Accident Analysis and Prevention 146 (2020) 105733

Contents lists available at ScienceDirect

Accident Analysis and Prevention

journal homepage: www.elsevier.com/locate/aap

Driving impairments and duration of distractions: Assessing crash risk by harnessing microscopic naturalistic driving data

Ramin Arvin, Asad J. Khattak*

Department of Civil & Environmental Engineering, The University of Tennessee, Knoxville, TN, United States

ARTICLE INFO

Keywords:
Crash risk
Impaired driving
Naturalistic driving
SHRP2
Distracted driving
Microscopic data

ABSTRACT

Distracted and impaired driving is a key contributing factor in crashes, leading to about 35% of all transportation-related deaths in recent years. Along these lines, cognitive issues like inattentiveness can further increase the chances of crash involvement. Despite its prevalence and importance, little is known about how the duration of these distractions is associated with critical events, such as crashes or near-crashes. With new sensors and increasing computational resources, it is possible to monitor drivers, vehicle performance, and roadway features to extract useful information, e.g., eyes off the road, indicating distraction and inattention. Using high-resolution microscopic SHRP2 naturalistic driving data, this study conducts in-depth analysis of both impairments and distractions. The data has more than 2 million seconds of observations in 7394 baselines (no event), 1228 near-crashes, and 617 crashes. The event data was processed and linked with driver behavior and roadway factors. The intervals of distracted driving during the period of observation (15 seconds) were extracted; next, rigorous fixed and random parameter logistic regression models of crash/near-crash risk were estimated. The results reveal that alcohol and drug impairment is associated with a substantial increase in crash/near-crash event involvement of 34%, and the highest correlations with crash risk include duration of distraction through dialing on a cellphone, texting while driving, and reaching for an object. Using detailed pre-crash data from instrumented vehicles, the study contributes by quantifying crash risk vis-à-vis detailed driving impairment and information on secondary task involvement, and discusses the implications of the results.

1. Introduction

Human-based errors such as distracted driving, alcohol/drug impairment, fatigue driving, and speeding are known as the main contributing causes of fatal crashes (Pietrasik 2018). In particular, distracted and impaired driving contributes to about 35% of all transportation-related deaths (10,497 fatalities in 2016), based on US Traffic Safety Facts (NHTSA 2017). While driving tasks require execution of several cognitive, sensory, and psychomotor skills (Young et al., 2007), it is common to observe drivers under impairment (Fan et al., 2019) and engaged in various non-driving tasks such as cellphone usage, interaction with other passengers, listening to music, and writing and reading (Stutts et al., 2005, Dingus et al., 2016, Kamrani et al., 2019). Impaired and distracted driving limits the driver's available attention to driving tasks such as vehicle position control and maintaining speed (Martin et al., 2013, Verstraete et al., 2014, Paolo Busardo et al., 2018). Distracted driving can be defined as "a diversion of attention from driving, because the driver is temporarily focusing on an object, person, task or event not related to driving, which reduces driver's awareness, decision making ability and/or performance, leading to an increased risk of corrective actions, near-crashes, or crashes" (Regan et al., 2008). With the advantage of new technologies, connectivity and cooperation between vehicles can substantially reduce human errors and the consequent crash risks (Mahdinia et al., 2020). Driver inattention contributes to an estimated 23 percent of police reported crashes (Klauer et al., 2006). In addition, the introduction and wide usage of cellphones worsened the situation (Engelberg et al., 2015, Arvin et al., 2017, Nasr Esfahani et al., 2019), especially among young drivers (Anon 2011). While a majority of drivers are aware of the associated risks with distracted driving, more than 25 percent still use their cellphone frequently while driving (Motamedi and Wang 2016). Cellphone distracted driving is one of the great challenges in the transportation field, as it contributes to 18 percent of fatal and 5 percent of injury crashes across the U.S. based on the police-reported crash data (Overton et al., 2015). However, these crash databases are deficient due to unreported crashes (around 50% of no-injury and 25% of minor-injury crashes were not reported to the police (NHTSA 2009)). Furthermore, such datasets under-report the prevalence of distracted driving and do not provide distraction duration.

* Corresponding author.
E-mail address: akhattak@utk.edu (A.J. Khattak).

https://doi.org/10.1016/j.aap.2020.105733
Received 8 November 2019; Received in revised form 13 July 2020; Accepted 7 August 2020
Available online 09 September 2020

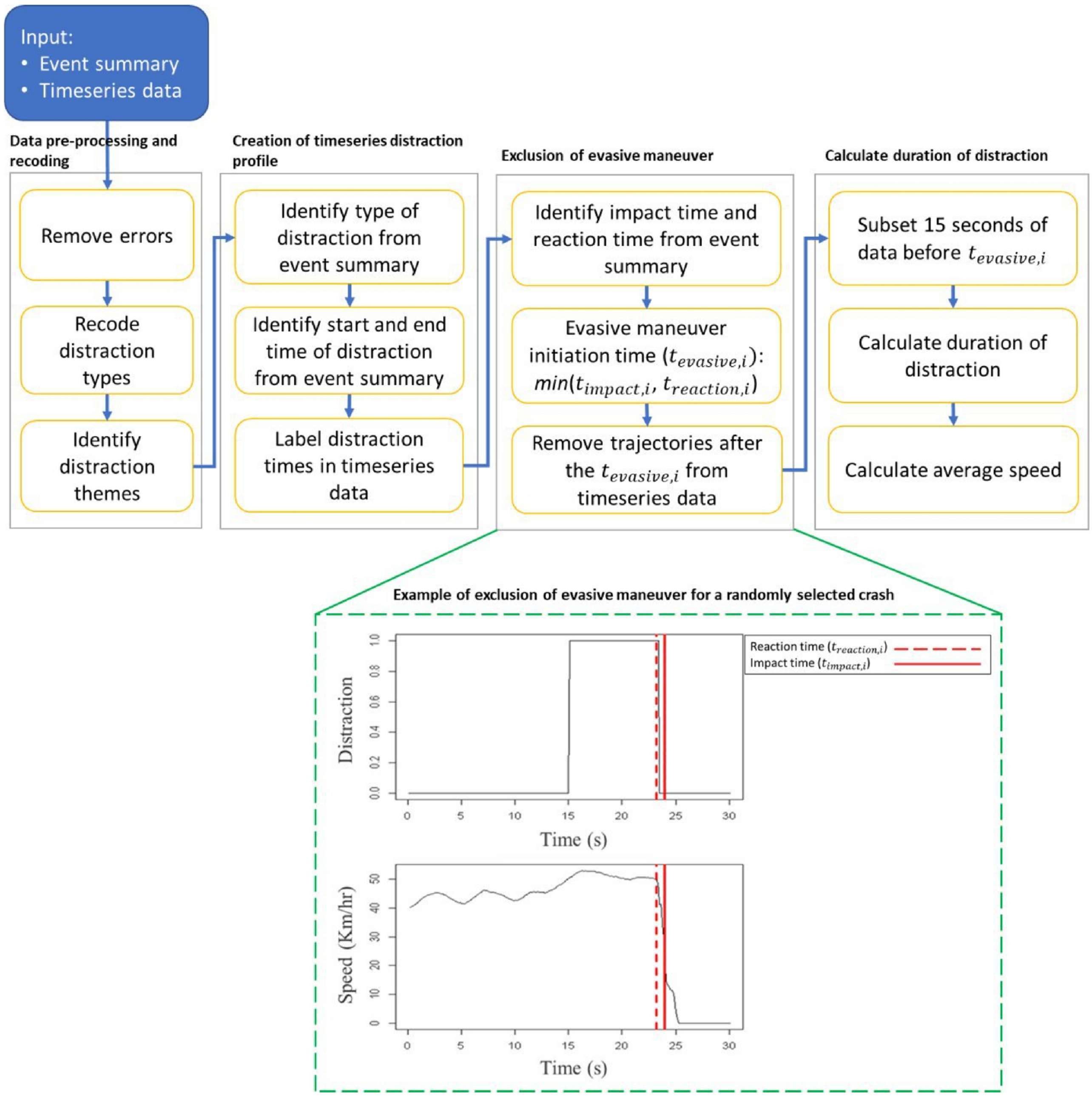


Fig. 1. Data processing framework.

Impaired driving, including alcohol/drug impairment, fatigue, emotional state, is also widely common. Although the share of alcohol-related traffic fatalities significantly dropped in the last few decades (from 48 percent in 1982 to 28% in 2016), it still remains the main contributing factor of fatal crashes. The estimated prevalence of alcohol related impaired driving among drivers aged 16 years and older is 11.6 percent (Lipari et al., 2016). Impairment substantially affects a driver's ability to control the vehicle and increases risk taking behaviors (Laude and Fillmore 2015). In terms of driver performance, impaired driving significantly increases the number of errors (Verster et al., 2009) and driver reaction time (Deery and Love 1996, Verster et al., 2009), and worsens lateral (Hartman et al., 2015) and longitudinal vehicle control (Hartman et al., 2016). While these studies mainly investigated the correlation between distracted and impaired driving with driving performance using a driving simulator (Rumschlag et al., 2015, Li et al., 2016), driving simulator sickness may affect the validity and reliability of results (Nickkar et al., 2019). Crash datasets suffer from unreported crashes and near-crashes, and a lack of detailed information on pre-crash driver states and behavior. While crash-only databases can only be used for frequency and prevalence of specific factors in crashes (Shinar and Gurion 2019), naturalistic driving study (NDS) data provides an opportunity to analyze the associated risks with these factors by using real data in real-world conditions. The second Strategic Highway Research Program (SHRP2), sponsored by the National Academy of Science, is the largest naturalistic driving data collection effort, with more than 3500 drivers (Dingus et al., 2015). It provides researchers with an opportunity to gain insight into factors leading to a crash/near-crash (CNC) event, especially a driver's state, behavior, and performance (Dingus, 2003, Dingus et al., 2011). Such a dataset helps researchers overcome limitations of traditional datasets and explore not only minor crashes, but also pre-crash driver states and behavior, specifically impairment and distraction profiles.

Overall, the goal of this study is to harness microscopic big data from multiple sources and link this information with driver behavior,

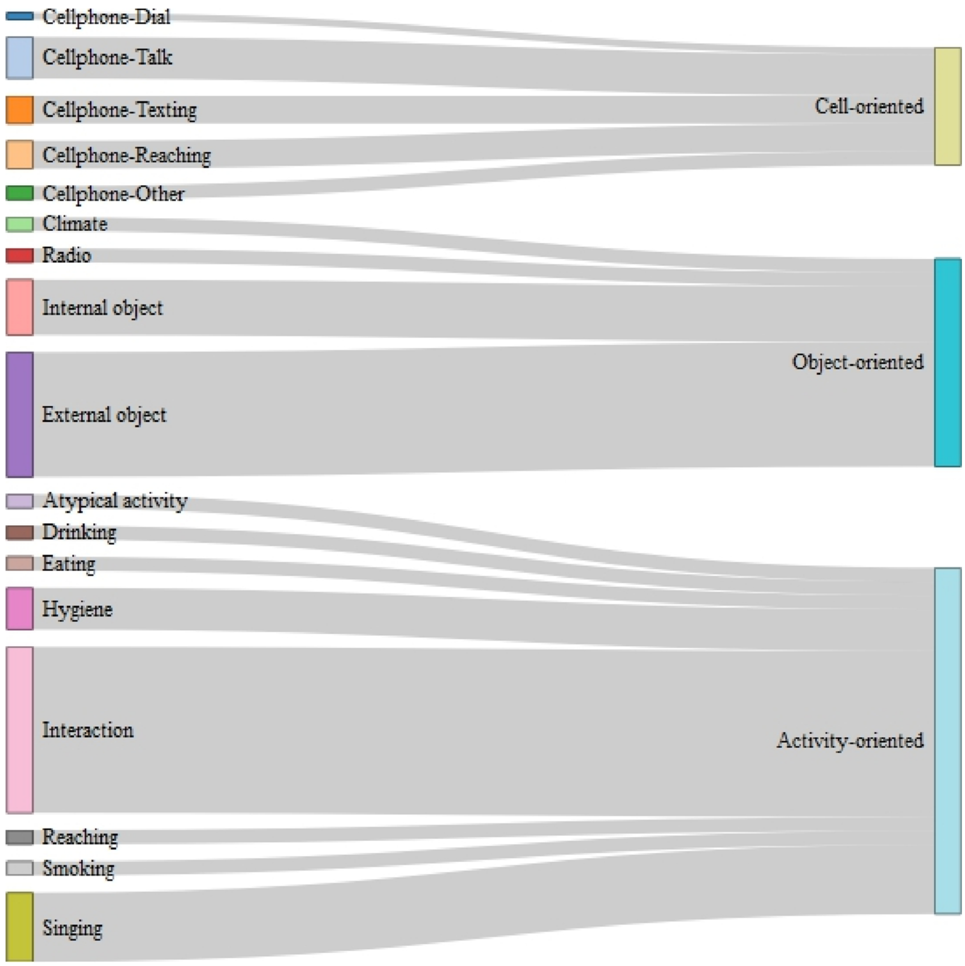


Fig. 2. Categorization of secondary tasks.

roadway, and environmental factors in order to evaluate impaired driving and the association of different distraction type durations on the probability of crashes and near-crash occurrence. Given that distracted driving and human error are the key contributing factors in crashes (Kludt et al., 2006, Shinar 2017, Razi-Ardakani et al., 2019), the findings of this research identify the role of impairments and distraction types that are highly associated with crash risk, and explore how impairment and duration of distraction affect driving performance and crash risk.

The paper is organized as follows. A comprehensive literature review on impaired and distracted driving identifies gaps in the literature. The methodology section discusses the paper's approach toward addressing the association of distracted and impaired driving on crash/near-crash risk. Next, the results of the analysis for different distraction types and impairments are provided and discussed. Finally, the conclusion summarizes the findings and contributions of this study and identifies areas for future studies.

2. Literature review

The impact of impaired and distracted driving on driving performance has been widely studied in the literature (Shinar 2017). Deviation of attention from driving tasks can delay reaction time (Drews et al., 2009, Choudhary and Velaga 2017, Gao and Davis 2017), deteriorate vehicle control (Shinar et al., 2005, Tractinsky et al., 2013, Young et al., 2014), and can lead to near-miss events (Hosking et al., 2009). The availability of microscopic naturalistic driving data has enabled research that studies driving behavior prior to critical events and their associations. Several papers have investigated the association of distraction on crash risk (Dingus et al., 2011, Dingus et al., 2016, Guo et al., 2017, Arvin et al., 2019b) and crash severity (Beanland et al., 2013, Arvin et al., 2019a). Since drivers receive almost all information from their eyes (Shinar 2008), recent studies have focused on secondary tasks in terms of removing eyes from the roadway, and have established a relationship between eyes-off-road and crash risk (Klauer et al., 2006, Simons-Morton et al. 2014, Victor et al., 2015). Glance location can be utilized to infer whether the driver is fully engaged in the driving task or not (Wickens et al., 2003, Taylor et al., 2013). It has been shown that drivers tend to not hold their glances away from the roadway for more than 1.6-2 seconds (Sodhi et al., 2002, Liang et al., 2014). Instead, drivers increase the number of times that they look away from the road (Victor et al., 2005). Several studies have tried to develop driver distraction warning systems that generate feedback to drivers and reduce crash risk (Ahlstrom et al., 2013).

In terms of impaired driving, few studies have investigated the association of alcohol/drug impairment on driving behavior using police-reported crashes (Romano and Voas 2011, Liu et al., 2016, Valen et al., 2019) and driving simulators (Dingus et al., 2016, Helland et al., 2016, McCartney et al., 2017). One of these studies explored the association of alcohol/drug-impaired driving on real-world crash and near-crash events using NDS data (Dingus et al., 2016). Several driving behavioral factors are explored using a binary logistic regression model to quantify the association of the presence of distraction and impairment on crash risk. However, the association of distraction duration on crash risk remains unknown. In regards with fatigue impairment, several studies have explored its contribution on driver performance (Philip et al., 2005, Meng et al., 2019) and safety (Williamson et al., 2011, Zhang et al., 2016), and tried to develop a framework to predict it (Morales

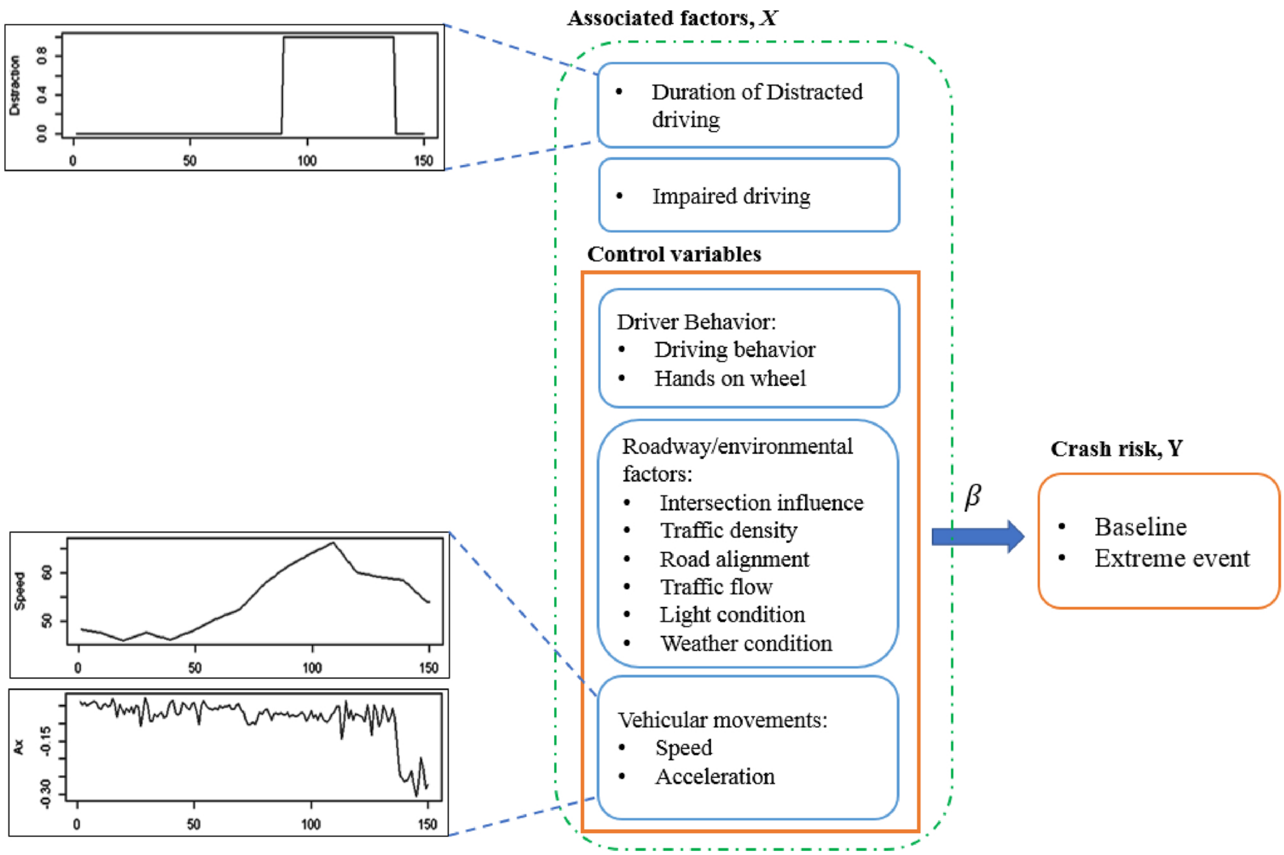


Fig. 3. Conceptual framework of the study.

et al., 2017, Mollicone et al., 2019). It is worth noting that along with distracted and impaired driving, the literature suggests that roadway and environmental factors such as weather conditions (Ghasemzadeh and Ahmed 2016, Parsa et al., 2020), road characteristics (Manan et al., 2017, Schorr et al., 2017), surface conditions (Wang and Zhang 2017, Rahimi et al., 2020), and traffic flow (Theofilatos and Yannis 2014, Zheng et al., 2017, Hoseinzadeh et al., 2020) are associated with crash risk and need to be considered in the analysis.

The impact of distraction on the probability of crash occurrence remains the main focus in the literature, but several gaps need to be addressed. First, distraction duration and driver impairment using naturalistic driving data while controlling for roadway/environmental factors are not explicitly explored. Second, the sample size is typically small, and the results may not be highly generalizable to other drivers and events. Finally, results are mainly based on safety surrogate measures using driving simulators instead of real-world crashes. This study contributes to the literature by developing an understanding of the influence of impaired driving and distracted driving duration, categorized by different sources, on the probability of CNC event occurrence, while controlling for other driver behavior, roadway, and environmental factors. This paper provides an in-depth analysis of the impact of distraction duration through different secondary tasks during the 15 seconds before a crash or near-crash involvement. Furthermore, the role of impaired (alcohol and drug) driving is investigated.

3. Data

3.1. Data description

More than 4 petabytes of various information were collected in the second Strategic Highway Research Program (SHRP2) data from 2010 to 2013, which makes it the most comprehensive naturalistic driving study. This high-quality and high-resolution data was captured via multiple sensors including cameras, accelerometers, alcohol sensors, forward sensors, and data acquisition systems (DAS) with 10 Hz frequency (Hankey et al., 2016). Each vehicle was instrumented with a DAS with the main components of radar unit, head unit, and main unit in order to collect data (Hankey et al., 2016). The radar unit was mounted on the front bumper to collect data on the surrounding environment. The head unit, mounted on the rear-view mirror, contained four cameras which collected data on the driver's face, driver's hands, vehicle cabin, and front windshield. Furthermore, the head unit was equipped with an ambient atmospheric analyzer to detect the presence of alcohol. All considered cameras continuously collected data except the cabin camera, which periodically took a photograph to monitor the presence of passengers in the vehicle. Finally, all the collected data were transmitted to the main unit, or hard drive for storage (Fraser and Jovanis 2013). The SHRP2 data has information on more than 3500 drivers from six states (Washington, New York, Pennsylvania, North Carolina, Florida, and Indiana) across the U.S., with more than five million trips covering more than 50 million miles travelled (Hankey et al., 2016). The NDS data includes vehicular movement data (e.g., speed, acceleration), along with information regarding the drivers' behavior, roadway factors, and environmental factors from the videos coded by the data reductionist using the appropriate protocols to ensure consistency and high quality.

Although more than 5 M trips are recorded in the raw SHRP2 NDS data, a data subset is used in the data reduction process by the Virginia Tech Transportation Institute (VTTI). In this process, all the crashes and near crash events are recorded in the final SHRP2 dataset. However, in order to study crash risk, baseline events are necessary in order to provide crucial information on normal driving and typical driving behavior (Antin et al., 2019). Therefore, more than 7.5 K baseline events were selected via case-cohort and case-crossover random sampling methods, which was stratified by drivers and driving time (Hankey et al., 2016). A significant effort was taken by the VTTI data reduction

Table 1
Descriptive statistics of the driver, vehicle, and roadway/environmental factors.

Variable	Category	Total (N = 9239)		Baseline (N = 7394)		CNC (N = 1845)	
		%	Freq.	%	Freq.	%	Freq.
Distraction	**Cellphone oriented**						
	Reaching	2.50%	231	2.11%	156	4.07%	75
	Dialing	0.18%	17	0.11%	8	0.49%	9
	Talking	3.56%	329	3.38%	250	4.28%	79
	Texting	2.24%	207	1.51%	112	5.15%	95
	Other	0.80%	74	0.73%	54	1.08%	20
	Object oriented						
	Climate	1.21%	112	1.12%	83	1.57%	29
	Radio	1.71%	158	1.65%	122	1.95%	36
	Internal	4.32%	399	3.90%	288	6.02%	111
	External	9.43%	871	9.44%	698	9.38%	173
	Activity oriented						
	Drinking	0.71%	66	0.76%	56	0.54%	10
	Eating	1.17%	108	1.20%	89	1.03%	19
	Smoking	0.80%	74	0.76%	56	0.98%	18
	Reaching	0.88%	81	0.57%	42	2.11%	39
	Interacting	12.88%	1190	13.23%	978	11.49%	212
	Atypical	1.79%	165	1.39%	103	3.36%	62
	Talking/singing	5.89%	544	5.88%	435	5.91%	109
	Hygiene	3.16%	292	3.02%	223	3.74%	69
	None (no distraction)	46.77%	4321	49.24%	3641	36.86%	680
Impairment	Emotional state	0.50%	46	0.28%	21	1.36%	25
	Drowsy/Fatigue	1.40%	129	1.23%	91	2.06%	38
	Alcohol/Drug	0.24%	22	0.05%	4	0.98%	18
	No impairment	97.60%	9016	98.24%	7264	94.96%	1752
	Other	0.28%	26	0.19%	14	0.65%	12
Weather	Adverse Conditions	6.13%	567	5.91%	437	7.05%	130
	Mist/Light Rain	4.09%	378	3.85%	285	5.04%	93
	No Adverse Conditions	89.77%	8294	90.24%	6,672	87.91%	1622
Density (Level-of-service)	A1	40.23%	3717	42.51%	3,143	31.11%	574
	A2	30.15%	2786	32.31%	2,389	21.52%	397
	B	20.16%	1863	18.49%	1,367	26.88%	496
	C	6.07%	561	4.56%	337	12.14%	224
	D	2.10%	194	1.27%	94	5.42%	100
	E	1.02%	94	0.72%	53	2.22%	41
	F	0.25%	23	0.14%	10	0.70%	13
	Unknown	0.01%	1	0.01%	1	0.0%	0
Road Alignment	Curve	13.60%	1256	13.97%	1034	12.03%	222
	Straight	86.40%	7983	86.03%	6,360	87.97%	1623

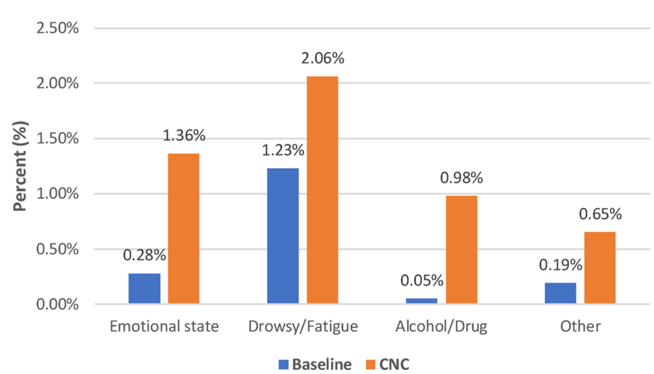


Fig. 4. Prevalence of impaired driving in baseline and crash/near-crash events.

team to manually code crash, near crash, and baseline event characteristics and collect the sequence of states, decisions, and actions prior to CNC events, which were not automatically recorded. It is worth noting that the same information was collected for the baseline events in order to maintain a form similar to CNC events. Further information on data reduction can be found in (Hankey et al., 2016). This study considers a subset of original SHRP2 data, containing 9239 trips taken by 1546 drivers with 7394 baseline events, 1228 near-crashes, and 617 crashes. The definition of a crash is “any contact that the subject vehicle has with an object, either moving or fixed, at any speed in which kinetic energy is measurably transferred or dissipated.” Even though near-crashes did not result in a crash, the data for crash events and near-crash events were combined in this study and defined as CNC events. For each CNC event, 30 seconds of vehicular movement data is available. It is worth noting that the data contains time in which the driver uses evasive maneuvers to avoid the CNC event and also the seconds after the occurrence of an CNC event. Since this paper examines the association of distracted driving before CNC event occurrence, the seconds after the crash were excluded, which will be further discussed. Moreover, since we are investigating the association of distraction duration with crash risk, the information on driver distraction needs to be linked with vehicle kinematics.

3.2. Data processing

The data contains detailed information on baseline and CNC events coded as categorical variables. The subset of data available in this study consist of three main files:

1- Event summary: detailed information on the event including

a) Event details: information on factors used to establish the CNC event characteristics and sequence of events prior to and throughout its occurrence, such as event type (baseline, crash, near-crash), event severity, time of reaction, impact time.

b) Driver state: systematic descriptions of the driver prior to and during an event such as driver distraction, impairment, start and end of distraction, and driver behavior.

c) Roadway and weather conditions: roadway/environmental

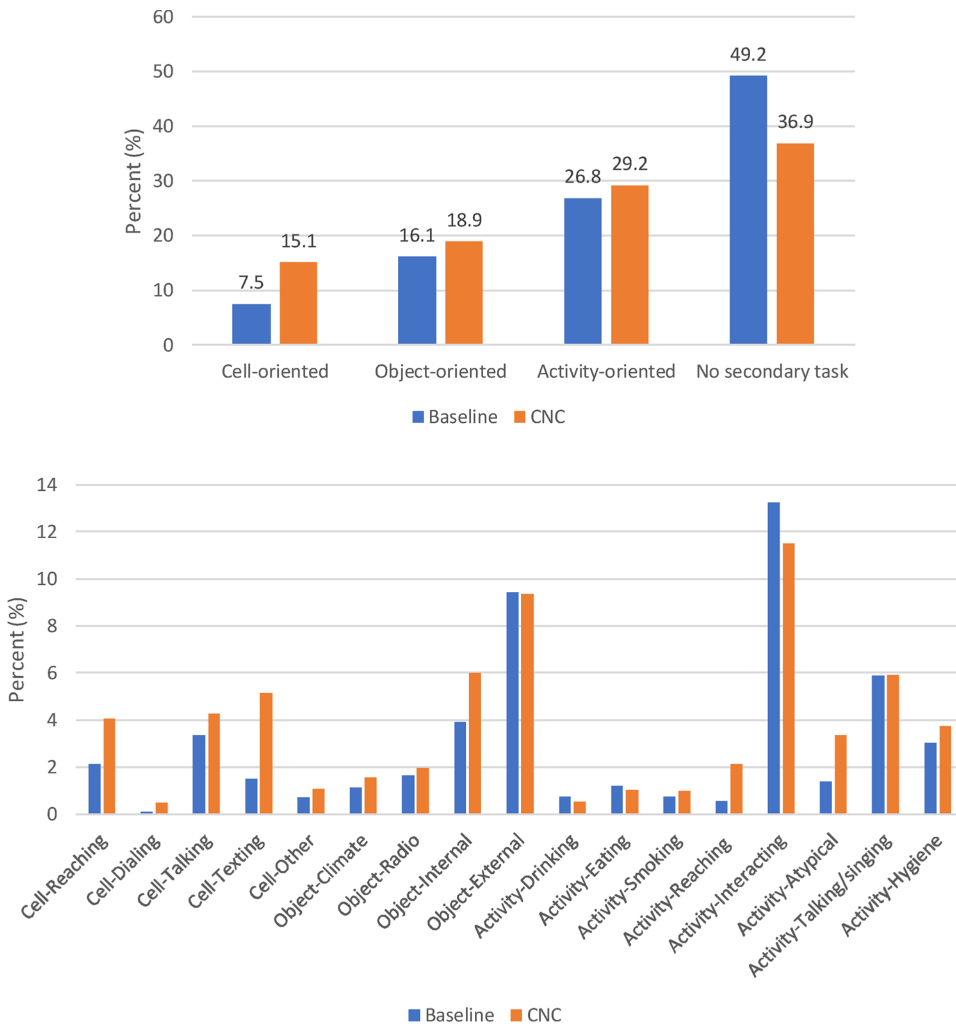


Fig. 5. Prevalence of three groups of distractions (a) and different distraction types (b) in baseline and CNC events.

conditions such as traffic flow, locality, weather, and surface condition.

2- Timeseries data: timeseries information (between 20 to 30 seconds) for each event (baseline and CNC) such as recording time information, video frames related to each time, and vehicle kinematics.

3- Video data: front camera video of each event.

This study utilized the first two files to extract evasive maneuver time and duration of distraction, and link this information with vehicular movements, driver behavior, and roadway/environmental factors. The workflow of the data processing is provided in Fig. 1. The input is the event summary and event timeseries data. The first step removes the errors and outliers, recodes distractions, and identifies distraction themes. The next step identifies distraction type, distraction start and end time, and labels the distraction seconds for each event. Following this, evasive maneuvers were removed from the analysis. It is vital to consider only the seconds of driving that contain typical driver behavior instead of the seconds that drivers are reacting to a crash stimulus. We need to exclude the seconds where the driver is reacting to the crash and the seconds after the crash occurrence. The time that driver started to react, and the time of impact are extracted from the trip summary. The minimum of these two values is selected as the start of evasive maneuver, and the trajectories after the evasive maneuver initiation are removed. For further demonstration, a speed profile, an acceleration profile, and a distraction profile of a random crash event are provided in the bottom of Fig. 1. In this event, the crash happened at the 24th second of the data stream and the driver reacted to the stimulus at the 23rd second. Therefore, the observations after second 23 are excluded for the purpose of this study. In other words, only the seconds of the data up to the second that the driver starts to react to the CNC event was considered in this study. Finally, for consistency in all events (both baselines and CNC events), we subset 15 seconds of data prior to the evasive maneuver and then calculate the distraction durations and vehicular movements.

3.2.1. Data recoding

As mentioned, the data contains rich and detailed information on driver behavior, roadway conditions, environment conditions, etc. The variable “secondary task” was coded into 62 different groups. However, there are similarities in some groups that allow the data to be merged into more intuitive and cleaner variables. Three themes of distractions are identified in the SHRP2 data (Fig. 2): cellphone-oriented, object-oriented, and activity oriented secondary tasks. In summary, cellphone-oriented distractions involve cellphone use while the object-oriented group focuses on distractions with objects, other than a cellphone, either inside or outside the vehicle’s cabin, such as the vehicle’s radio, climate control, objects inside the vehicle, and objects outside the cabin. The activity-oriented group is focused on activities and tasks, such as eating, drinking, smoking, reaching for an object, interacting with other passengers, singing and talking by him/herself, hygiene, and atypical activities. It is worth noting that Fig. 2 also provides the common secondary tasks in the SHRP2 dataset and methodology for recoding and grouping these distractions into three main groups. The thicknesses of the recorded secondary task in the dataset represent the approximate proportion of the grouped category.

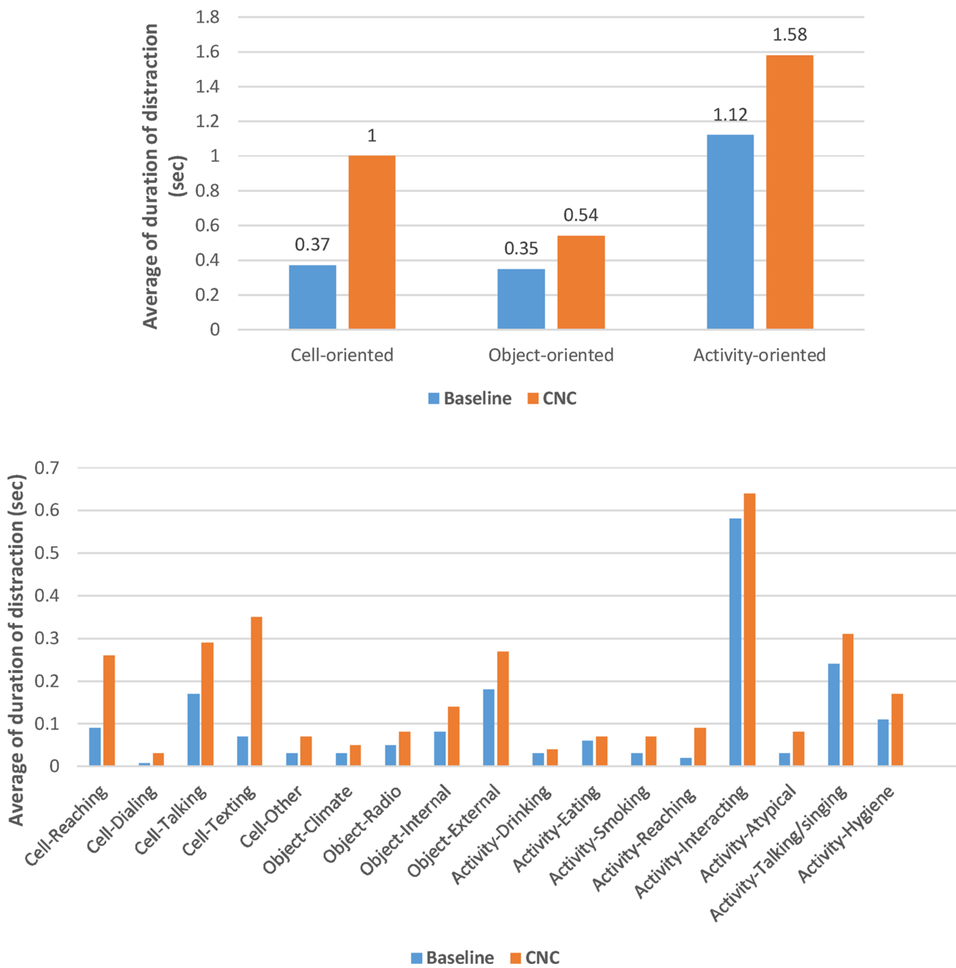


Fig. 6. Average of duration of distraction for different distraction groups (top) and distraction types (bottom) for baseline and CNC.

4. Methodology

The main motivation of this study is to explore the association of distracted driving duration and impairment on the probability of CNC events. While significant literature exists on the investigation of correlation of distracted driving on crash risk and severity, the association of the duration of distracted driving on the probability of CNC events remains unknown. In order to untangle this problem, a binary logistic regression approach was utilized for modeling, a widely used method in the literature in cases where the variable of interest has a binary nature (Dingus et al., 2016, Mokhtarimousavi et al., 2019, Nazari et al., 2019, Boggs et al., 2020). Along with distraction duration, vehicular movements, driver behavior, and roadway/environmental factors were considered as control variables. The study framework is shown in Fig. 3.

Upon linking the events with other factors, the descriptive statistics provided in section 5.2 were used to gain initial insights. Next, fixed and random parameter binary logit models are estimated to quantify the correlation of distracted duration on crash risk. In the following, more details on the modeling framework is provided.

4.1. Random parameter logistic regression

In the fixed parameter approach, the estimated parameters are fixed across observations, and the estimations are not allowed to vary. The probability of involvement in an CNC event can be written as (Washington et al., 2010):

$$logit\,(P_i) = \log\left[\frac{P_i}{1-P_i}\right] = \alpha + \beta X \tag{1}$$

where, P_i denotes the probability that event i is an CNC event; β is a vector of estimated parameters, X is a vector of independent variables; and, α is the model intercept. The likelihood can be written as (Washington et al., 2010):

$$L(\beta) = \prod_{i=1}^{n} \pi(x_i)^{y_i}(1-\pi(x_i))^{i-y_i} \tag{2}$$

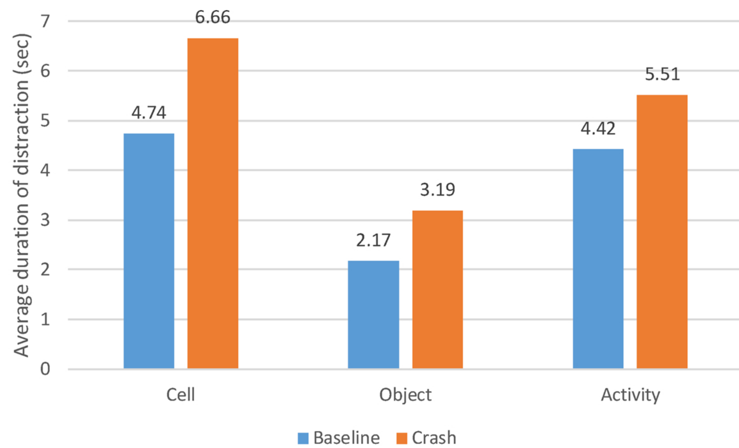
where y_i is the outcome of observation i, and n is the number of observations.

However, the fixed parameter model assumes that the variation of coefficients across the observations is fixed, which might not be the case. This issue must be addressed due to heterogeneity among events and drivers through several observed and unobserved factors (Kamrani et al., 2018, Wali et al., 2019). The correlations between CNC events and contributing factors significantly vary across events, and it is crucial to account for this heterogeneity in the modeling process. One of the well-known approaches to account for unobserved heterogeneity is a random parameter approach which is widely used in the safety literature (Ukkusuri et al., 2011, Wali et al., 2018a, 2018b, Azimi et al., 2019, Esfahani and Song 2019), and allows estimated parameters to vary across events. This can be written as (Train 2009):

$$S_{in} = \beta_i X_{in} + \varepsilon_{in} + \eta_{in} \tag{3}$$

where η_{in} denotes the random term with pre-specified distribution and a mean of zero. Depending on the assumption of random term distribution, the outcome probability can be written as (Train 2009):

$$P_{in} = \int \frac{\exp(\beta_i X_{in})}{\sum_I \exp(\beta_i X_{in})} f(\beta\varphi)d\beta \tag{4}$$



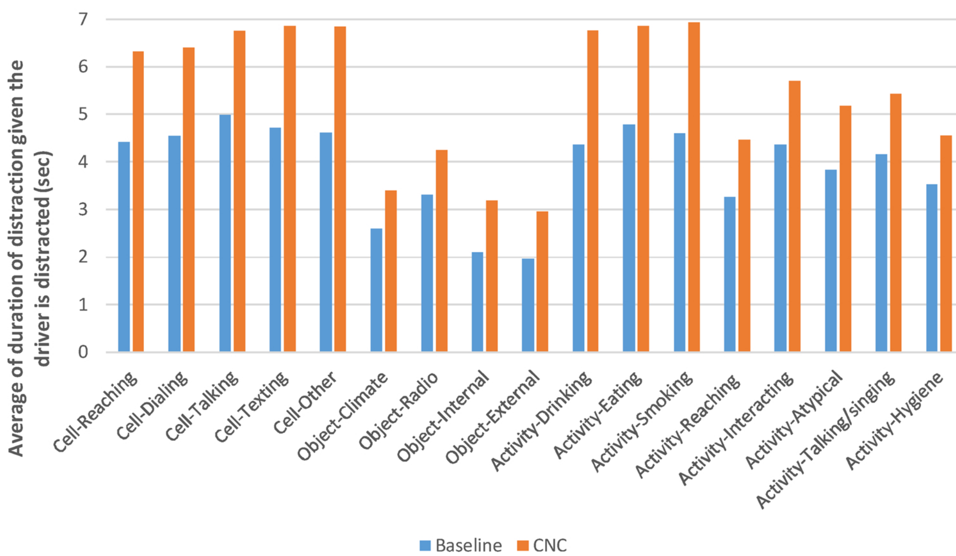


Fig. 7. Average distraction duration once it is initiated in cell-oriented, object-oriented, and activity-oriented groups (top), and distraction types (bottom) in baseline and CNC events.

where $f(\beta\varphi)$ is the density function of β, and φ is a parameter vector of the density distribution also sometimes referred to as a mixing distribution (Washington et al., 2010). While the fixed parameter model uses a maximum likelihood estimator, the random parameter model utilizes the simulated maximum likelihood estimator with 150 Halton draws. Different functional forms for random parameter variables are used, such as uniform, triangle, normal, and Weibull. To evaluate and compare the developed models, Akaike Information Criteria (AIC) was utilized. A lower AIC denotes a model with a better fit to the data and a three-point reduction in AIC represents a significant improvement in the model fit (Bozdogan 1987).

5. Results

This section provides an in-depth analysis of the impact of distracted and impaired driving on the probability of crash occurrence. First, the descriptive statistics of variables for the baseline and CNC events are provided and discussed. Next, the modeling results are provided. Finally, the impact of distraction on the probability of crash occurrence probability is described in detail in the discussion section.

5.1. Descriptive statistics

Table 1 provides the descriptive statistics of the key variables. The table consists of three sections, driver related variables, roadway/environmental factors, and vehicular movements. The driver variables include distraction type and impairment. The considered roadway/environmental factors include light and weather condition, density of traffic, road alignment, construction zone, intersection influence, and roadway type. The results are also separated between baseline and CNC events. Descriptive statistics for the baseline and CNC events have a substantial difference, especially in terms of driver factors. This indicates that further analysis is needed to explore the association of these factors on the probability of a CNC event.

Fig. 4 provides the prevalence of impaired driving in CNC and baseline events. It can be inferred that emotional state, drowsy/fatigue, alcohol/drug, and other impairments are substantially higher in CNC events than baseline, which highlights the correlation of impaired driving on crash risk. As an illustration, drowsy and fatigue driving occurred in 2.06% of CNC events, but in only 1.23% of baseline events. Referring to alcohol and drugs, it was present in 0.05% of baseline events, and in 0.98% of CNC events.

As discussed in section 3.2.1, the secondary tasks associated with distracted driving are grouped into three main categories: cell-phone oriented distraction, object-oriented distraction, and activity-oriented distraction. Fig. 5 (top) provides the prevalence of different categories among baseline and CNC events. Based on the results, it can be observed that distracted driving was present in 50.8% of crashes, and in 63.1% of baseline events. In addition, the prevalence of all distraction categories is higher in CNC events compared to the baseline. Fig. 5

Table 2
Modeling results for cellphone-oriented distraction duration.

Variable	Fixed parameter				Random parameter			
	β	Std. Err.	P-value	ME	β	Std. Err.	P-value	ME
Intercept	−0.994	0.089	< 0.001	-	−0.600	0.063	< 0.001	-
Duration of Cellphone distraction								
Reaching for cellphone	0.223	0.029	< 0.001	2.9%	0.173	0.023	< 0.001	2.6%
Dialing	0.473	0.115	< 0.001	6.1%	0.370	0.097	< 0.001	5.6%
Talking with cellphone	0.144	0.025	< 0.001	1.9%	0.114	0.019	< 0.001	1.7%
Texting with cellphone	0.295	0.030	< 0.001	3.8%	0.239	0.027	< 0.001	3.6%
Other cell distraction	0.173	0.050	0.001	2.3%	0.128	0.041	0.002	2.0%
Impairment (Base: No impairment)								
Emotional state	2.400	0.634	< 0.001	44.0%	1.841	0.408	< 0.001	28.1%
Drowsy/Fatigue	1.060	0.255	< 0.001	16.9%	0.832	0.192	< 0.001	12.7%
Other	2.171	0.599	< 0.001	39.2%	1.881	0.525	< 0.001	28.7%
Alcohol/Drug	2.220	0.898	0.013	39.2%	1.920	0.953	0.044	29.3%
Traffic density (Base: A1)								
A2	0.322	0.104	0.002	4.1%	0.253	0.076	0.001	3.9%
B	0.997	0.105	< 0.001	14.5%	0.776	0.080	< 0.001	11.8%
C	1.430	0.144	< 0.001	23.8%	1.109	0.108	< 0.001	16.9%
D	1.615	0.208	< 0.001	27.8%	1.211	0.143	< 0.001	18.5%
E	0.976	0.307	0.002	15.0%	0.703	0.217	0.001	10.7%
F	1.008	0.543	0.064	16.0%	0.696	0.447	0.120	10.6%
Vehicular movement								
Average Speed over 15 seconds	−0.023	0.001	< 0.001	−0.3%	−0.023	0.001	< 0.001	−0.4%
Speed Std	-	-	-	-	0.016	0.001	< 0.001	-
Summary Statistics								
Number of observations	5227				5227			
LL at Null	−2555.7				−2555.7			
LL at convergence	−2153.2				−2148.6			
McFadden's R-Squared	0.157				0.159			
AIC	4340.4				4333.2			

(bottom) illustrates the presence of different distraction types in baseline and CNC events. Based on the results, the prevalence of most distraction types were substantially higher in CNC events compared to the baselines. As an illustration, texting while driving was present in 1.51% and 5.15% of baseline and CNC events, respectively.

5.2. Duration of distracted driving

The correlation of each distraction duration with crash risk is discussed here. Fig. 6 provides the average distraction duration for each distraction type within the 15 seconds of data. Fig. 6 (top) shows the average distraction duration for three distraction categories for both baseline and CNC events. Comparing the two groups, there is a substantial difference between the duration of distraction in CNC events compared to baseline events. On average, duration of distraction in cellphone-oriented group is 0.37 and 1.01 seconds in baseline and CNC events, respectively. The duration of the secondary task in object-oriented group is 0.35 and 0.54 seconds for baseline and CNC events. Finally, distraction duration in activity-oriented distractions is 1.12 and 1.58 seconds in baseline and CNC events. These time differences imply that the prevalence of distraction is higher, and the duration of the distraction is longer in CNC events. A similar pattern can be observed in all distraction types. Fig. 6 (bottom) provides average distraction durations in different secondary task categories. As an illustration, when considering texting while driving distraction, drivers were distracted on average for 0.07 seconds within baseline events, while in the CNC events the distraction duration was 0.35 seconds. Distraction by objects inside the vehicle follows a similar pattern, indicating that on average, drivers were distracted longer compared to baselines (0.14 vs 0.08 seconds). Furthermore, distraction duration of the category “atypical” is substantially higher in CNC events compared to baseline events (0.08 vs. 0.03 seconds).

While Fig. 6 provides the average distraction durations in baseline and CNC events including zero duration for events with no secondary task, so it is not clear how long these distractions last once initiated. Fig. 7 illustrates average distraction duration given that a driver is distracted with that secondary task for baselines and CNCs. In other words, Fig. 7 provides the average distraction duration, given that a driver is distracted. Cellphone-oriented distractions last for 6.66 seconds in CNC events, and 4.74 seconds in baselines. Referring to object-oriented distractions, they last an average of 3.19 seconds and 2.17 seconds for CNC and baselines events, respectively. Activity-oriented distractions were 5.51 seconds and 4.42 seconds on average in CNC and baseline events, respectively. These statistics imply that the duration of initiated distracted driving is higher in CNC events, suggesting that there is a significant correlation between the duration of distracted driving and crash risk. Statistical modeling will provide more insights on the significance of these variables and their association with near-crash and crash risks, which will be discussed in the next section.

5.3. Modeling results

The descriptive statistics of the data presented in the previous section revealed meaningful relationships between duration of distraction and crash risk. However, without controlling for other factors such as driving behavior and roadway/environmental factors, these relations might not be generalizable or conclusive. As discussed in the methodology section, this study utilized a fixed and a random parameter binary logistic regression model to explore the association of the duration of distracted driving with the probability of crash occurrence. The random parameter model addresses unobserved heterogeneity. A parameter is considered to be random in two different conditions: only standard deviation is significant, or both mean and standard deviation are significant. Along with the duration of distraction and impaired driving factors, driver behavior and roadway environmental variables are considered in the model as control variables. To perform the model selection, intuition, variable significance, and model parsimony were considered and AIC was used to score model performance.

Four specific models are developed to explore the association of impaired driving and duration of distraction on CNC events. The first

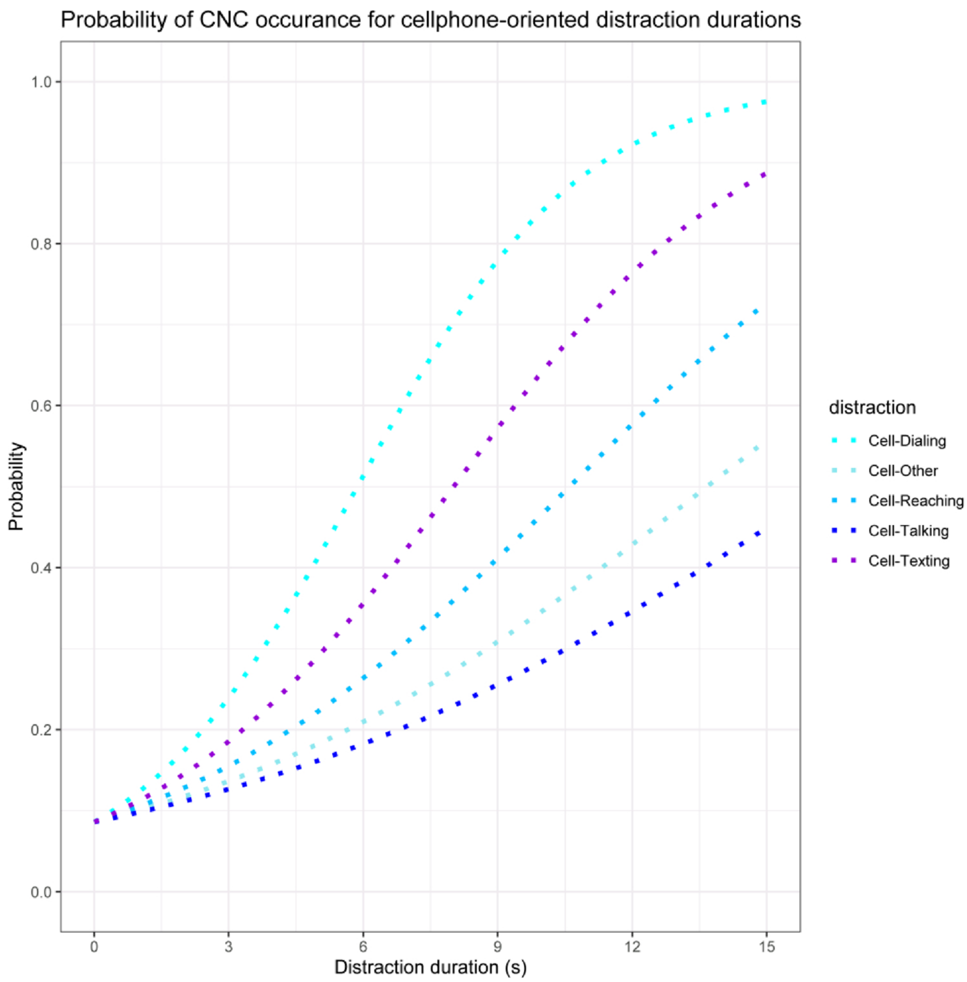


Fig. 8. Probability of CNC event occurrence for different cellphone-oriented distractions.

three models focus on distraction duration in terms of cellphone-oriented, object-oriented, and activity-oriented distractions. The last model explores the association of impaired driving on crash risk controlling for driver distraction, vehicular movements, and roadway/environmental factors.

5.3.1. Cellphone-oriented distraction model

This model explores the association of duration of distractions involving cellphone use while driving on the probability of CNC occurrence. The subset of data utilized in the analysis of this section includes events with no secondary tasks and cellphone-oriented distractions. The hypothesis behind this analysis is that an increase in cellphone duration use will increase the probability of CNC occurrence, controlling for other variables. The modeling results of the fixed and random parameter logistic regression models are provided in Table 2. The random-parameter logistic regression model performs better, in terms of goodness of fit, and all the distraction variables are significant at the 95% confidence interval. Therefore, the discussion focuses on random-parameter model estimates.

Overall, cellphone-oriented distraction duration is positively and significantly contributed to CNC risk, controlling for other variables. Marginal effect analysis is provided in Table 2 to quantify the association of each distraction duration on the probability of CNC events. Results reveal that dialing with a cellphone has the highest impact on crash risk, and a one second increase in dialing with a cellphone will increase CNC by 5.6% on average, controlling for other variables. This is in line with findings of Klauer et. al (Klauer et al., 2014), which discussed that distraction with dialing has the highest impact on crash risk among other cellphone distractions. Furthermore, texting while driving has a significant and substantial association on CNC risk. A one second increase in texting while driving is associated with an average increase of the CNC risk of 3.6%. Referring to reaching for a cellphone, a one second distraction is associated with a 2.6% increase in CNC occurrence probability. Finally, talking with a cellphone and other cellphone use increases CNC probability by 1.7% and 2.0%, respectively.

A marginal effect analysis for distraction duration ranging from zero to 15 seconds is provided to quantify the association of different cellphone distraction durations on the probability of CNC occurrence (Fig. 8). The results indicate that there is a substantial variation among different cellphone-oriented distractions. Dialing a cellphone and texting while driving have the highest impact on the probability of CNC occurrence. These distractions involve driver's visual, manual, and cognitive capabilities by taking the driver's eye off the road, hands off the wheel, and mind off the driving tasks (Sherin et al., 2014). On the other hand, talking on a cellphone has the lowest impact on CNC occurrence out of the other cellphone-oriented distractions, since it requires a lower level of engagement compared to other categories.

5.3.2. Object-oriented distraction model

The second group of distractions includes the secondary tasks in which the driver engages with objects other than cellphones. As discussed earlier, these objects include the vehicle's radio, climate control, objects inside the vehicle, and external objects. This model provides an in-depth analysis of the correlation of duration of object-oriented distractions on crash risk. The data used in this section includes events

Table 3
Modeling results for object-oriented distraction duration.

Variable	Fixed parameter				Random parameter			
	β	Std. Err.	P-value	ME	β	Std. Err.	P-value	ME
Intercept	−0.980	0.083	< 0.001	-	−0.559	0.060	< 0.001	-
Duration of Object distraction								
Climate control	0.162	0.064	0.011	2.1%	0.123	0.051	0.016	1.7%
Radio control	0.149	0.049	0.003	1.9%	0.118	0.039	0.003	1.6%
Object inside the vehicle	0.179	0.040	< 0.001	2.3%	0.143	0.034	< 0.001	2.0%
Object External the cabin	0.154	0.032	< 0.001	2.0%	0.122	0.024	< 0.001	1.7%
Impairment (Base: No impairment)								
Emotional state	2.828	0.682	< 0.001	52.8%	2.162	0.413	< 0.001	30.2%
Drowsy/Fatigue	0.972	0.244	< 0.001	15.3%	0.796	0.192	< 0.001	11.1%
Other	2.810	0.686	< 0.001	52.5%	2.271	0.576	< 0.001	31.7%
Alcohol/Drug	1.788	0.966	0.064	31.9%	1.643	0.874	0.060	23.0%
Traffic density (Base: A1)								
A2	0.264	0.099	0.008	3.4%	0.215	0.074	0.004	3.0%
B	0.986	0.097	< 0.001	14.4%	0.782	0.074	< 0.001	10.9%
C	1.439	0.137	< 0.001	24.1%	1.149	0.105	< 0.001	16.1%
D	1.814	0.202	< 0.001	32.4%	1.385	0.144	< 0.001	19.4%
E	0.869	0.301	0.004	13.5%	0.651	0.205	0.002	9.1%
F	0.962	0.599	0.109	15.2%	0.676	0.467	0.148	9.5%
Vehicular movement								
Average Speed over 15 seconds	−0.023	0.001	< 0.001	−0.3%	−0.025	0.001	< 0.001	−0.4%
Std of Average Speed	-	-	-	-	0.018	0.001	< 0.001	-
Summary Statistics								
Number of observations	5875				5875			
LL at Null	2741.2				2741.2			
LL at convergence	2400.2				2392.3			
McFadden R-Squared	0.124				0.127			
AIC	4832.4				4818.6			

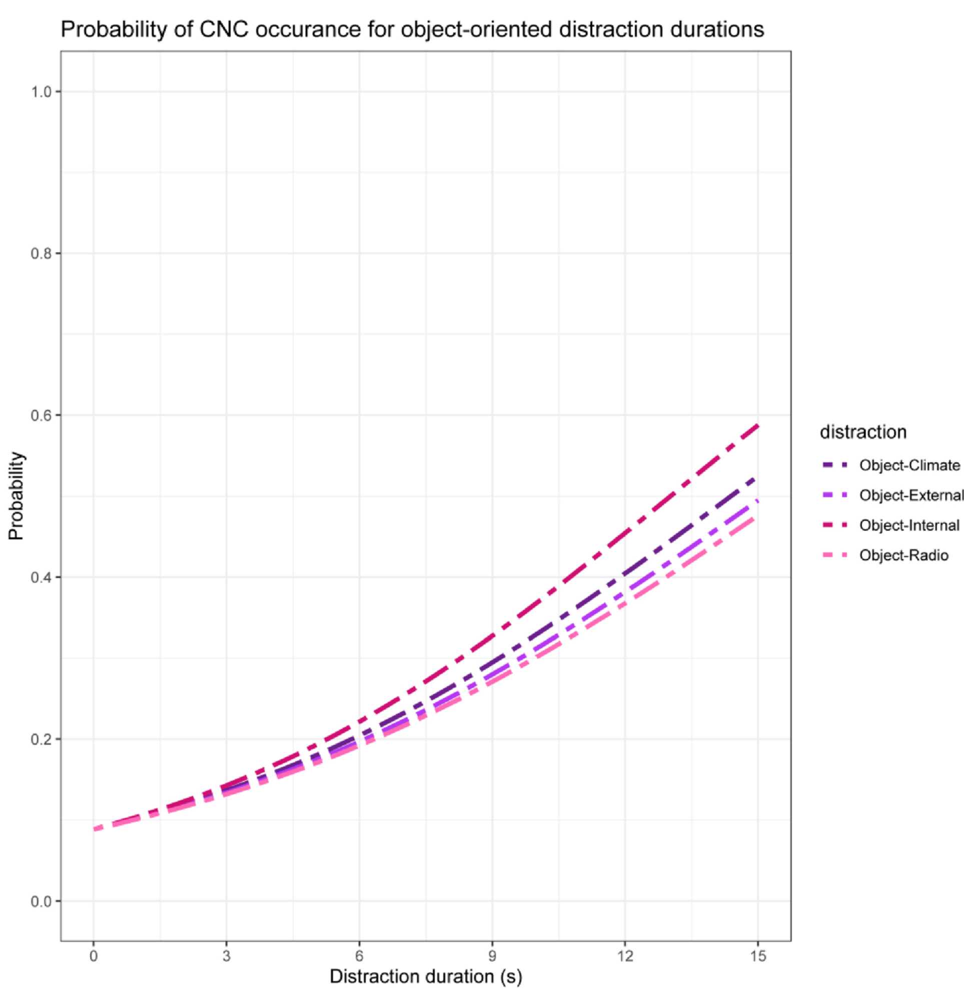


Fig. 9. Probability of CNC event occurrence for different object-oriented distractions.

Table 4
Modeling results for object-oriented distraction duration.

Variable	Fixed parameter				Random parameter			
	β	Std. Err.	P-value	ME	β	Std. Err.	P-value	ME
Intercept	−1.016	0.079	< 0.001	-	−0.598	0.057	< 0.001	-
Duration of activity distraction								
Drinking	0.092	0.064	0.128	1.2%	0.071	0.045	0.117	1.0%
Eating	0.099	0.045	0.032	1.3%	0.073	0.034	0.034	1.1%
Smoking	0.140	0.053	0.009	1.8%	0.109	0.039	0.006	1.6%
Reaching	0.307	0.067	< 0.001	3.9%	0.235	0.056	< 0.001	3.5%
Interacting	0.089	0.017	< 0.001	1.0%	0.054	0.013	< 0.001	0.8%
Interaction Std	-	-	-	-	0.114	0.018	< 0.001	-
Atypical	0.338	0.045	< 0.001	4.3%	0.270	0.038	< 0.001	4.0%
Talking/singing	0.143	0.024	< 0.001	1.8%	0.071	0.020	< 0.001	1.0%
Talking/Singing Std	-	-	-	-	0.212	0.031	< 0.001	-
Hygiene	0.189	0.034	< 0.001	2.4%	0.140	0.026	< 0.001	2.1%
Impairment (Base: No impairment)								
Emotional state	1.173	0.375	0.002	19.3%	0.965	0.271	< 0.001	14.2%
Drowsy/Fatigue	1.179	0.241	< 0.001	19.4%	0.905	0.183	< 0.001	13.3%
Other	1.590	0.494	0.001	27.8%	1.367	0.372	< 0.001	20.1%
Alcohol/Drug	3.179	0.789	< 0.001	58.7%	2.700	0.647	< 0.001	39.8%
Traffic density (Base: A1)								
A2	0.292	0.090	0.001	3.8%	0.233	0.067	0.001	3.4%
B	0.855	0.091	< 0.001	12.3%	0.669	0.069	< 0.001	9.9%
C	1.415	0.126	< 0.001	23.7%	1.107	0.095	< 0.001	16.3%
D	1.776	0.186	< 0.001	31.7%	1.361	0.133	< 0.001	20.0%
E	0.854	0.278	0.002	13.3%	0.638	0.189	0.001	9.4%
F	1.347	0.534	0.012	22.8%	0.944	0.430	0.028	13.9%
Vehicular movement								
Average Speed over 15 seconds	−0.023	0.001	< 0.001	−0.3%	−0.023	0.001	< 0.001	−0.3%
Speed Std	-	-	-	-	0.016	0.001	< 0.001	-
Summary Statistics								
Number of observations	6874				6874			
LL at null	3264.1				3264.1			
LL at convergence	2826.0				2819.2			
McFadden's R-Squared	0.134				0.136			
AIC	5692.0				5685.7			

with no secondary task and object-oriented distractions (no distraction vs object-oriented distraction). The key hypothesis is that object-oriented distractions are positively correlated with crash risk. Fixed-parameter and random-parameter logistic regression models are estimated to quantify association of object-oriented distraction duration on CNC probability (Table 3). By capturing unobserved heterogeneity, the random-parameter model outperformed the fixed model, in terms of goodness of fit. According to the results, all object-oriented distractions are significant at the 95% confidence interval and positively associated with CNC probability. In the following, the discussion of random-parameter model is provided.

Controlling for driver impairment, roadway/environmental factors, and vehicular movements, object-oriented distractions increase the likelihood of involvement in CNC events. Marginal effect (ME) analysis (provided in Table 3) helps us quantify association of a one second increase in duration of object-oriented distractions on CNC probability. Overall, the ME results revealed that object-oriented distractions increase the probability of CNCs. The results indicate that a one second increase in distraction with the vehicle's climate control or radio increases the likelihood of involvement in CNC events by 1.7% and 1.6%, respectively. Additional one second distractions with internal and external objects on average increase the CNC likelihood by 2.0% and 1.7%, respectively, controlling for other variables. These statistics suggest that although the contribution of object-oriented distractions is significant on crash risk, there is not a substantial variation among different types of objects.

Fig. 9 provides the probability of involvement in CNC events for different object-oriented distraction durations ranging from zero to 15 seconds. It can be inferred that the risk associated with objects inside the cabin (except cellphone) is higher compared to other objects. On the other hand, radio control has the lowest risk compared to the other objects included in our study. Potentially, the main reason for this reduced risk is that a radio integrated into the vehicle requires a lower level of engagement compared to other objects. The results are in line with the findings of the literature, confirming that the association of distraction with integrated vehicle objects is lower compared to other objects (inside or outside the cabin) (Dingus et al., 2016, Guo et al., 2017).

5.3.3. Activity oriented distraction

The last group of secondary tasks encompasses in-vehicle activities other than driving. This section explores the contribution of the duration of these activities on the likelihood of CNC occurrence, controlling for other variables. A subset of data which contains activity-oriented distractions are used in the analysis of this section. As illustrated in the descriptive statistics, the main hypothesis is that an increase in the duration of activity-oriented secondary tasks will increase the probability of involvement in a CNC event. Similar to the cellphone-oriented and object-oriented analysis, fixed and random parameter logistic regression models are used to quantify the correlation of the duration of in-vehicle activities on crash risk (Table 4). By comparing the goodness of fit measures, it can be inferred that random-parameter model performs better by capturing unobserved heterogeneity. The results revealed that all the variables are significant at the 95% CI, except for drinking duration which is significant at the 90% CI.

Referring to the random parameter model, all of the activity-oriented distractions positively increase the probability of CNC events. A one second increase in duration of drinking and eating while driving will increase the likelihood of a CNC by 1.0% and 1.1%, respectively. Smoking while driving is positively associated with the CNC likelihood such that a one second increase in duration is associated with a 1.6% increase in CNC probability. Reaching for an object is found to be

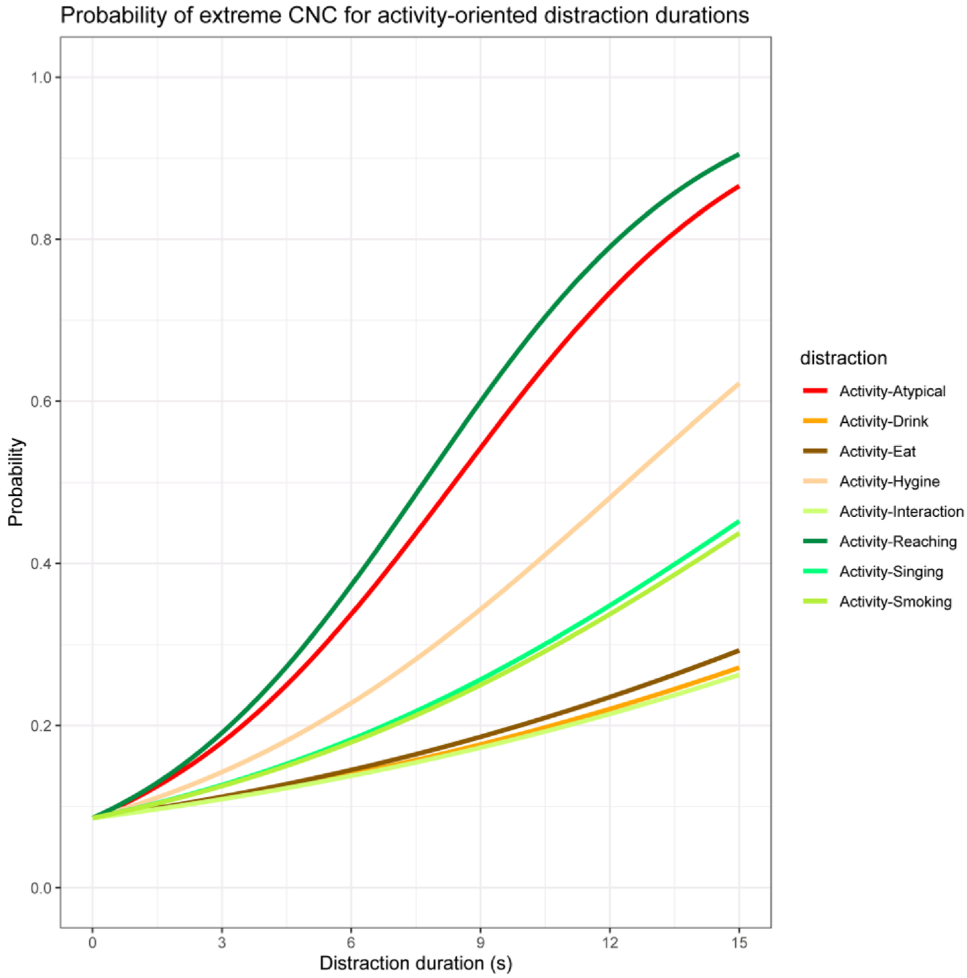


Fig. 10. Probability of CNC event occurrence for different activity-oriented distractions.

positively associated with crash risk. On average, a one second increase in the duration of object reaching is associated with 3.5% increase in CNC risk. While interaction with other passengers is a widely common activity among drivers, the results reveal that its duration is positively correlated with crash risk. A one second increase in the interaction with other passengers increases the likelihood of a CNC event by 0.8%, which was the lowest risk among the activity-oriented distractions. On the other hand, atypical activities while driving (e.g. reading, writing, interaction with pet, removing insect from car) has the highest CNC compared to other activity-oriented distractions, with a one second increase in duration of atypical activities increasing the chance of a CNC event by 4.0%, controlling for other variables. A one second increase in the duration of talking/singing and personal hygiene is associated with an increase in the CNC event probability by 1.0% and 2.1%, respectively.

The association of different distraction durations ranging from zero to 15 seconds on the probability of a CNC event is provided in Fig. 10. Based on the results, there is substantial variation among the impacts of different distraction types on crash risk. Durations of reaching for objects and atypical activity have the highest CNC risk, since these activities are a visual-manual task and require the cognitive attention of drivers. On the other hand, interaction duration with other passengers and drinking while driving have the lowest risk among activity-oriented distractions.

5.3.4. Impaired driving model

This section aims to quantify the association of different impairments on CNC risk, controlling for driver distraction, roadway/environmental factors, and vehicular movements. The full dataset of 9239 events is used for this analysis, including no-distraction events, and all secondary tasks. In order to quantify the contribution of impaired driving on CNC risk, fixed and random parameter logistic regression models are developed, and the results are provided in the Table 5. Similar to the previous models, the random-parameter model performs better in terms of goodness of fit and all the variables are significant at the 95% CI, except duration of drinking while driving which is significant at the 90% CI.

Based on the random-parameter model, all of the impaired driving variables significantly increase the likelihood of a CNC event. Specifically, marginal effect analysis revealed that, on average, emotional impairment increases the probability of a CNC event by 18.5%, controlling for other variables, which is in line with previous studies (Dingus et al., 2016). Furthermore, drowsy and fatigued driving is associated with an increased probability of a CNC event by 11.6%, which is in line with the literature (Klauer et al., 2006, Lee et al., 2016). Alcohol/drug related impairments are associated with a 34.0% increase in the probability of CNC involvement. The results are consistent with the findings of Dingus et al (Dingus et al., 2016) who found that alcohol and drug impairment increases the crash risk 35.9 times. Other impairment types are associated with 21.0% higher crash/near-crash risk.

5.4. Discussion

5.4.1. Distracted driving

This study identified three main groups of distraction (cellphone-oriented, object-oriented, and activity-oriented distractions) and

Table 5
Logistic regression model to quantify association of impaired driving on CNC probability.

Variable	Fixed parameter				Random parameter			
	β	Std. Err.	P-value	ME	β	Std. Err.	P-value	ME
Intercept	−1.117	0.070	< 0.001	-	−0.709	0.049	< 0.001	-
Cell Oriented								
Reaching	0.251	0.029	< 0.001	3.3%	0.189	0.023	< 0.001	3.0%
Dialing	0.503	0.116	< 0.001	6.6%	0.381	0.094	< 0.001	6.1%
Talking	0.173	0.025	< 0.001	2.3%	0.130	0.019	< 0.001	2.1%
Texting	0.322	0.030	< 0.001	4.2%	0.251	0.027	< 0.001	4.0%
Other	0.199	0.051	< 0.001	2.6%	0.145	0.041	< 0.001	2.3%
Object Oriented								
Climate	0.203	0.064	0.001	2.7%	0.147	0.051	0.004	2.4%
Radio	0.183	0.049	< 0.001	2.4%	0.137	0.038	< 0.001	2.2%
Internal	0.217	0.040	< 0.001	2.9%	0.163	0.033	< 0.001	2.6%
External	0.198	0.031	< 0.001	2.6%	0.147	0.024	< 0.001	2.4%
Activity oriented								
Drinking	0.115	0.064	0.072	1.5%	0.083	0.045	0.064	1.3%
Eating	0.113	0.046	0.014	1.5%	0.083	0.035	0.016	1.3%
Smoking	0.161	0.053	0.002	2.1%	0.122	0.039	0.002	2.0%
Reaching	0.328	0.068	< 0.001	4.3%	0.247	0.055	< 0.001	4.0%
Interacting	0.110	0.017	< 0.001	1.4%	0.072	0.013	< 0.001	1.2%
Std. Interaction	-	-	-	-	0.089	0.017	< 0.001	-
Atypical	0.300	0.037	< 0.001	4.0%	0.235	0.030	< 0.001	3.8%
Talking/singing	0.163	0.024	< 0.001	2.1%	0.092	0.019	< 0.001	1.5%
Std Talk/sing	-	-	-	-	0.179	0.029	< 0.001	-
Hygiene	0.210	0.034	< 0.001	2.8%	0.155	0.026	< 0.001	2.5%
Driving impairment (Base: No impairment)								
Emotional state	1.442	0.326	< 0.001	24.7%	1.154	0.233	< 0.001	18.5%
Drowsy/Fatigue	0.960	0.221	< 0.001	15.3%	0.721	0.159	< 0.001	11.6%
Other	1.567	0.427	< 0.001	27.2%	1.308	0.306	< 0.001	21.0%
Alcohol/Drug	2.560	0.599	< 0.001	46.9%	2.122	0.496	< 0.001	34.0%
Traffic density (Base: A1)								
A2	0.286	0.077	< 0.001	3.9%	0.218	0.057	< 0.001	3.5%
B	1.000	0.077	< 0.001	14.9%	0.768	0.058	< 0.001	12.3%
C	1.441	0.108	< 0.001	24.3%	1.101	0.080	< 0.001	17.7%
D	1.676	0.163	< 0.001	29.4%	1.243	0.111	< 0.001	19.9%
E	0.965	0.230	< 0.001	15.4%	0.712	0.161	< 0.001	11.4%
F	1.109	0.470	0.018	18.1%	0.758	0.366	0.039	12.2%
Vehicular movement								
Average Speed over 15 seconds	−0.024	0.001	< 0.001	−0.3%	−0.022	0.001	< 0.001	−0.4%
Speed Std	-	-	-	-	0.014	0.001	< 0.001	-
Summary Statistics								
Number of observations	9239				9239			
Null Deviance	−4619.3				−4619.3			
Model Deviance	−3872.2				−3866.6			
McFadden's R-Squared	0.162				0.163			
AIC	7802.4				7797.7			

quantified their durations to study their association with crash risk. Three specific models for each group of distraction are developed. The most notable finding of this paper is that duration of all types of distracted driving are positively and significantly associated with the probability of the occurrence of a safety critical event (near-crash and crash events). The results suggest that the association of distraction duration with crash risk is non-linear and with an increase in secondary task engagement, crash risk increases following a sigmoid function. In order to perform a comparison of between different distraction groups, the marginal effect plots of the three developed models are integrated and provided in Fig. 11. The figure suggests that there is a substantial variation among different secondary tasks. The riskiest distraction types are Dialing with a cellphone, reaching for an object, and texting with cellphone while driving. These distractions require not only visual attention of drivers, but also disengage drivers' manual, and cognitive capabilities. By comparing the groups of distractions, it can be inferred that the influence of cellphone-oriented distraction durations are substantially higher compared to activity-oriented and object-oriented distractions, which implies the importance of cellphone prohibition while driving. On the other hand, some distraction types durations have a lower risk compared to other secondary tasks, but their risks are still significant and substantial. Based on the results, interacting with other passengers, drinking, and eating has the lowest risk compared to other distraction types. Duration of interaction with passengers has a less negative effect on driving performance, and this could be due to the fact that the responsibility of monitoring environment could be shared among passengers (Overton et al., 2015).

5.4.2. Driver impairment

Impaired driving is known as one of the significant risk factors in vehicle crashes, since it can slow the brain's information processing speed and delay its normal function, leading to deterioration in hand-eye coordination (Berning et al., 2015). Therefore, it is crucial to quantify the associations of impaired driving on crash risk. The modeling results (Table 5) reveal that all types of impairment increase the likelihood of CNC events, controlling for other variables. Specifically, alcohol/drug related impairments are associated with a 34 percent increase in the probability of crash/near-crash involvement. The results are consistent with the findings of Dingus et al (Dingus et al., 2016) who found that alcohol and drug impairment increases the crash risk 35.9 times. Furthermore, drowsy and fatigued driving are associated with increased probability of CNC event by 11.6 percent, which is in line with the literature (Klauer et al., 2006, Lee et al., 2016). In line with previous studies (Dingus et al., 2016), emotional driving (i.e.

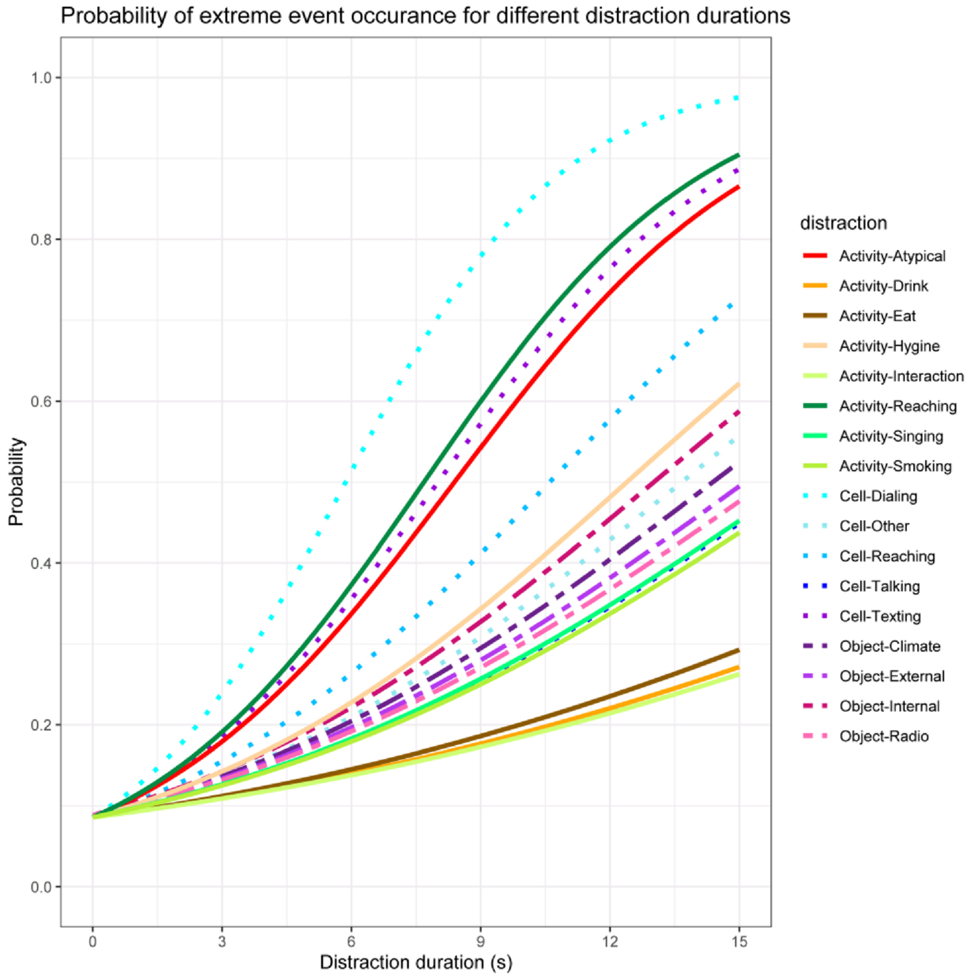


Fig. 11. Probability of CNC event occurrence with increasing duration of distraction for all types of secondary tasks.

sadness/crying, anger, other emotional states) increased the probability of involvement in an CNC event by 18.5 percent. Other impairment types are associated with 21 percent higher crash risk.

5.4.3. Roadway/environmental factors

Roadway and environmental factors are included in the models to control for other contributing factors. The modeling results suggest that higher traffic density in terms of level of service increase the likelihood of crash involvement. The results are in line with previous studies where the chance of a crash or near crash in congested traffic is higher compared to the free-flow state (Kamrani et al., 2019). Furthermore, driving at higher speeds decreases the likelihood of an CNC event, since the vehicle has lower conflict with other vehicles and surrounding environment which decreases the probability of crash involvement. Further details are provided in Table 5.

6. Limitations

The drivers participating in SHRP2 NDS might not represent the driving population, since they were voluntarily hired with monetary incentives (self-selected). Although the data are collected professionally with federal support and specific protocols are used for data collection and coding, there still might be some human error in coding the information, especially from the recorded videos. The proportion of crashes and near crashes compared to baselines are not truly reflective of real-world conditions, as CNC events are relatively rare, and this fact might affect the results.

7. Conclusions

Generally, human error is known to be the key contributing factor in traffic crashes. The availability of microscopic information collected through instrumented vehicles on instantaneous driving behavior and instantaneous decisions of drivers has enabled the exploration of the association of driver behavior with crash occurrence and near-crash events. This study sheds light on this association by performing an in-depth analysis on pre-crash driving that leads to safety critical event involvement. The main contributions of this paper are (1) linking large-scale data on instantaneous driver distraction and vehicular movements with driving behavior, roadway, and environmental factors, and (2) using rigorous methods for exploring the association of impairments and duration of distracted driving through different secondary tasks on the likelihood of involvement in a Crash/Near-Crash (CNC) event. The study uses the SHRP2 NDS dataset, containing 9239 baselines and CNC events. A unique database was created by analyzing more than 1.8 million observations and creating time-series profile of distracted driving, and linking it to the vehicle kinematics, driving behavior, and roadway/environmental factors. The time where the drivers were reacting to crash stimuli and the period after a crash were removed from the analysis. In this research, 15 seconds of the data was considered for each event. Three main themes of secondary tasks are identified, and analysis is performed on each group.

The descriptive analysis shows that there is a substantial difference in the prevalence of impaired and distracted driving between baselines and CNC events. Moreover, the analysis of distraction duration revealed that duration is also significantly different among baseline and CNC events. The fixed and random parameter binary logistic regression model is estimated to model the association of distraction duration on the probability of the CNC event occurrence. The modeling results reveal that duration of all types of distractions is one of the leading indicators of CNC event occurrence and longer durations significantly and substantially increase crash risk. Based on the results, dialing and texting with cellphone distractions and reaching for an object distraction types have the highest association with crash risk compared to other distraction types. A one second increase in dialing and texting distraction will increase the chances of a crash for 5.6 and 3.6 percent, respectively. In terms of impaired driving, alcohol/drugs substantially increase the chances of CNC event involvement by 34.0 percent. It is worth noting that vehicular movements and roadway/environmental factors are also modeled as the controlling factors. Overall, the results point to exploring and evaluating countermeasures that can reduce the most dangerous types of impaired and distracted driving.

Authorship contribution statement

Ramin Arvin: Study concept and design, Data processing, Analysis and interpretation, manuscript preparation. Asad J. Khattak: Study concept and design, Analysis and interpretation, manuscript preparation, Supervision

Declaration of Competing Interest

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

Acknowledgements

This research is funded by the U.S. Department of Transportation (USDOT) under Project R-23 through the Collaborative Sciences Center for Road Safety (CSCRS), a consortium led by The University of North Carolina at Chapel Hill in partnership with The University of Tennessee. The data was provided by Dr. Tom Karnowski, Oak Ridge National Laboratory, for which the authors are very grateful. Any opinions, findings, conclusions and recommendations are those of the authors and do not necessarily reflect views of the sponsors. The authors thank Ms. Kinzee Clark and Mr. Zachary Jerome for editing the manuscript.

Appendix A. Supplementary data

Supplementary material related to this article can be found, in the online version, at doi:https://doi.org/10.1016/j.aap.2020.105733.

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