

# Driver crash risk factors and prevalence evaluation using naturalistic driving data

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**The accurate evaluation of crash causal factors can provide fundamental information for effective transportation policy, vehicle design, and driver education. Naturalistic driving (ND) data collected with multiple onboard video cameras and sensors provide a unique opportunity to evaluate risk factors during the seconds leading up to a crash. This paper uses a National Academy of Sciences-sponsored ND dataset comprising 905 injurious and property damage crash events, the magnitude of which allows the first direct analysis (to our knowledge) of causal factors using crashes only. The results show that crash causation has shifted dramatically in recent years, with driver-related factors (i.e., error, impairment, fatigue, and distraction) present in almost 90% of crashes. The results also definitively show that distraction is detrimental to driver safety, with handheld electronic devices having high use rates and risk.**

naturalistic driving | crash risk | driver distraction | driver impairment | driver error

During recent years, the percentage of crashes involving some type of driver error or impairment before the crash was thought to be as high as 94% (1). Factors such as vehicle failures, roadway design or condition, or environment composed lower crash percentages. Naturalistic driving studies (NDSs) offer a unique opportunity to study driver performance and behavior experienced in the real world with actual consequences and risks (2–4). The NDS research method developed at the Virginia Tech Transportation Institute (VTTI) involves equipping volunteer participants' vehicles with advanced, unobtrusive instrumentation (e.g., cameras, sensors, radar) that automatically and continuously collects driving parameters—including speed, time to collision, global positioning system (GPS) location, acceleration, and eye glance behavior—from key-on to key-off (2, 5). The recently completed Second Strategic Highway Research Program Naturalistic Driving Study (SHRP 2 NDS), sponsored by the Transportation Research Board (TRB) of the National Academy of Sciences (NAS), is the largest NDS of its kind, capturing more than 35 million miles of continuous naturalistic driving data and 2 petabytes (PB) of video, kinematic, and audio data from more than 3,500 participants (5).

NDSs provide insight into the factors that cause crashes, giving researchers the opportunity to observe actual driver behavior and to accurately understand drivers' performance during the minutes or seconds leading up to a crash (6, 7). However, previous NDSs captured a relatively small number of crashes (2, 8). To obtain a statistically valid sample of crash factors in earlier NDSs, surrogate measures (e.g., near-crash events) were integrated into analyses. Near-crashes are operationally defined as having the observable factors that could lead to a crash, with one difference present: the performance of a successful evasive maneuver. Although previous studies used near-crashes as a surrogate for estimating crash risk, the accuracy and validity of combining crashes and near-crashes to estimate driver risk are just beginning to be understood (9). With the completion of the SHRP 2 NDS, however, researchers now have access to an order-of-magnitude larger sample size that

allows the sole use of crash events to determine the safety outcome for risk factor evaluation.

Using the SHRP 2 NDS crash database, this paper focuses on and addresses the following categories of driver performance and behavior that contribute to crash events: (i) observable impairment, which was determined from a 20-s precrash video segment; observable impairment includes apparent drug/alcohol influence, drowsiness/fatigue, or emotion (i.e., anger, sadness, crying, and/or emotional agitation) that clearly impacted driver performance; (ii) driver performance error, including a variety of vehicle operation and maneuver errors (e.g., failing to yield properly to other traffic, making an improper turn); (iii) momentary driver judgment error, including such factors as aggressive driving and speeding; (iv) observable driver distraction determined from a 6-s precrash video segment, including the use of in-vehicle and handheld devices, active interaction with passengers, and outside distractions.

## Materials and Methods

**Database and Instrumentation.** The SHRP 2 NDS dataset comprises more than 2 PB of continuous naturalistic driving data collected during a 3-y period from more than 3,500 participants, aged 16–98, who resided near the following six site centers: Buffalo, NY; Tampa, FL; Seattle, WA; Durham, NC; Bloomington, IN; and State College, PA. The naturalistic driving data were collected automatically from key-on to key-off for every trip taken in one of the volunteer participants' vehicles using the VTTI-developed Next Generation (NextGen) data acquisition system (DAS).

The DAS comprises multiple video images and a still image of the cabin, permanently blurred to protect the anonymity of nonconsented passengers. Video output of the DAS includes a quadrant image containing (i) the forward roadway, (ii) the driver's face and driver-side views, (iii) right rear view, and (iv) a view of the driver's interactions with the steering wheel and center

## Significance

**This paper presents findings about the riskiest factors faced by drivers as informed through the first large-scale, crash-only analysis of naturalistic driving data. Results indicate that many secondary tasks or activities, particularly resulting from the use of handheld electronic devices, are of detriment to driver safety. The analysis uses a large naturalistic database comprising continuous in situ observations made via multiple onboard video cameras and sensors that gathered information from more than 3,500 drivers across a 3-y period.**

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Data deposition: The SHRP 2 NDS is housed on InSight with access instructions available at <https://insight.shrp2nds.us/>. A description of the dataset used in this analysis is available at [ezid.cdlib.org/id/doi:10.15787/VTT1VC7C](https://ezid.cdlib.org/id/doi:10.15787/VTT1VC7C).

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stack of the vehicle. The DAS also incorporates machine vision-based applications, accelerometers and rate sensors in three dimensions (i.e.,  $x$ ,  $y$ , and  $z$  axes), GPS, forward radar, illuminance and passive cabin alcohol presence sensors, turn signal state, vehicle network data (as available), and an incident push button. This button could be pressed by the participant whenever an incident of possible interest occurred; doing so not only placed a marker within the data stream for later analysis, it also opened a 30-s audio recording channel so the participant could briefly describe the incident. Data collected from various onboard systems were processed and stored in the DAS continuously for the entire trip.

Customized machine-vision software incorporated into the VTTI DAS hardware includes lane-tracking information and the driver's head position and rotational angle. DAS units also feature cellular machine-to-machine technology that accepts software upgrades to installed units, transmits events of interest (e.g., crashes) to project servers, and disseminates DAS function reports (i.e., self-"health checks") from the field to researchers and engineers at the home base. These combined capabilities ensure that important information is being relayed and that the DAS is functioning properly.

The DAS was custom-designed to include six primary components: main unit, head unit, network box, radar, radar interface box, and solid-state data drive. The main unit houses the computing engine for the system. The electronics for the main unit are encased in a rugged plastic enclosure with room for the solid-state drive on which data are initially stored.

The SHRP 2 NDS was administered by SHRP 2 of the TRB of the NAS. As such, access to the website and its data are controlled by user-access levels. The information available is determined by user status. By federal law, TRB must monitor usage of the data to ensure compliance with data privacy laws established by the responsible Institutional Review Boards (IRBs). For further information about the SHRP 2 NDS database and DAS instrumentation and management, please refer to ref. 5.

**Recruitment.** An approximate equal mix of male and female drivers compose the SHRP 2 NDS dataset, with 1,703 female drivers and 1,559 male drivers (280 drivers chose not to provide gender information). Two categories of participants are identified in the SHRP 2 NDS: (i) primary participants, who were the focus of the study and recruitment; and (ii) secondary participants. Primary participants agreed to have data collected from their main vehicle when driven during their participation in the study. Primary participants underwent a battery of functional assessments related to driving capability and were asked to fill in several questionnaires related to health, risk taking, etc. Primary participants who were minors at the time of the study enrollment provided assent to participate; consent for their participation was provided by a parent or guardian. Secondary participants were other adults who regularly drove one of the instrumented vehicles and granted consent to have their driving data analyzed. Secondary participants were only asked to fill in basic demographics and driving history questionnaires.

Participants of the SHRP 2 NDS were covered by the *Code of Federal Regulations* (45 CFR 46). To ensure 45 CFR 46 compliance, all human subjects research conducted during the study was reviewed by several IRBs, including the NAS IRB, the Virginia Tech IRB, and the IRB of record for each of the contractor organizations that managed the six data collection sites. Informed consent was obtained from all participants.

For more detailed information about the SHRP 2 NDS recruitment process, please refer to ref. 5.

**Event Classification.** Data from the SHRP 2 NDS were protected using a sophisticated data encryption process. Once data were transferred, decrypted, and ingested into the final research repository, they were protected by role-based security. This limited a user's access based on IRB approvals or the need to access data elements as guided by SHRP 2 staff. Quality health checks were regularly performed, including automated quality checks of sensor and video data. Once ingested into the repository, data were analyzed by trained data reductionists and researchers.

SHRP 2 NDS data were standardized via variables outlined in a data dictionary, and safety-critical events were classified based on kinematic and video analyses. To date, more than 1,500 crashes, including minor collisions, have been identified in the SHRP 2 NDS dataset. Potential crashes were classified via participant reports, automatic crash notification algorithms on the DAS, and similar controller area network algorithms run on ingested data. Once possible events of interest were identified, the classification of actual crashes occurred via video review, with events categorized as one of the following: severity 1 [i.e., airbag/injury/rollover/high delta-V crash (virtually all such crashes would be police reported)], severity 2 (police-reportable crashes, including police-reported crashes and others of similar severity that

were not reported), severity 3 (crashes involving physical contact with another object), or severity 4 (tire strike, low-risk crashes).

For more detailed information about SHRP 2 NDS event classification, please refer to ref. 5.

**Analysis.** During this study, a case-cohort approach was used to evaluate the risk associated with each contributing factor of a crash (8, 10). This approach assesses time-variant risk factors for crashes and controls by contrasting exposure information derived from short time windows—typically those that are seconds long—to maintain relative homogeneous exposure within the window. The controls are short, free of safety-critical events, and comprise normal driving episodes, thus representing the exposure of risk factors during normal driving conditions. It has been shown that, under a proper control sampling scheme, the odds ratio estimation based on contrasting exposures for crashes and controls is an approximate to-the-risk rate ratio (10).

The exposure for crashes (i.e., cases) was extracted from short time windows (6 s for distraction and 20 s for error or impairment) of video surrounding the onset of crashes. These windows of time were reviewed by trained data analysts (5). A rigorous protocol was implemented to ensure the accuracy of the reduction information (Fig. S1).

To estimate the exposure under the normal, noncrash driving condition, a two-staged stratified random sampling method was used to select 19,732 control driving segments greater than 5 mph. The control driving episode was the same length as the crash exposure reduction to ensure the consistency of exposure information. The first stage determined the number of baselines for each driver proportional to driving time. The second stage involved total random sampling within a driver. The sample data reduction protocol for crashes was implemented within the control driving epochs to extract the exposure information. A description of the dataset used in this analysis and relative access instructions are available in ref. 11.

The stratified random baselines also provided an opportunity to estimate the prevalence of each factor, which can be calculated as the percentage of control (i.e., normal) driving segments with the factor of interest present.

As multiple crashes and baselines can be derived from one driver, a mixed-effect random logistics model was adopted to incorporate the driver-specific correlation. This model is shown as follows:

$$Y_{ij} \sim \text{Bernoulli}(p_{ij}),$$

$$\text{logit}(p_{ij}) = \beta_0 + \beta_1 X_{ij} + \alpha_i,$$

where  $Y_{ij}$  is the response variable for driver  $i$ , event  $j$ .  $Y_{ij} = \begin{cases} 1 & \text{crash} \\ 0 & \text{baseline} \end{cases}$ .  $p_{ij}$  is the probability of being in a crash;  $\beta_0$  and  $\beta_1$  are the regression coefficients;  $\alpha_i$  is a driver-specific random term;  $X_{ij}$  is the indicator variable for a contributing factor. The odds ratio can be calculated as  $\exp(\beta_1)$ .

Analyses were conducted for both crashes and controls overall for each of the four major categories (i.e., impairment, performance error, judgment error, and distraction). Analyses were also performed for subcategories of each major category (e.g., radio interaction within distraction). The risks associated with all contributing factors were then evaluated through a comparison with alert, attentive, and sober driving episodes (operationally defined herein as "model" driving). Thus, it is important to note that the resulting odds ratios reflect the elevated driving risk for a contributing factor compared with the model driving condition.

Several criteria were used for determining the exposed group. As impairment typically has a higher safety impact than distraction, impairment was excluded from the distraction assessment, but distraction was included in the impairment analysis. Distraction and impairment were not filtered in the driving error evaluations as the latter differs in many aspects from distraction and impairment.

## Findings

Crash events were gathered and analyzed in detail through video observations and measurements of 3,542 drivers recruited for the SHRP 2 NDS. The drivers were recruited from six data collection sites across the United States and included drivers aged 16–98, approximately equally divided by gender (5). Although all age groups of drivers were represented, drivers under age 25 and over age 65 were purposefully oversampled relative to the general US driver population because these groups have an elevated crash risk (8, 12).

The SHRP 2 NDS crashes investigated in this paper included only those during which injury or property damage occurred.

Minor collisions where there was no property damage and near-crashes were not included. Thus, to our knowledge, this paper represents the first crash-only analysis using an NDS dataset where there is sufficient statistical power to assess both the risk and prevalence associated with a variety of causal factors.

Fig. 1 illustrates the overall prevalence of distraction and error in crashes. For this figure, error includes both driver/performance judgement errors with and without impairment. As shown, 87.7% of the crashes in the SHRP 2 NDS had at least one of the error/impairment or distraction factors present. Prior research estimates that up to 94% of crashes involve these factors (1). Thus, it seems that the main categories used in this analysis capture the majority of cases in which driver errors, impairment, or distraction are present. It is also important to note that, unlike data derived from police accident reports, naturalistic data allow analysts to directly observe via video precrash and crash events as they occur (2). Thus, 87.7% may be a more accurate estimate of driver error, impairment, and distraction as contributing factors—at least as they are defined here.

Other important findings from Fig. 1 show that nearly three-quarters of the crashes (i.e., 73.7%) involved some type of error; 68.3% of crashes involved some type of observable distraction; and 54.5% of crashes involved both. These findings conclusively show the detrimental impact of distraction alone and in combination with a variety of other sources of error and impairment.

Fig. 2 shows the odds ratios for each of the four major categories and their relative subcategories. Also shown in Fig. 2 are the 95% confidence intervals for the odds ratios (in parentheses) and the observed prevalence of each category (i.e., the percentage of time a factor was present during the normal driving condition).

**Overall Risk and Prevalence Findings.** As shown in Fig. 2, numerous factors significantly increase driving risk (i.e., odds ratio greater than the neutral value of 1.0). These risk estimates provide crucial information for educating drivers, law enforcement officials, driver educators, vehicle designers, and policymakers regarding what constitutes the greatest risks to drivers. From an overall perspective, the driver performance error category had the highest risk at 18.2 times the risk of model driving. Within that category, several subcategories had high odds ratios, including inexperience with the vehicle or roadway, right-of-way error, and sudden or improper braking or stopping. These particular errors had estimated risks that were hundreds of times higher than model driving, although the prevalence of these riskiest errors was low.

The prevalence data also show interesting numbers overall. Notably, more than 50% of the time, some type of distraction prevents drivers from engaging in the primary task of driving. When combined with an odds ratio 2.0 times higher than model driving, it is clear that driving while distracted is detrimental to

driver safety. To put such prevalence into perspective, of the 905 injurious and property damage crashes captured in the SHRP 2 NDS database, only 0.1% involved some form of vehicle failure (e.g., mechanical breakdown or flat tire).

**Observable Impairment.** Three types of impairment were included in the operational definition of this category: apparent drug/alcohol impairment; drowsiness/fatigue; and emotion, including visible anger, sadness, crying, and/or emotional agitation. Recall that these sources of impairment had to be observable from a 20-s video segment that occurred just before the crash, or as part of a stratified random baseline segment. Thus, it is likely that these cases of impairment represent more severe scenarios that may be more easily observed (e.g., apparent anger) and exclude some cases that were less severe (e.g., anger that may be less apparent and, thus, not observable).

As shown in Fig. 2, overall impairment was observed in 1.92% of the baselines and increased the risk of a crash by 5.2 times compared with model driving. Observable drug/alcohol impairment increased the crash risk ~35.9 times and had a prevalence of nearly 0.1%. Based on recent research (13), one would expect drug/alcohol impairment to be somewhat higher and the odds ratio to be somewhat lower than these values, thus supporting previous statements that this analysis likely represents the more severe impairment cases present in the SHRP 2 NDS dataset. Drowsiness/fatigue is risky at an individual case level (i.e., odds ratio of 3.4) and was observed in 1.57% of baselines.

The SHRP 2 NDS analysis provides unique insight into another category operationally defined as impairment: an observable elevated emotional state, most frequently anger but including sadness, crying, and/or emotional agitation. The risk of driving while in such an elevated emotional state is 9.8 times higher than model driving. Although not as prevalent as some of the other driver behaviors shown in Fig. 2, driving while in an elevated emotional state is not rare, occurring in ~0.2% of baselines.

**Driver Performance Error.** As shown in Fig. 2 and described above, driver performance error increases the overall risk of a crash by 18.2 times compared with model driving. The prevalence of some type of performance error occurring during a trip was 4.81% overall. In general, performance errors increase crash risk greatly, although most are not prevalent. The more prevalent driver performance errors are failing to signal (2.27% of baselines), a stop/yield sign violation (1.05% of baselines), driving too slowly (0.97% of baselines), and making an improper turn (0.51% of baselines).

**Driver Judgment Error.** This category has been operationally defined to include aspects of a momentary lapse of driver judgment, such as speeding well above the speed limit or driving too fast for conditions. Driver judgment error also includes other forms of aggressive driving (e.g., illegal passing or following too closely). As shown in Fig. 2, this category has both a high odds ratio overall (i.e., 11.1 times the risk of model driving) and a relatively high prevalence of occurrence (4.22% of baselines). Fig. 2 also shows that all of the judgment error subcategories, as defined, have high odds ratios ranging from 5.3 to 34.8. Of note is that the prevalence values for some driver judgment errors are low, including following too closely (observed in 0.07% of baselines). This is notable because this factor appears frequently on police accident reports and in crash investigations. It has been suspected for some time that factors such as following too closely have become a “catch-all” category on police reports and in crash investigations because it is difficult to retroactively assess what happened leading up to an event such as a rear-end crash (14). By contrast, it may also be suspected that some categories, such as distraction, have been underreported for a number of years for similar reasons.

Distracted	Error	Impaired	Prevalence
YES	YES	YES	3.4%
		NO	51.1%
	NO	YES	0.1%
		NO	13.7%
NO	YES	YES	2.7%
		NO	16.5%
	NO	YES	0.2%
		NO	12.3%
Total			100%

Fig. 1. Prevalence of driver factors before crashes.



	O.R. (95% CI)	Baseline Prevalence
<b>Observable Impairment*</b>		
Overall	5.2 (3.8 - 7.1)	1.92%
Drug/alcohol	35.9 (17.0 – 75.8)	0.08%
Drowsiness/fatigue	3.4 (2.3 - 5.1)	1.57%
Emotion (anger, sadness, crying, and/or emotional agitation)	9.8 (5.0 – 19.0)	0.22%
<b>Driver Performance Error</b>		
Overall	18.2 (14.8 – 22.3)	4.81%
Major error sub-categories (observed in crash and baseline events)		
Apparent inexperience with vehicle/roadway	204.5 (111.1 – 376.6)	0.07%
Blind spot error	55.1 (21.6 – 140.6)	0.05%
Improper turn	92.1 (68.8 – 123.4)	0.51%
Right-of-way error	936.1 (123.8 – 7078.3)	0.01%
Signal violation	28.3 (15.9 – 50.2)	0.19%
Stop/yield sign violation	7.4 (4.9 – 11.4)	1.05%
Wrong side of road	22.3 (12.0 - 41.5)	0.19%
Driving too slowly	2.3 (1.1 – 4.8)	0.97%
Sudden or improper braking/stopping	247.8 (53.1 - 1156.2)	0.01%
Failed to signal	2.5 (1.5 - 4.0)	2.27%
<b>Driver Momentary Judgment Error (Speeding/Aggressive Driving)</b>		
Overall	11.1 (9.0 - 13.8)	4.22%
Aggressive driving (general observed behavior)	34.8 (17.2 – 70.5)	0.10%
Speeding (over limit and too fast for conditions)	12.8 (10.1 - 16.2)	2.77%
Speeding/unsafe in work zone	14.2 (3.9 – 52.0)	0.05%
Illegal/unsafe passing	14.4 (7.2 - 28.8)	0.18%
Following too closely	13.5 (4.4 - 41.4)	0.07%
Intentional signal violation	15.3 (7.9 – 29.9)	0.19%
Intentional stop/yield sign violation	5.3 (3.4 – 8.4)	1.04%
<b>Observable Distraction**</b>		
Overall	2.0 (1.8 - 2.4)	51.93%
Major distraction sub-categories (observed in crash and baseline events)		
In-vehicle radio	1.9 (1.2 – 3.0)	2.21%
In-vehicle climate control	2.3 (1.1 – 5.0)	0.56%
In-vehicle device (other)	4.6 (2.9 – 7.4)	0.83%
Total in-vehicle device	2.5 (1.8 - 3.4)	3.53%
Cell browse	2.7 (1.5 – 5.1)	0.73%
Cell dial (handheld)	12.2 (5.6 - 26.4)	0.14%
Cell reach	4.8 (2.7 - 8.4)	0.58%
Cell text (handheld)	6.1 (4.5 - 8.2)	1.91%
Cell talk (handheld)	2.2 (1.6 - 3.1)	3.24%
Total cell (handheld)	3.6 (2.9 - 4.5)	6.40%
Child rear seat	0.5 (0.1 – 1.9)	0.80%
Interaction with adult/teen passenger	1.4 (1.1 – 1.8)	14.58%
Reading/writing (includes tablet)	9.9 (3.6 - 26.9)	0.09%
Eating	1.8 (1.1 - 2.9)	1.90%
Drinking (non-alcohol)	1.8 (1.0 - 3.3)	1.22%
Personal hygiene	1.4 (0.8 - 2.5)	1.69%
Reaching for object (non-cell phone)	9.1 (6.5 - 12.6)	1.08%
Dancing in seat to music	1.0 (0.4 - 2.3)	1.10%
Extended glance duration to external object	7.1 (4.8 - 10.4)	0.93%

The baseline prevalence of a factor represents the percentage of time the factor was present during the normal driving condition.

\*Observable from 20-second pre-crash and baseline sample video segments

\*\*Observable from 6-second pre-crash and baseline sample video segments

**Fig. 2.** Odds ratios and prevalence of impairment, errors, and distraction.

**Observable Distraction.** A remarkable finding of this analysis is how often drivers engage in potentially distracting activities. As shown in Fig. 2, drivers engaged in such activities during 51.93% of baselines overall; Fig. 1 shows that distraction was a factor in 68.3% of the 905 injurious and property damage crashes observed in the SHRP 2 NDS. Overall, the risk of distraction while driving was 2.0 times

higher than model driving. In essence, this means drivers are at double the risk for more than one-half of their trips when they choose to engage in a distracting activity. Calculating a population-attributable risk for distraction overall shows that potentially 36%, or 4 million of the nearly 11 million crashes occurring in the United States annually (15), could be avoided if no distraction was present.

Of the individual distracting activities listed in Fig. 2, those that require the driver's eyes to be away from the forward roadway have the highest risk (i.e., risk greater than the 2.0 overall distraction risk). Thus, handheld cell dialing (odds ratio of 12.2), reading/writing (odds ratio of 9.9), and reaching for a non-cell phone object (odds ratio of 9.1) had the highest risks. Other activities that require eyes-off-road time resulting in increased crash risk include texting on a handheld cell phone (odds ratios of 6.1), reaching for a handheld cell phone (odds ratio of 4.8), browsing on a cell phone (e.g., reading email or checking stocks; odds ratio of 2.7), extended glance duration to an external object (odds ratio of 7.1), interacting with a nonradio/non-heating, ventilation, and air conditioning (HVAC) in-vehicle device (e.g., touchscreen menus; odds ratio of 4.6), and adjusting the HVAC controls of the vehicle (odds ratio of 2.3).

In terms of prevalence, observable interaction with an adult/teen passenger was the highest (14.58% of baselines). Passenger interaction had a risk 1.4 times higher than model driving. Previous research conducted using crash databases showed that an adult driver traveling with passengers generally experienced what is known as a protective effect, or an odds ratio below the neutral value of 1.0 (16). There are likely several reasons why the results found herein differ. First, comparisons made in the SHRP 2 NDS use model driving in which data analysts have verified that the baseline group is alert, attentive, and sober, at least from direct observation. This is not the case with previous crash database analyses. Another factor may be that the cases analyzed in this study included only observable passenger interactions. By contrast, prior crash database analyses could only determine passenger presence, not active interactions. Last, there is a large sample of teenaged drivers present in the SHRP 2 NDS dataset. Prior research shows that teen drivers traveling with a teen passenger have a higher crash risk (17–19).

Other distracting activities that drivers perform in a car were somewhat more benign in terms of risk, including eating and drinking (nonalcohol); personal hygiene, which included a variety of factors, such as a driver fixing his or her hair and nails; or tuning the radio. An interesting finding in the SHRP 2 NDS crashes is the absence of factors previously thought to increase driver risk. For example, media sources often talk about putting on makeup as a distracting activity, but no crashes in the SHRP 2 NDS occurred when such an activity was performed, probably due to a very low prevalence. Similarly, previous research, the media, and parents often talk about distraction associated with interacting with children in the back seat as a dangerous activity (e.g., ref. 20). However, the results of this study show that interacting with children in the rear seat has a protective effect, with an odds ratio significantly less than 1.0 (i.e., 0.5). This may be because parents generally drive more safely with children in the car. Thus, parents adapt their driving behavior accordingly when interacting with their children in the back seat by slowing down or increasing headway in traffic.

A recent controversy relative to driving distraction is the risk associated with talking on a cell phone. Some epidemiological studies conducted overseas (21) and laboratory studies in the United States (22) have shown that such behavior is risky, whereas smaller NDSs and other epidemiological studies have shown that it is not (8, 23). The SHRP 2 NDS results estimate the risk of talking on a handheld cell phone to be 2.2 times higher than model driving, or slightly higher than the overall distraction risk. This result seems consistent with other naturalistic and epidemiological studies when one considers the following: (i) the comparison made within the SHRP 2 NDS uses model driving, as defined previously, which is not true of crash database analyses; and (ii) a recent study (9) showed that odds ratios are somewhat underestimated when minor collisions and near-crashes are used as surrogates for crashes in the estimates obtained in previous NDSs. Because this analysis is (to our

knowledge) the first of its kind to use only crashes, the determined odds ratio of 2.2 for talking on a handheld cell phone seems consistent and accurate.

It is important to note the overall impact of handheld cell phones on crash risk. The overall risk of interacting with a handheld cell phone is 3.6 times higher than model driving. This is consistent with a large-scale epidemiological study performed in Australia that estimated the overall risk of handheld cell phone use to be 4.9 (21). Although not the highest risk seen in Fig. 2, the prevalence (6.40%) makes handheld cell phone use of particular concern. The results of this study provide hard and conclusive evidence that crashes and resulting injuries would be reduced if drivers did not use handheld cell phones, thus supporting previous recommendations that handheld cell phones be banned from moving vehicles, except in cases of emergency (24).

## Discussion

On average, the crash rate—particularly the fatal crash rate—has generally been declining in the United States for several decades (25). This improvement is due to a variety of factors, including the reliability and crashworthiness of vehicles and the design and conditions of US roadways. Despite this improvement, the United States has not kept pace with other developed countries in terms of traffic safety. After being ranked near the top in the 1990s in terms of low fatality rates, the United States currently ranks 17th in fatalities per mile traveled out of 29 countries with available data and is ranked behind countries in Europe, Asia, and the Middle East (26). A large part of the reason why the United States has fallen behind in traffic safety may be attributed to factors associated with driver behavior and performance. Almost 20 y ago, VTTI embarked on the development of a new research method (i.e., NDS) to better understand specifically which driver performance and behavioral factors were causing crashes (2). This method involved instrumenting drivers' own cars with unobtrusive video cameras and other sensors to collect continuous driving data for several months or even years. The goal of the NDSs was to assist in the development of improved countermeasures, from crash avoidance systems to better driver education.

In 2006, TRB of NAS sponsored the first large-scale NDS that covered 3,542 drivers participating 1–2 y at six data collection sites across the United States. The resulting database, which was completed and became active in April 2015, contains more than 35 million miles of continuous naturalistic driving data (5, 11). The analysis described herein is (to our knowledge) the first of its kind to use crashes only (i.e., 905 injurious and property damage crashes in the SHRP 2 NDS) to determine the risk and prevalence of a number of driver factors associated with crashes, including observable impairment, driver performance errors, driver judgment errors, and observable driver distraction. Model driving episodes (i.e., alert, attentive, and sober) were drawn from a stratified random sampling of 19,732 baseline events used as a comparison group. The baseline samples were stratified by the number of hours that each participant drove during the SHRP 2 NDS. For the purposes of this paper, the contributing factors were compared with model driving, a calculation that cannot be accomplished using crash databases. That is, the comparisons shown here are the risks associated with a particular driver behavior or performance factor compared with cases of model driving performance and behavior. It is important to note that this study is (to our knowledge) the first of its kind to use a sufficiently large number of captured crash events for analysis without the need for surrogate measures.

Several important previously unidentified discoveries were made in this analysis, including the following: (i) Driving while observably angry, sad, crying, and/or emotionally agitated increases the risk of a crash by 9.8 times compared with model driving. (ii) Several driver performance errors, including committing a

right-of-way error, sudden or improper braking or stopping, and being unfamiliar with a vehicle or roadway, had the highest risks of any contributing factors analyzed for this study. The risk estimates for these errors were hundreds of times higher than model driving. (iii) Driver judgment errors (e.g., speeding well above the speed limit or traveling too fast for conditions) and other aggressive driving behaviors increase crash risk 11.1 times more than model driving. (iv) Interacting with in-vehicle devices that do not include the more standard radio or HVAC tasks, such as using a touchscreen interface, had a high odds ratio (i.e., 4.6 times higher than model driving) and a fairly high baseline prevalence (0.83% of trips). (v) Several factors previously thought to constitute significant driver risk factors, such as particular distractions (e.g., applying makeup) or errors (e.g., following too closely), were found to be much lower in prevalence in this analysis. Other factors posed much lower risks than previously thought, or even had a protective effect (e.g., interacting with children in the rear seat).

The conclusions made herein will better inform policymakers, driver educators, law enforcement agencies, vehicle designers, and the general public about the risks of various sources of impairment, error, and distraction so that appropriate actions may be taken to help mitigate such risks.

The most notable finding from this study is the degree to which distraction can be of detriment to drivers in the United States. Drivers are engaging in distracting activities more than 50% of the time while they are driving, resulting in a crash risk that is 2.0 times higher than model driving. Activities that require a driver to take his or her eyes off of the forward roadway result in the greatest risks. Actively interacting with an adult or teenaged passenger is the most prevalent individual activity, but it has a

relatively low associated risk. By contrast, interacting with a handheld cell phone occurs more than 6% of the time, with a risk that is 3.6 times higher than model driving. In addition, cell phone activities have changed even in recent years with the emergence of texting and browsing online. This is probably the single factor that has created the greatest increase in US crashes in recent years, working against the general trend of crash and fatality reduction. An increased need or want to remain connected and productive via cell phones (27) has the potential to escalate distraction-related crashes into the future.

Estimating the population-attributable risk for distraction overall shows that potentially 4 million of the 11 million crashes that occur each year in the United States (15) could be avoided if distraction was not a factor. As stated, the SHRP 2 NDS sample had a purposeful overrepresentation of younger drivers because they are at higher risk in general (8), meaning that this estimate may be somewhat high for the general population today. However, younger drivers represent the beginning of a new generation of drivers who engage in a full range of distracting behaviors (e.g., browsing on a cell phone) relative to their older counterparts. Thus, these estimates could well represent the near future if decisive actions are not taken to reduce distraction-related crashes. Although it is obviously not feasible to eliminate all driving distraction, countermeasures such as continued driver awareness and education programs, better enforcement of existing laws (e.g., handheld cell phone bans in some states), and emerging crash avoidance systems on vehicles (e.g., forward collision warnings, automated braking systems) could have a measureable impact on reducing distraction-related crashes.

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