



Determining the risk of driver-at-fault events associated with common distraction types using naturalistic driving data

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ABSTRACT

Introduction: Studies thus far have focused on automobile accidents that involve driver distraction. However, it is hard to discern whether distraction played a role if fault designation is missing because an accident could be caused by an unexpected external event over which the driver has no control. This study seeks to determine the effect of distraction in driver-at-fault events. **Method:** Two generalized linear mixed models, one with at-fault safety critical events (SCE) and the other with all-cause SCEs as the outcomes, were developed to compare the odds associated with common distraction types using data from the SHRP2 naturalistic driving study. **Results:** Adjusting for environment and driver variation, 6 of 10 common distraction types significantly increased the risk of at-fault SCEs by 20–1330%. The three most hazardous sources of distraction were handling in-cabin objects (OR = 14.3), mobile device use (OR = 2.4), and external distraction (OR = 1.8). Mobile device use and external distraction were also among the most commonly occurring distraction types (10.1% and 11.0%, respectively). **Conclusions:** Focusing on at-fault events improves our understanding of the role of distraction in potentially avoidable automobile accidents. The in-cabin distraction that requires eye-hand coordination presents the most danger to drivers' ability in maintaining fault-free, safe driving. **Practical Applications:** The high risk of at-fault SCEs associated with in-cabin distraction should motivate the smart design of the interior and in-vehicle information system that requires less visual attention and manual effort.

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1. Introduction

Road safety involves an intricate web of interplaying roles by the driver, the traffic, and the road, and not every element is under the control of the driver. Distractions have long been established as a leading cause of automobile accidents. Studies thus far have focused on automobile accidents that involve driver distraction. However, it is hard to discern whether distraction played a role if fault designation is missing, because an accident could be caused by an unexpected external event through no fault of the driver. Understanding the human factors involved in at-fault crashes may be most relevant to pinpointing risky driver behaviors that are potentially avoidable. Therefore, this study seeks to determine the effect of distraction in at-fault safety critical events (SCEs) by: (a) teasing out the effect of distraction from common traffic scenarios and road conditions, and (b) comparing the strength of association between distraction and at-fault SCEs against all-cause SCEs regardless of fault designation.

1.1. Distraction

Studies have examined the prevalence, the effects, and the mechanism of driver distraction on automobile accidents. Eight percent of fatal crashes and 15% of injury crashes in 2018 (most recent year available) were reported as affected by distraction, and that was 2,841 people killed and 400,000 people injured (National Highway Traffic Safety Administration, 2020). By consumption of attention resources, researchers put distraction into two classes: (a) visual distraction (eyes-off-the-road) and (b) cognitive distraction (mind-off-the-road), with cognitive distraction disrupting the allocation of visual resources to driving scenes and slowing the process of oncoming information (Liang & Lee, 2014; Savage et al., 2020). Common distractions include cell-phone use, interaction with passengers, eating, and adjusting the radio or climate controls. Cell phone use and texting, especially among teen drivers, has been extensively studied (Yannis et al., 2014; Carney et al., 2018; Ebadi et al., 2019; Qin et al., 2019; Seaman et al., 2017); driver interaction with passengers has also been studied (Theofilatos et al., 2018; Zhang et al., 2019). Driver distraction can be detected by video recognition and even solely relying on

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vehicular data with high accuracy in a nonintrusive fashion (Eraqi et al., 2019; Ye et al., 2017).

1.2. At-fault accidents

There is limited literature that specifically studies at-fault accidents as opposed to all-cause automobile accidents. Fault determination requires manual analysis, lacks a universal definition (Dorn & af Wåhlberg, 2019), and is not always available in datasets. The U.S. Department of Transportation identified 17 Unsafe Driving Acts (UDA) to be the criteria for fault assignment (i.e., fault was assigned if any factor was coded for a given driver), including judgment, speed-related, right-of-way or headway-related, and lane change or lane position problems (Council et al., 2003). Existing studies on at-fault accidents focused on driver characteristics (Sagar et al., 2020; Penmetsa et al., 2017; Tseng, 2012) and improper driving maneuvers (Mohammadzadeh Moghaddam et al., 2017; Wu & Hsu, 2021). The lack of studies on predicting at-fault crashes was also noted (Wu & Hsu, 2021). No studies have examined the association between distraction and at-fault events by our search.

1.3. Risk estimation

To estimate road injury risks, studies traditionally rely on police and emergency department records (Regev et al., 2018; Sagar et al., 2020), which are representative of the population, although crash-specific details are not always fully recalled or captured (Regev et al., 2017). To analyze driver or environment impacts on accidents, simulated studies can capture a wide array of variables during a trip, but the studies usually focus on a small subset of the population of interest (e.g., teenage drivers). Large-scale naturalistic driving studies may enjoy the best of both worlds. On one hand, its study size and naturalistic setting can be used to construct study designs reflective of real-world exposure. On the other hand, it captures a variety of variables via pre-fitted motion and vision sensors that can be helpful for retrospective analysis of what transpired on the road, possibly with high fidelity.

In summary, the past literature indicates that driver distraction plays an important role in automobile accidents, but there is a need to further verify these findings with fault data. None of the previous studies have associated at-fault accidents with specific distraction types. Such an analysis could help define the effect of distraction on drivers' ability to maintain safe, fault-free driving and inform efforts to improve road safety by reducing hazardous driver distraction.

2. Materials and methods

2.1. Data source

Data from the 2nd Strategic Highway Research Program (SHRP2) Naturalistic Driving Study (NDS) (Dingus et al., 2014) were used for this study. The dataset included human expert annotated variables based on video recordings of trips that captured the activities and environments both inside and outside of the cabin of the subject vehicles in real-world road settings. Annotated variables from the video reduction process make it possible to retrospectively analyze the characteristics of the trips involving at-fault incidents, including the dependent variables derived from "event severity" and "fault," the independent variables derived from "secondary tasks," and seven control variables including weather, lighting, roadway surface, profile (e.g., uphill, downhill) and curvature, presence of roadway junctions, as well as traffic density.

2.2. Study design

The SHRP2 dataset allows a case-cohort study design that is appropriate for time-variant risk exposure approximated by the odds ratio (Dingus et al., 2016; Guo, 2009). In this study, cases were identified as SCEs that include all levels of crashes but low-risk tire strikes as well as near crashes. Non-cases were sampled from the baseline in a balanced fashion that the number of trips selected for each driver is proportional to the total traveling time when they were in the study (i.e., balanced-sample baseline; Hankey et al., 2016). Said in another way, the cases and non-cases were in terms of the outcome of a trip (i.e., whether an SCE took place), and all of the trips may be exposed to the independent variable (i.e., distraction). The cases were further differentiated by fault assignment, namely, at-fault SCEs, in which the subject vehicle driver was at fault, and all-cause SCEs regardless of fault. As a result, a total of 7,962 all-cause SCEs, among which 4,908 were at-fault, and 19,998 balanced-sample baseline trips were selected for the analysis (Table 1). They were generated by 3,542 participating drivers.

2.3. Data analysis

We designed a generalized linear mixed model (GLMM) with random intercepts as one driver can generate multiple trips in the dataset. The rationale behind choosing this model is two-fold: first, a multivariate regression can produce adjusted risk estimates that account for scenarios when multiple distraction types or environmental risk factors were present concurrently. Second, compared to regular linear regression, the mixed-effect model can reflect the latent heterogeneity in driver characteristics that might impact the individuals' risk levels when distracted. The model is as follows:

$$g(E(y)) = X\beta + Zu + \varepsilon$$

$$E(y) = P(Y = y|X, Z)$$

$$g(\cdot) = \log\left(\frac{p}{1-p}\right)$$

where y is the outcome variable; $g(\cdot)$ is the logistic link function for a binomial outcome; p is the estimated probability of a positive outcome; X is a matrix of N trips and q variables; β is a $q \times 1$ vector of the fixed-effect regression coefficients; Z is a matrix of N trips and d drivers designating the driver-specific random effects; u is a $d \times 1$ vector of the random intercepts; and ε is the general error term not explained by the model.

Two separate models were run, one with at-fault SCEs as the outcome and the other with all-cause SCEs, because we wanted to understand whether a particular kind of distraction particularly increases the driver's at-fault risk compared to all-cause SCEs.

The input variables, types of distraction, were engineered from the annotated secondary tasks. First, the secondary tasks were mapped into 10 distraction types (Table 2) in addition to a "no secondary task" category based on their semantic meanings and the ordering found in the SHRP2 Researcher Dictionary for Video

Table 1
Event distribution.

Result in safety critical events?		Subject vehicle driver at fault?	
		Yes	No or NA
Yes	Crash	766	282
	Near crash	4,142	2,772
No	Baseline	0	19,998

Table 2
Distraction type mapping.

Distraction Type	Secondary Tasks
Entertainment	- Talking/singing, audience unknown - Dancing - Reading - Writing
External distraction	- Looking at previous crash or incident - Looking at pedestrian - Looking at animal - Looking at an object external to the vehicle - Distracted by construction - Other external distraction
Food and beverage	- Reaching for food-related or drink-related item - Eating with utensils - Eating without utensils - Drinking with lid and straw - Drinking with lid, no straw - Drinking with straw, no lid - Drinking from open container
In-cabin objects	- Moving object in vehicle - Insect in vehicle - Pet in vehicle - Object dropped by driver - Reaching for object, other - Object in vehicle, other
Interaction	- Passenger in adjacent seat - interaction - Passenger in rear seat - interaction - Child in adjacent seat - interaction - Child in rear seat - interaction
IVIS (in-vehicle information system)	- Adjusting/monitoring climate control - Adjusting/monitoring radio - Inserting/retrieving CD (or similar) - Adjusting/monitoring other devices integral to vehicle
Mobile device	- Cell phone, holding - Cell phone, talking/listening, hand-held - Cell phone, talking/listening, hands-free - Cell phone, texting - Cell phone, browsing - Cell phone, dialing, hand-held - Cell phone, dialing, hand-held using quick keys - Cell phone, dialing, hand-held using voice-activated software - Cell phone, locating/reaching/answering - Cell phone, other - Table device, locating/reaching - Tablet device, operating - Tablet device, viewing - Tablet device, other
Personal hygiene	- Reaching for personal body-related item - Combing/brushing/fixing hair - Applying make-up - Shaving - Brushing/flossing teeth - Biting nails/cuticles - Removing/adjusting clothing - Removing/adjusting jewelry - Removing/inserting/adjusting contact lenses or glasses - Other personal hygiene
Smoking	- Reaching for cigar/cigarette - Lighting cigar/cigarette - Extinguishing cigar/cigarette
Other secondary tasks	- Other nonspecific internal eye glance - Other secondary task - Unknown type (secondary task present)

Reduction Data (Virginia Tech Transportation Institute, 2015). For example, all secondary tasks involving a cell phone or a tablet were grouped into “mobile device.” Next, the distraction types were

converted into dummy variables. Finally, because up to three secondary tasks were annotated, the three corresponding distraction types were combined for each trip. If a trip involved two secondary tasks belonging to the same distraction category, the category was labeled as 1 denoting the presence of one or more secondary tasks in the same distraction category. For example, a driver can be annotated as both dialing and subsequently talking on the phone during the video epoch. This treatment is due to the consideration that secondary tasks within the same category tend to involve a series of related tasks, whereas having two secondary tasks in different categories suggests a higher level of distraction that is non-trivial.

The control variables were treated as categorical with the least demanding driving scenario as the reference group for regression. For example, ‘no adverse weather condition’ was coded 0 and all other adverse weather conditions were coded 1. The analysis was performed in R using library lme4 (Bates et al., 2015; R Core Team, 2020).

3. Results

3.1. Distribution of distraction types

Distraction occurs frequently, in fact, the majority (55.8%) of the selected trips involved one or more distraction types (Table 3). Interaction with a passenger (14.5%), external distraction (11.0%), and mobile device use (10.1%) were among the most common distraction, while smoking (1.1%), food & beverage consumption (3.1%), and adjusting the in-vehicle information system (IVIS) (3.9%) were the least common. Next, we will examine the risk level associated with individual distraction types.

3.2. Risk estimate

Overall speaking, the presence of distraction, regardless of type, doubled the odds of SCEs (OR = 2.1), and the difference between at-fault and all-cause SCEs was minimal (Table 4). Delving into the specific categories, 6 of 10 distraction types significantly increased the risk of at-fault and all-cause SCEs to varying degrees after adjusting for environmental factors (Fig. 1). While *entertainment*, *personal hygiene*, *IVIS*, *external distraction* and *mobile device use*, in ascending order of ORs, increased the odds of at-fault SCEs by 20–140%, the odds of at-fault SCEs was raised by 1330% related to *in-cabin objects*. Among the individual secondary tasks grouped under in-cabin objects, “moving object in vehicle” (e.g., an object fell off the seat when the driver stopped hard at a traffic light) and “reaching for object, other” not only had the most occurrences but also disproportionately associated with at-fault events ($p < 0.001$) (Table 5).

Comparing the estimated ORs of at-fault to all-cause SCEs, the lower bounds of the at-fault ORs associated with *external distraction*

Table 3
Proportion of distraction types (N = 27,960).

Distraction Type	n (%)
Entertainment	2,453 (8.8)
External	3,072 (11.0)
Food & Beverage	853 (3.1)
IVIS	1,082 (3.9)
In-Cabin Objects	2,101 (7.5)
Interaction	4,062 (14.5)
Mobile Device	2,812 (10.1)
Personal Hygiene	1,149 (4.1)
Smoking	305 (1.1)
Other	1,015 (3.6)
None	12,651 (45.2)

Table 4
Odds ratios of safety critical events associated with distraction types.

	At-fault SCEs		All-cause SCEs	
	Odds Ratio (95% CI)	p-value	Odds Ratio (95% CI)	p-value
Distraction, regardless of type	2.1 (2.0–2.3)	<0.001 ***	2.1 (1.9–2.2)	<0.001 ***
Entertainment	1.2 (1.0–1.3)	0.024 *	1.1 (1.0–1.2)	0.067
External	1.8 (1.6–2.0)	<0.001 ***	1.3 (1.2–1.4)	<0.001 ***
Food & Beverage	0.8 (0.6–1.0)	0.031 *	0.7 (0.6–0.9)	0.001 **
In-cabin Objects	14.3 (12.4–16.5)	<0.001 ***	12.3 (10.8–13.9)	<0.001 ***
Interaction	0.9 (0.8–1.1)	0.260	0.9 (0.8–0.9)	0.001 **
IVIS	1.7 (1.4–2.1)	<0.001 ***	1.4 (1.2–1.7)	<0.001 ***
Mobile Device	2.4 (2.2–2.7)	<0.001 ***	1.8 (1.6–2.0)	<0.001 ***
Personal Hygiene	1.6 (1.4–2.0)	<0.001 ***	1.4 (1.2–1.6)	<0.001 ***
Smoking	1.2 (0.8–1.8)	0.355	1.1 (0.8–1.5)	0.653
Other	0.9 (0.7–1.1)	0.155	0.8 (0.6–0.9)	0.004 **

Significance codes: <0.001 *****, 0.001–0.01 ****, 0.01–0.05 ***.

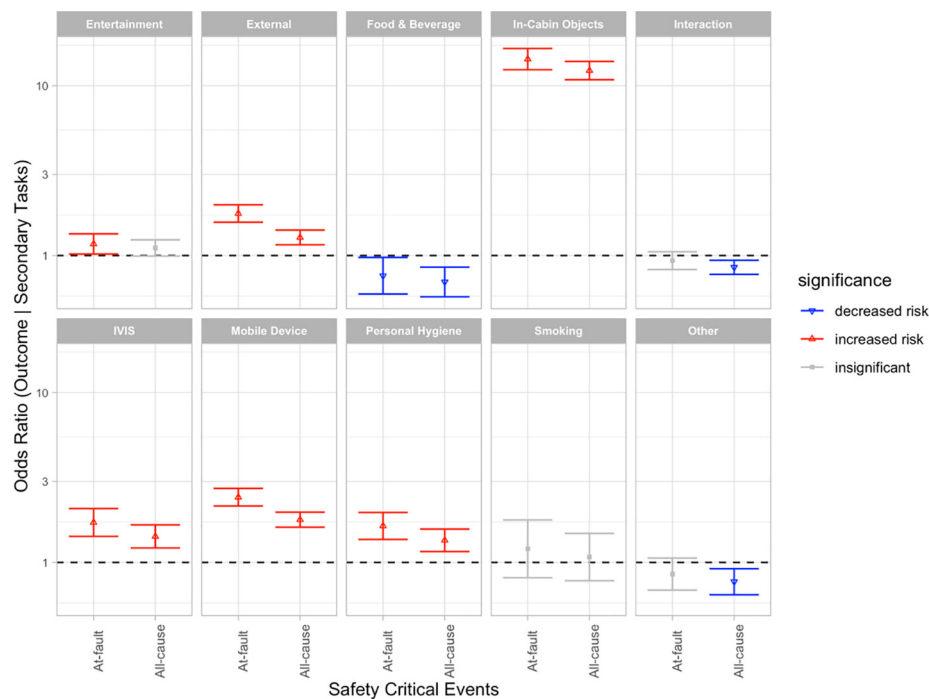


Fig. 1. Odds ratio comparison of at-fault and all-cause SCEs by distraction type.

tion and mobile device use were higher than the upper bounds of the ORs of all-cause SCEs without overlap (Fig. 1), suggesting that these distraction types significantly increased the risks of faulty driving that led to an SCE.

On the other hand, food and beverage consumption in driving significantly decreased the odds of at-fault and all-cause SCEs by 20–30%. Interacting with a passenger and other secondary tasks in the vehicle did not modify the risk of at-fault SCEs but slightly reduce

the chance of all-cause SCEs. In other words, although not significantly, having these two distractions still raised the chance of at-fault SCEs compared to all-cause SCEs. Smoking was not significantly associated with either at-fault or all-cause SCEs.

4. Discussion

4.1. Principal findings

In this study, we quantified the at-fault SCE risks associated with common distraction types using a mixed-effect model that allows for driver variation. The most hazardous source of distraction is in-cabin objects (OR = 14.3) followed by mobile device use (OR = 2.4) and external distraction (OR = 1.8), with the latter two also showing an elevated risk of at-fault SCEs beyond that of all-cause SCEs. Not only were mobile device use and external distraction the most dangerous among distraction types, but they were also among the most commonly occurring (10.1% and 11.0%, respectively).

Table 5
Distribution of secondary tasks related to “in-cabin objects” distraction.

Secondary Task	Subject vehicle driver at fault?	
	Yes	No or NA
Moving object in vehicle	772	447
Reaching for object, other	321	208
Object in vehicle, other	248	434
Pet in vehicle	21	47
Object dropped by driver	2	2
Insect in vehicle	1	0

The study findings are consistent with previous research about the detrimental effect of mobile device use on driver performance, and also highlighted another type of activities, namely, in-cabin objects, that has an even greater impact. The distraction of in-cabin objects results in manual activities that require the coordinated control of the eye movement with hand movement and the processing of visual input to guide reaching or grasping. Considering the commonality between the manipulation of in-cabin objects and mobile device use, it seems the most dangerous distraction types involve transient inattention from both eyes-off-the-road and hand-off-the-wheel. Compared to in-cabin objects, external distraction implies eyes-off-the road but does not require hands-off-wheel, or more importantly, eye-hand coordination.

On the flip side, we also examined what variables are not significantly associated with at-fault SCEs. When drivers have food and beverages or interaction with passengers, their overall risk of SCEs was slightly reduced, suggesting a small protective effect. This may be explained by lower traveling speed or less challenging traveling conditions when the driver carries out such tasks and it is worth investigating as a next step. Interaction with passengers is more of a cognitive distraction than visual, therefore, our finding is consistent with previous research that visual distraction has much stronger effects on driving performance and accident hazard (Peissner et al., 2011). Still, the odds ratios of at-fault SCEs were slightly raised by these two distractions. In addition, smoking is the only annotated distraction that is not significantly associated with at-fault or all-cause SCEs. Considering these three distraction types altogether, none of them direct the driver's visual attention off the roadway ahead in a substantial way, which might be the reason why they are relatively harmless compared to others.

4.2. Limitations and future research

The study findings should be interpreted with limitations. First, the grouping of distraction types is manual and based on the semantic meanings of the descriptions of the secondary task, not characterized by quantifiable measures of the extent of visual/cognitive distraction it causes. The result is distraction types understood by common sense and meaningful sample sizes of subgroups that reduce biases related to small samples in regression. A future research direction is to study how the secondary tasks can be clustered based on how they affect the kinematic measures of the vehicle. Second, the reasons that certain distraction types are more (or less) hazardous were not examined in this study. For example, we speculated that food and beverage consumption may be associated with lower vehicle speed, thus, reducing the risk of all-cause SCEs. However, the theory requires further investigation. Research on how drivers adapt their driving behaviors while engaging in secondary tasks is needed (Oviedo-Trespalacios et al., 2016). Third, driver characteristics were not included as control variables in the study. This was a deliberate decision to be compatible with the mixed-effect model that already factors in a random effect on individual drivers. Including driver characteristics (e.g., gender and age) would make interpretation of the coefficients counterintuitive – we would be suggesting “for the same driver, their at-fault risk may be modified if they change gender/age.” Although not explicitly controlling for tangible driver characteristics, the mixed-effect model does account for driver heterogeneity.

4.3. Practical applications

The high risk of at-fault SCEs associated with in-cabin objects serves as empirical evidence that in-cabin activities that require eye-hand coordination present grave danger to drivers' ability to maintain fault-free maneuver of the vehicle. Most straightforwardly,

this should motivate the design of the vehicle interior that securely stores owner items while allowing for easy access. Although in this study IVIS (OR = 1.7) has a much lower risk than in-cabin objects, the study finding is cautionary for the design of future IVIS, given the rising popularity of touchscreen control panels that require much more visual attention and manual effort compared to physical knobs. In our wild but realistic imagination, we envision that future connected wearable technology can detect driver states such as drowsiness and perspiration to automatically inform in-cabin climate control and adjust to driver comfort without manual input. In addition, our findings provide hazardous distraction types that computer vision based in-cabin sensing technologies (Kaliouby et al., 2020) can learn to recognize.

5. Conclusions

Focusing on at-fault events improves our understanding of the effect of distraction in potentially avoidable automobile accidents. Adjusting for environment and driver variation, 6 out of 10 common distraction types significantly increase the risk of at-fault SCEs by 20–1330%. The three most hazardous sources of distraction were handling in-cabin objects (OR = 14.3), mobile device use (OR = 2.4), and external distraction (OR = 1.8), with the latter two also among the most commonly occurring (10.1% and 11.0%, respectively). The study findings provide evidence that in-cabin distraction that require eye-hand coordination presents grave danger to drivers' ability to maintain fault-free, safe driving.

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.

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