10.1016/j.trf.2019.08.024

[19] Vision Zero Network (n.d.) What Is Vision Zero? https://visionzeronetwork.org/about/what-is-vision-zero/

[20] Min, K. and Ando, A. (2020) Analysis on Characteristics of Dangerous Driving Events via Recorded Data of Drive-Recorder. *Transportation Research Procedia*, **48**, 1342-1363. https://doi.org/10.1016/j.trpro.2020.08.164

[21] Dutta, U., Zhong, X. and Gsouda, N. (2022) Analysis of Global Road Traffic Death Data Using a Clustering Approach. *Current Urban Studies*, **10**, 275-292. https://doi.org/10.4236/cus.2022.102017

[22] Rolison, J.J. and Moutari, S. (2020) Combinations of Factors Contribute to Young Driver Crashes. *Journal of Safety Research*, **73**, 171-177. https://doi.org/10.1016/j.jsr.2020.02.017

[23] Liu, Q., Wang, X., Liu, S., Yu, C. and Glaser, Y. (2024) Analysis of Pre-Crash Scenarios and Contributing Factors for Autonomous Vehicle Crashes at Intersections. *Accident Analysis & Prevention*, **195**, Article 107383. https://doi.org/10.1016/j.aap.2023.107383

[24] Salmon, P.M., Naughton, M., Hulme, A. and McLean, S. (2022) Bicycle Crash Contributory Factors: A Systematic Review. *Safety Science*, **145**, Article 105511. https://doi.org/10.1016/j.ssci.2021.105511

[25] Zhang, F., Noh, E.Y., Subramanian, R. and Chen, C.-L. (2019) Crash Investigation Sampling System: Sample Design and Weighting. DOT HS-812-804. National Highway Traffic Safety Administration.

[26] Zhang, F. and Chen, C.-L. (2013) NASS-CDS: Sample Design and Weights. DOT HS-811-807. National Highway Traffic Safety Administration.

[27] NHTSA (2016) Data Modernization.

[28] AASHTO and Highway Safety Manual. (2010) American Association of State Highway and Transportation Officials.

[29] Fambro, D.B., Fitzpatrick, K. and Koppa, R.J. (1997) Determination of Stopping Sight Distances, NCHRP Report 400. Transportation Research Board National Research Council.

[30] Wood, J.S. and Zhang, S. (2020) Evaluating Relationships between Perception-Reaction Times, Emergency Deceleration Rates, and Crash Outcomes Using Naturalistic Driving Data. *Transportation Research Record: Journal of the Transportation Research Board*, **2675**, 213-223. https://doi.org/10.1177/0361198120966602

[31] Kish, L. (1992) Weighing for Unequal Pi. *Journal of Official Statistics*, **8**, 183-200.

[32] Treat, J.R. *et al.* (1979) Tri-Level Study of the Causes of Traffic Accidents: Executive Summary. DOT HS-805 099. National Highway Traffic Safety Administration.

[33] Campbell, J.L. *et al.* (2012) Human Factors Guidelines for Road Systems: Second Edition. The National Academies Press. https://doi.org/10.17226/22706

[34] Shinar, D. (2017) Traffic Safety and Human Behavior. 2nd Edition, Emerald Group Publishing Limited.

[35] Shinar, D., Schechtman, E. and Compton, R. (2001) Self-Reports of Safe Driving Behaviors in Relationship to Sex, Age, Education and Income in the US Adult Driving Population. *Accident Analysis & Prevention*, **33**, 111-116. https://doi.org/10.1016/s0001-4575(00)00021-x

[36] De Pelsmacker, P. and Janssens, W. (2007) The Effect of Norms, Attitudes and Habits on Speeding Behavior: Scale Development and Model Building and Estimation. *Accident Analysis & Prevention*, **39**, 6-15. https://doi.org/10.1016/j.aap.2006.05.011

[37] Ryan, M. (2019) Intelligent Speed Assistance Technologies: A Review. *Proceedings of the ITRN* 2019, Belfast, 5-6 September 2019.

[38] Richard, C. Magee, K. Bacon-Abdelmoteleb, P. and Brown, J. (2017) Countermeasures That Work: A Highway Safety Countermeasure Guide for State Highway Safety Offices. Ninth Edition, National Highway Traffic Safety Administration.

[39] Donnell, E.T., Himes, S., Mahoney, K., Porter, R.J. and McGee, H. (2009) Speed Concepts: Informational Guide. United States Department of Transportation.

[40] Porter, R.J. and Wood, J.S. (2013) Exploring Endogeneity of Macroscopic Speed Parameters: Empirical Study during Low Volume Conditions in Construction Work Zones. *Transportation Letters*, **5**, 27-37. https://doi.org/10.1179/1942786712z.0000000004

[41] Donnell, E.T., Porter, R.J., Li, L., Hamilton, I., Himes, S. and Wood, J.S. (2019) Reducing Roadway Departure Crashes at Horizontal Curve Sections on Two-Lane Rural Highways. FHWA-SA-19-005. https://rosap.ntl.bts.gov/view/dot/55604

[42] Hallmark, S.L., Hawkins, N. and Smadi, O. (2012) Evaluation of Low-Cost Treatments on Rural Two-Lane Roads: Report No. IHRB Project TR-579, Midwest Transportation Consortium and Iowa Department of Transportation.

[43] Albin, R., *et al.* (2016) Low-Cost Treatments for Horizontal Curve Safety 2016. FHWA-SA-15-084. United States Department of Transportation.

[44] TRB (1998) Special Report 254: Managing Speed: Review of Current Practice for Setting and Enforcing Speed Limits.

[45] NHTSA (n.d.) Drunk Driving. https://www.nhtsa.gov/risky-driving/drunk-driving

[46] Rimini-Doering, M., Altmueller, T., Ladstaetter, U. and Rossmeier, M. (2005) Effects of Lane Departure Warning on Drowsy Drivers' Performance and State in a Simulator. *Driving Assessment Conference*, 3, 88-95. https://doi.org/10.17077/drivingassessment.1147

[47] Chovan, J.D., Tijerina, L., Everson, J., Pierowicz, J. and Hendricks, D. (1994) Examination of Intersection, Left Turn Across Path Crashes of Transportation National Highway and Potential IVHS Countermeasures. National Highway Traffic Safety Administration.

[48] Mueller, A.S., Cicchino, J.B. and Zuby, D.S. (2020) What Humanlike Errors Do Autonomous Vehicles Need to Avoid to Maximize Safety? *Journal of Safety Research*, **75**, 310-318. https://doi.org/10.1016/j.jsr.2020.10.005

[49] The Association of Centers for the Study of Congress (1966) National Traffic and

Motor Vehicle Safety Act the Legislation.
http://acsc.lib.udel.edu/exhibits/show/legislation/traffic-and-motor-vehicle-safe

[50] AASHTO (2011) Roadside Design Guide, 4th Edition, American Association of State Highway and Transportation Officials.

[51] AASHTO (2018) A Policy on Geometric Design of Highways and Streets. 7th Edition, American Association of State Highway and Transportation Officials.

[52] van Ratingen, M.R. (2022) Consumer Ratings and Their Role in Improving Vehicle Safety. In: Edvardsson Björnberg, K., Hansson, S.O., Belin, M.Å. and Tingvall, C., Eds., *The Vision Zero Handbook*, Springer International Publishing, 755-788. https://doi.org/10.1007/978-3-030-76505-7_30

[53] Armstrong, C.D. (2019) Accident Reconstruction Series—Biomechanics, vol. 11. SAE International.

[54] Joodaki, H., Gepner, B., McMurry, T. and Kerrigan, J. (2019) Comparison of Injuries of Belted Occupants among Different BMI Categories in Frontal Crashes. *International Journal of Obesity*, **44**, 1319-1329. https://doi.org/10.1038/s41366-019-0481-2

[55] Byrne, J.P., Mann, N.C., Dai, M., Mason, S.A., Karanicolas, P., Rizoli, S., *et al.* (2019) Association between Emergency Medical Service Response Time and Motor Vehicle Crash Mortality in the United States. *JAMA Surgery*, **154**, 286-293. https://doi.org/10.1001/jamasurg.2018.5097

[56] Jung, S., Qin, X. and Oh, C. (2016) Systemwide Impacts of Emergency Medical Services Resources on Freeway Crash Severity. *Transportation Research Record: Journal of the Transportation Research Board*, **2582**, 51-60. https://doi.org/10.3141/2582-07

[57] Hershman, L.L. (2001) The US New Car Assessment Program (NCAP): Past, Present and Future: 2001-06-0245. SAE Technical Paper.