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How are different sources of distraction associated with at-fault crashes among drivers of different age gender groups?

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ABSTRACT

Introduction: Distracted driving has been well researched, however the comparison between different age-gender groups on the impact of distracted driving has not been explored. Most crash analysis research does not distinguish driver responsibility, so the role that distractions has in at-fault crashes is unknown. Without distinguishing at-fault crashes from all-cause crashes, distracted driving's detrimental effects could be underestimated.
Objective: This study aims to systematically assess the risk of at-fault crashes associated with different sources of distraction among six groups by driver age (Teens 16–19, Adults 20–64, Seniors 65+) and gender.
Methods: Crashes where a study participant was deemed at fault were identified using human expert annotated variables from the Strategic Highway Research Program 2 (SHRP2) Naturalistic Driving Study dataset. Generalized linear mixed models were performed to assess the adjusted odds ratios of 10 distraction types associated with the at-fault crashes while controlling for environmental factors.
Results: The main findings are (1) The highest contributing distraction types in at-fault crashes were In-Cabin Objects, Mobile Device, External Scenes, and In-Vehicle Information Systems (IVIS) as indicated by their influence on multiple age-gender groups and the magnitude of odds ratios; (2) Teens and adults were more distraction-prone than seniors, although seniors had the greatest at-fault crash risks associated with In-Cabin Objects, Mobile Device, and IVIS; (3) Distractions impacted females and males similarly; (4) At-fault crashes were more likely to have the significant distraction types present than all-cause crashes.
Conclusion: This study adds to the limited literature on at-fault crashes particularly as it explores the role of driver demographics and distracted driving. Analyzing the risks of distracted driving by age-gender group shows that specific activities can be riskier for a certain population. The effects of distractions may be overlooked without fault determination. Distractions by external scenes, in-vehicle technologies, and in-cabin objects should not be overlooked, in addition to mobile device use.

1. Introduction

Distractions are closely associated with motor vehicle crashes and have been the subject of crash analysis and road safety research. In its most recent report, the National Highway Traffic Safety Administration (NHTSA) found that 8% of fatal crashes and 15% of injury crashes were affected by distractions (National Highway Traffic Safety Administration, 2020). As far as we know, this study is the first to systematically assess the at-fault crash risk associated with different distraction types among six age-gender groups using the Strategic Highway Research Program 2 (SHRP2) Naturalistic Driving Study (NDS) dataset.

1.1. Distraction in motor vehicle crashes

Distraction is defined as "a specific type of inattention that occurs when drivers divert their attention from the driving task to focus on some other activity instead" by the NHTSA, although distraction and driver inattention are often used interchangeably (National Highway Traffic Safety Administration, 2020). Common distractions include cell phone use and texting, eating, interacting with passengers, and adjusting in-vehicle technologies, among which cell phone use has garnered national and international attention. The detrimental effects of texting have been extensively studied with simulators and closed test tracks, usually focusing on one age group and without differentiating gender

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differences (Caird et al., 2014).

Several studies sought to re-assess crash risk related to driver distractions as data from naturalistic driving studies such as the SHRP2 became available, which provided high-fidelity recordings of driver behaviors and traffic conditions in a naturalistic driving environment. For example, Dingus et al., performed univariate, mixed-effect logistic regression to examine a variety of driver distractions and impairments as risk factors; the authors highlighted that handheld electronic devices had high use rates and risk (Dingus et al., 2016). Another study found that the highest correlations with crash risk included the duration of distractions through dialing on a cellphone, texting, and reaching for an object (Arvin and Khattak, 2020). Among different distractions related to cellphones, visual-manual tasks increased the odds of severe crashes more so than overall cellphone distraction and cellphone talking (Lu et al., 2020). Drivers used both hands to manipulate the phone during 17% of phone use time, and the standard deviations of speed, headway, and lane offset were significantly lower during phone use periods (Wang et al., 2020).

In terms of driver demographics, Lu et al., cautioned that unaccounted income level and age could lead to biased risk estimation (Lu et al., 2020). Another group of researchers found that texting in the WhatsApp app deteriorated driving performances for all age groups, especially for older participants (Ortiz et al., 2018). Passenger presence significantly increased the mean proportion of time having elevated g-force events in curves among young drivers, and male drivers may better maintain a lane position than females (Zhang et al., 2019).

Studies have also analyzed the ranking of perceived risks of different distraction types by drivers, arguably shaped by their policy environment. One study revealed that drivers ranked tasks that are unnecessary or socially frowned upon to be riskier, such as mobile phone use, reading (a map or book), and grooming, whereas familiar and socially acceptable tasks such as listening to music, talking to passengers and looking at road signs were considered to have low risk levels (Patel et al., 2008). Parnell et al., highlighted how policymakers worldwide chose to strictly penalizes the use of handheld cell phones since the early 2000's but largely overlooked other in-vehicle technologies, thereby creating a relaxed condition that allows for driver distraction from in-vehicle devices (Parnell et al., 2017). In an updated study by the same group, the authors observed that youngers drivers in Australia perceived the law on non-phone-call use of smart mobile devices facilitated by Bluetooth to be ambiguous, although such use presents a competing draw of the driver's cognitive capacity (Kaviani et al., 2021).

1.2. At-fault crashes associated with driver distraction and characteristics

Research on the characteristics of at-fault crashes is limited. Fault assignment lacks standard analytical procedures. Responsibility determination may be difficult at the roadside because drivers' recounts could be inaccurate due to the shock of the crash or the incentive to avoid penalization (Bakiri et al., 2013). Third-party retrospective analyses of crash recordings have also been employed to determine fault. The U.S. Department of Transportation identified 17 Unsafe Driving Acts (UDA), including driver judgment, speed-related, right-of-way or headway-related, and lane position-related, to be the criteria for fault assignment (Council et al., 2003). In contrast, Robertson and Drummer tackled the problem from the opposite angle. They developed a crash responsibility instrument that counted the presence of mitigating factors considered to reduce driver responsibility: road environment, vehicular factors, traffic conditions, type of crash, traffic rule obedience, and difficulty of the driving task; if a sufficient number of mitigating factors were found, the driver was deemed not responsible for the crash (Robertson and Drummer, 1994). A modified version of the instrument was adapted in interviews with emergency department patients involved in road injuries and was found to have a moderately high agreement with human expert evaluation of driver responsibility (Bakiri et al., 2013).

Despite the rich literature on the effects of distraction and driver characteristics on crash risk, few studies examined their effects specifically on at-fault crashes. Among the limited studies on driver responsibility, Bakiri et al. found that picking up an object inside the vehicle, smoking, and inattention due to distracting events occurring outside were associated with an increased probability of being at fault in France (Bakiri et al., 2013). Having a distracted mind prior to a crash as well as the propensity to mind wander in everyday life were shown to be independently associated with responsibility for a traffic crash (Gil-Jardiné et al., 2017). Teen drivers who were found at fault in a crash had a significantly lower perception of risk than those who were not at fault (Penmetsa et al., 2017). Senior drivers aged 65+ were more likely than younger drivers to be at fault in a crash (Sagar et al., 2020). Years of driving experience, annual driving distance, and use of a location tracking system were found to be significantly associated with at-fault crashes by bus drivers in Taiwan (Tseng, 2012).

To summarize, this study seeks to address two research gaps in the distracted driving literature: (1) a systematic comparison of different age-gender groups on the impact of distracted driving is needed because driver demographics and driving environments can confound the effect of distractions; (2) Most crash analyses do not distinguish driver responsibility. Little is known about the impact of distraction on at-fault crashes. The detrimental effect of distraction could be underestimated if a certain distraction type was only prevalent in at-fault scenarios, as lumping at-fault crashes into all-cause crashes would attenuate the concentration of the distraction. As such, this study aims to address these two unknowns by evaluating the risk of at-fault crashes associated with common distraction types among six driver age-gender groups adjusting for environmental factors.

2. Material and methods

2.1. Data source

The study analyzed data from the Strategic Highway Research Program 2 (SHRP2) Naturalistic Driving Study (NDS) (Dingus et al., 2014; Hankey et al., 2016). Over a study period of three years, 50 million miles were driven at six study sites in the United States: Florida, Indiana, New York, North Carolina, Pennsylvania, and Washington. Study participants' vehicles were instrumented with cameras and radars capable of capturing the external environment, traffic condition, as well as in-cabin activities of the driver. Total video recordings accumulated over a million hours. This allows for retrospective analyses of the circumstances involved in motor vehicle crashes. A standardized data reduction effort was carried out at the Virginia Technology Transportation Institute (VTTI), where trained data reductionists annotated the video recordings of sampled segments of trips following a pre-established data dictionary. The unit of analysis is six-second clips (epochs), five seconds before and one second after the onset of a crash, which captured the preceding sequence of events and driver behaviors. For trips that did not involve a crash, driver distractions and other variables were also annotated based on video samples randomly selected with the overarching goal that the total sampled time for each driver was proportional to their total driving time in the study.

2.1.1. Human subjects protection

The SHRP2 NDS was approved by the Institutional Review Boards of the Virginia Tech and the National Academy of Sciences (NAS). Issuance of a Certificate of Confidentiality was initiated through the National Institutes of Health (NIH). Study participants consented to have data collected from their main vehicle when it was driven during the study period, as well as to provide a broad set of functional assessments; participants who were minors at the time of study provided assent to participate, and consent for participation was provided by a parent. Participants were compensated for study participation (Dingus et al., 2014).

The current study is a secondary data analysis of the SHRP2 NDS dataset. The data use of this study (Protocol Number 1902007017) was exempt by the Drexel University Institutional Review Board (IRB) because no identifiable private information of participants was obtained or analyzed.

2.1.2. Responsibility determination

Data reductionists assigned responsible party only when it was observable that one party committed an error that led to a crash; otherwise, a crash was deemed “unable to determine fault” (5/1039, 0.5%). The responsible party could be a study participant (757/1039, 72.9%), the driver of vehicle 2 or non-motorist (176/1039, 16.9%), or the driver of vehicle 3 or non-motorist (2/1039, 0.2%). If a crash was caused by animals or objects on the road, “not applicable” was assigned (98/1039, 9.4%). If part of the video recording was missing or there was visual obstruction that limited the reviewer’s perspective, the trip was deemed “fault unknown” (1/1039, 0.1%). In this study, at-fault crashes referred to those whose responsible party was a study participant, not the driver of vehicle 2 or vehicle 3 as their distraction states would be unknown. Crashes deemed “unable to determine fault”, “fault unknown”, or “not applicable” were excluded from the analysis.

2.2. Study design

The risk of motor vehicle crashes is considered time-variant, that is, the longer a driver is on the road, the greater their exposure to risk factors. In naturalistic driving studies, the total duration of risk exposure (e.g., distractions) cannot be accurately determined by manual effort due to the sheer volume of data. Guo proved that such risk exposure can be approximated by the odds ratio using a stratified baseline sampling strategy that ensures the risk exposure levels are consistent with the population from which the cases were drawn; the comparison of an exposure status for cases and controls can shed light on the risk level associated with the exposure of interest (Guo, 2009).

In this study, cases are crashes, defined as any contact that the study participant’s vehicle had with a moving or fixed object, at any speed in which kinetic energy is measurably transferred or dissipated. Such cases included severe crash (marked by an airbag deployment or bodily injury of involved parties, 107/1039, 10.3%), police-reportable crash (marked by significant property damage or acceleration greater than $\pm 1.3\,g$, 177/1039, 17.0%), and minor crash (physical contact with another object but did not reach the previous two levels, 755/1039, 72.7%). The SHRP2 NDS also includes as crashes non-premeditated departures of the roadway where at least one tire hit unintended travel surface. Those were excluded from this study because they present low risk to drivers. The control consists of uneventful trips sampled in a balanced fashion that proportionally reflects each driver’s total traveling time in the study (Hankey et al., 2016).

The study population ($N = 3{,}453$) drove a total of 20,767 qualifying trips, of which 1,039 resulted in crashes or 757 at-fault crashes. These trips were stratified into six groups by driver age (Teens 16–19, Adults 20–64, Seniors 65+) and gender in this study (Table 1). Trips of which the driver’s age or gender was unknown were excluded.

Table 1
Number of trips by age-gender group.

	Teen Female	Teen Male	Adult Female	Adult Male	Senior Female	Senior Male
Case - At-fault Crashes	110	91	200	184	84	88
Case - All-cause Crashes	148	116	293	264	105	113
Control - Balanced-Sample Baseline	1414	1260	6666	5881	1862	2645

2.3. Data analysis

Because most study participants generated more than one trip recording, univariate mixed-effect logistic models had been used in similar studies in the past to factor in the random effects of individual driver characteristics (Dingus et al., 2016; Klauer et al., 2014). The current study constructed six generalized linear mixed models (GLMMs) for each age-gender group to respectively estimate their crash risks associated with different distraction types while adjusting for environmental risk factors. Such a design can (1) reflect the latent heterogeneity in driver characteristics not otherwise captured by age and gender, (2) remove the bias related to the imbalance of environmental exposure in naturalistic driving studies pointed out by (Lu et al., 2020). The model is as follows:

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

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

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

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.

Each GLMM incorporated 18 independent variables, including 10 distraction types as predictors, and seven environmental factors and one unique identifier of the study participant as covariates. The dependent variable was whether a trip resulted in an at-fault crash. The only difference between the six models was the underlying age-gender subgroup.

We categorized distraction types based on the grouping of the annotated secondary tasks from the SHRP2 Researcher Dictionary for Video Reduction Data (Virginia Tech Transportation Institute, 2015). For example, the category Mobile Device included all annotated driver movements involving a cell phone or a tablet. The mapping details can be found in Appendix A. Accordingly, the 10 distraction types were Entertainment, External Scenes, Food & Beverage, In-Cabin Objects, Interaction with Passengers, In-Vehicle Information Systems (IVIS), Mobile Device, Personal Hygiene, Smoking, and Other. They were then converted into dummy variables in the model. To be specific, label value 1 denoted the presence of one or more secondary tasks in the same distraction category, and 0 suggested the absence of the distraction. A trip can involve more than one distraction category as input variables. In addition, we included seven environmental factors as control variables: Weather, Lighting Condition, Presence of Junction, Road Alignment, Road Grade, Surface Condition, and Traffic Density. They were treated as categorical variables with the least demanding driving scenario as the reference group for the generalized linear regression. The mapping of the environmental variables is included in Appendix B.

We used the lme4 package (Bates et al., 2015) in R (R Core Team, 2020) to estimate the model parameters via maximum likelihood, which implemented the adaptive Gauss-Hermite quadrature approximation that is less likely to produce biased fixed-effect estimates in GLMMs when compared to the penalized quasi-likelihood approach (Capanu et al., 2013; Pan and Thompson, 2003).

2.3.1. Goodness-of-fit

While no confirmatory tests are available to assess the adequacy of the fixed effects in linear mixed models, the most commonly used method is to test for the significance of additional terms in embedded models (Bates, 2010; Pan and Lin, 2005; Tang et al., 2014). To evaluate the goodness-of-fit of the models, we used the likelihood ratio tests to compare the deviance of the full model fit with the null model, which were constructed as follows. In addition, two alternative hypotheses, i.e., one with only distraction types as predictors, the other with only environmental covariates, were also included in the comparison.

$$\begin{aligned} \text{glmm.full}: \text{Outcome} \sim\ & \text{Entertainment} + \text{IVIS} + \text{InCabinObjects} \\ & + \text{ExternalScenes} + \text{FoodBeverage} + \text{PersonalHygiene} + \text{Interaction} \\ & + \text{MobileDevice} + \text{Smoking} + \text{OtherSecondaryTasks} \\ & + \text{weatherBinary} + \text{surfaceBinary} + \text{gradeBinary} \\ & + \text{alignmentBinary} + \text{lightingFactor} \\ & + \text{trafficDensityFactor} + \text{intersectionFactor} \\ & + (1|\text{anonymousParticipantID}) \end{aligned} \quad (1)$$

$$\begin{aligned} \text{glmm.distractions.only}: \text{Outcome} \sim\ & \text{Entertainment} + \text{IVIS} \\ & + \text{InCabinObjects} + \text{ExternalScenes} + \text{FoodBeverage} \\ & + \text{PersonalHygiene} + \text{Interaction} + \text{MobileDevice} \\ & + \text{Smoking} + \text{OtherSecondaryTasks} \\ & + (1|\text{anonymousParticipantID}) \end{aligned} \quad (2)$$

$$\begin{aligned} \text{glmm\_environment\_only}: \text{Outcome} \sim\ & \text{weatherBinary} + \text{surfaceBinary} \\ & + \text{gradeBinary} + \text{alignmentBinary} + \text{lightingFactor} \\ & + \text{trafficDensityFactor} + \text{intersectionFactor} \\ & + (1|\text{anonymousParticipantID}) \end{aligned} \quad (3)$$

$$glmm\_null: \ Outcome \sim \ 1 + (1|anonymousParticipantID) \quad (4)$$

For all six age-gender groups, the distractions-only model had significantly lower deviance than that of the null model; and the full model had significantly lower deviance than that of the distraction-only model. The deviance, chi-squared, degree of freedom, and p value can be found in Appendix C. Bates cautioned that this approach of using a chi-squared distribution to calculate a p value for the change in the deviance is conservative in the sense that it is larger than a simulation-based p value (Bates, 2010). Thus, the full models in the current study were shown to have better fit than the null model even using this conservative approach.

2.3.2. *Multiplicity adjustment*

Multiple subgroup comparisons introduce multiplicity that could lead to inflated type I error. Multiplicity adjustment therefore is recommended, especially when the analysis is to test specified subgroup hypotheses to inform decision making (Li et al., 2017). The Bonferroni adjustment is a classical method to adjust for multiplicity by requiring a significance level of α/k, where k is the number of comparisons and α is the desired experiment-wise error rate. The disadvantages of this approach include low power and being overly conservative (Li et al., 2017). This study used the Benjamini-Hochberg (BH) procedure, which ensures the overall false discovery rate (i.e. the expected proportion of the rejected null hypotheses which are erroneously rejected) is less than the desired experiment-wise error rate and has more power than the Bonferroni adjustment (Benjamini and Hochberg, 1995).

2.3.3. *Compare at-fault crash risk to all-cause crash risk*

To assess if distraction is associated with at-fault crashes in a similar fashion as they do with all-cause crashes, the same set of analyses was also performed on all crashes identified in the study without fault determination, of which results were compared.

3. Results

3.1. *Prevalence of distractions*

The prevalence of distractions in everyday driving can be approximated by the randomly and proportionally sampled control group. The three most common distractions for teens were Interaction, Entertainment, and Mobile Device. For adults, these distractions were Interaction, External Scenes, and Mobile Device (joint second). Interaction, External Scenes, and Entertainment (a distant third) were the most common distractions for seniors. Table 2 presents the diversity in common distraction types among different age-gender groups. For instance, using chi-squared test, we showed that teens were more likely to be distracted by Entertainment and Interaction than adults ($\chi^2_1 = 20.64$, $P < .001$) and seniors ($\chi^2_1 = 199.99$, $P < .001$). The prevalence of Mobile Device was significantly higher among teens ($\chi^2_1 = 365.41$, $P < .001$) and adults ($\chi^2_1 = 400.05$, $P < .001$) than seniors, while the prevalence of External Scenes distraction was significantly higher among seniors than teens ($\chi^2_1 = 62.36$, $P < .001$). Overall speaking, teens ($\chi^2_1 = 193.21$, $P < .001$) and adults ($\chi^2_1 = 274.54$, $P < .001$) were more distraction-prone than seniors as evident in the prevalence of No Distraction.

3.2. *Effects of distraction on different age-gender groups*

Table 3 shows the exponentiated coefficients for each distraction type, which are odds ratios of the distractions being associated with at-fault or all-cause crashes. In-Cabin Objects had large odds ratios ranging between 5.46 and 13.27, significant for all six groups, with the greatest effect on senior males (OR = 13.27, 95% CI 5.78–30.50). Mobile Device related distractions impacted all groups but senior females, with the greatest impact on senior males (OR = 8.01, 95% CI 1.99–32.18). The odds ratios of External Scenes distraction being involved in at-fault crashes ranged from 1.24 to 2.74, significant among all six groups but adult males. In-Vehicle Information System (IVIS) had significant association with teen males, adult females, adult males, and senior females, affecting senior females the most (OR = 4.12, 95% CI 1.74–9.76). Food & Beverage and Personal Hygiene distractions increased the odds of at-fault crash risk by 3.09 (95% CI 1.16–8.26) for teen females and 1.93

Table 2
Prevalence of distraction by type and driver age-gender group.

	Teen Female	Teen Male	Adult Female	Adult Male	Senior Female	Senior Male
Number of Trips Involving Distraction	n (%)	n (%)	n (%)	n (%)	n (%)	n (%)
Entertainment	193 (13.6)	134 (10.6)	650 (9.8)	520 (8.8)	73 (3.9)	86 (3.3)
External Scenes	84 (5.9)	124 (9.8)	584 (8.8)	720 (12.2)	234 (12.6)	367 (13.9)
Food & Beverage	41 (2.9)	34 (2.7)	281 (4.2)	202 (3.4)	39 (2.1)	52 (2)
In-Cabin Objects	26 (1.8)	26 (2.1)	179 (2.7)	155 (2.6)	39 (2.1)	38 (1.4)
Interaction	278 (19.7)	244 (19.4)	983 (14.7)	920 (15.6)	280 (15)	407 (15.4)
IVIS	62 (4.4)	51 (4)	244 (3.7)	227 (3.9)	52 (2.8)	69 (2.6)
Mobile Device	165 (11.7)	126 (10)	730 (11)	573 (9.7)	27 (1.5)	18 (0.7)
Personal Hygiene	74 (5.2)	48 (3.8)	328 (4.9)	213 (3.6)	40 (2.1)	45 (1.7)
Smoking	8 (0.6)	5 (0.4)	92 (1.4)	74 (1.3)	12 (0.6)	28 (1.1)
Other	53 (3.7)	60 (4.8)	260 (3.9)	249 (4.2)	50 (2.7)	98 (3.7)
No Distraction	587 (41.5)	558 (44.3)	3022 (45.3)	2671 (45.4)	1114 (59.8)	1580 (59.7)

Table 3
The association between distraction and at-fault crashes or all-cause crashes in odds ratios and 95% confidence intervals.

	At-Fault Crashes		All-Cause Crashes	
	OR (95% CI)		OR (95% CI)	
	Teen Female	Teen Male	Teen Female	Teen Male
Entertainment	1.52 (0.83, 2.77)	1.13 (0.55, 2.34)	1.42 (0.84, 2.38)	1.06 (0.55, 2.05)
External Scenes	2.40 (1.21, 4.73) *	2.08 (1.10, 3.95) *	1.91 (1.02, 3.58)	1.64 (0.90, 3.00)
Food & Beverage	3.09 (1.16, 8.26)	0.32 (0.04, 2.71)	2.18 (0.84, 5.68)	0.59 (0.13, 2.80)
In-Cabin Objects	7.51 (3.48, 16.20) ***	5.56 (2.34, 13.19) ***	6.72 (3.35, 13.49) ***	5.46 (2.50, 11.90) ***
Interaction	1.08 (0.61, 1.91)	1.18 (0.65, 2.13)	1.05 (0.64, 1.71)	1.32 (0.80, 2.19)
IVIS	1.16 (0.43, 3.15)	3.12 (1.39, 7.01) *	0.99 (0.40, 2.45)	2.72 (1.31, 5.64) *
Mobile Device	3.12 (1.80, 5.40) ***	3.26 (1.83, 5.79) ***	2.34 (1.43, 3.83) ***	2.80 (1.66, 4.73) ***
Personal Hygiene	1.52 (0.61, 3.78)	1.07 (0.31, 3.69)	1.55 (0.73, 3.30)	1.40 (0.53, 3.74)
Smoking	3.14 (0.61, 16.17)	5.84 (0.92, 37.13)	2.63 (0.53, 13.15)	4.26 (0.70, 26.03)
Other	2.70 (1.15, 6.37)	0.88 (0.29, 2.63)	2.63 (1.26, 5.50)	0.89 (0.34, 2.36)
	Adult Female	**Adult Male**	**Adult Female**	**Adult Male**
Entertainment	1.09 (0.65, 1.81)	0.90 (0.50, 1.62)	1.18 (0.78, 1.77)	1.18 (0.76, 1.84)
External Scenes	2.23 (1.43, 3.47) ***	1.24 (0.77, 1.98)	1.65 (1.11, 2.45) *	1.40 (0.97, 2.04)
Food & Beverage	0.79 (0.34, 1.81)	1.10 (0.44, 2.71)	0.95 (0.50, 1.79)	1.07 (0.51, 2.23)
In-Cabin Objects	11.20 (7.23, 17.35) ***	7.74 (4.69, 12.76) ***	10.80 (7.58, 15.38) ***	6.77 (4.44, 10.34) ***
Interaction	1.01 (0.63, 1.63)	1.26 (0.81, 1.95)	1.20 (0.83, 1.72)	1.19 (0.82, 1.72)
IVIS	2.53 (1.38, 4.62) *	2.49 (1.35, 4.59) *	1.80 (1.04, 3.12)	2.58 (1.57, 4.25) ***
Mobile Device	3.27 (2.22, 4.81) ***	2.80 (1.85, 4.23) ***	2.85 (2.07, 3.92) ***	2.10 (1.46, 3.03) ***
Personal Hygiene	1.93 (1.07, 3.48)	0.99 (0.38, 2.58)	1.59 (0.95, 2.64)	1.36 (0.69, 2.70)
Smoking	0.55 (0.07, 4.17)	1.77 (0.57, 5.52)	0.60 (0.14, 2.59)	1.22 (0.41, 3.59)
Other	1.08 (0.48, 2.42)	0.80 (0.32, 2.03)	0.91 (0.45, 1.84)	0.93 (0.46, 1.87)
	Senior Female	**Senior Male**	**Senior Female**	**Senior Male**
Entertainment	1.06 (0.34, 3.32)	0.68 (0.16, 2.99)	1.37 (0.54, 3.50)	0.52 (0.12, 2.28)
External Scenes	2.26 (1.25, 4.10) *	2.74 (1.61, 4.64) ***	1.98 (1.15, 3.42) *	1.98 (1.20, 3.27) *
Food & Beverage	1.32 (0.32, 5.41)	Not enough cases	1.58 (0.48, 5.24)	0.36 (0.04, 2.98)
In-Cabin Objects	11.53 (5.41, 24.57) ***	13.27 (5.78, 30.50) ***	8.94 (4.41, 18.13) ***	11.32 (5.32, 24.08) ***
Interaction	1.05 (0.51, 2.16)	0.57 (0.26, 1.23)	1.13 (0.62, 2.08)	0.72 (0.38, 1.35)
IVIS	4.12 (1.74, 9.76) *	0.64 (0.14, 2.93)	2.82 (1.22, 6.50) *	0.80 (0.23, 2.81)
Mobile Device	2.00 (0.40, 9.87)	8.01 (1.99, 32.18) ***	1.53 (0.32, 7.21)	6.10 (1.54, 24.09) *
Personal Hygiene	1.39 (0.31, 6.27)	1.27 (0.24, 6.71)	1.09 (0.25, 4.77)	1.84 (0.53, 6.37)
Smoking	2.27 (0.23, 22.22)	1.23 (0.15, 10.35)	1.75 (0.19, 16.09)	0.94 (0.11, 7.89)
Other	2.03 (0.59, 6.97)	1.29 (0.43, 3.81)	1.49 (0.45, 4.92)	1.00 (0.34, 2.90)

Significance codes: $P < 0.001$ "***", 0.001 <= P < 0.01 "**", 0.01 <= P < 0.05 "*".

(95% CI 1.07–3.48) for adult females, respectively, although their adjusted p values became greater than the predefined threshold ($\alpha = 0.05$). The at-fault crash risks associated with distractions by age-gender groups were visualized in Fig. 1. The coefficients, standard errors, and adjusted p values from the model outputs are included in Appendix D.

Comparing to the odds ratios associated with all-cause crashes, the estimated risks were more pronounced among at-fault crashes as indicated by the higher odds ratios. External Scenes distraction was significantly associated with at-fault risks across all groups except adult males, but it had smaller associations with all-cause crashes among only three of the six age-gender groups.

4. Discussion

To summarize the study findings, we found that at-fault crashes were more likely to have the significant distraction types present than all-cause crashes. The distraction types that contributed most to at-fault crashes included In-Cabin Objects, Mobile Device, External Scenes, and In-Vehicle Information Systems (IVIS). Specific distraction types influenced specific age-gender groups differently. While teens and adults were more likely to be distracted during driving than seniors, seniors were more prone to at-fault crash risks associated with In-Cabin Objects, Mobile Device and IVIS.

In-Cabin Objects were associated with an elevated risk of at-fault crashes for all age-gender groups, and Mobile Device, External Scenes and IVIS for most groups. They all involve a component of visual redirection off the roadway ahead. Furthermore, In-Cabin Objects, IVIS, and Mobile Device also involve coordinated eye-hand movement to maneuver and interact with an object inside the cabin.

Comparing the study findings to previous research, the estimated odds ratios of all-cause crashes are similar to those reported in the (Dingus et al., 2016) study, which also used the SHRP2 dataset but without fault determination and environmental variables. For example, Dingus et al., reported the univariate crash odds ratio was 2.5 associated with "in-vehicle device" (similar to IVIS), 3.6 with cell phone use (similar to Mobile Device), 7.1 with "extended glance duration to external object" (similar to External Scenes), and 9.1 with "reaching for a non-cell phone object" (similar to In-Cabin Objects). By distinguishing between different age-gender groups, we recognized that the associated risks differed from the aggregate numbers. For example, the all-cause crash risk associated with mobile device use was almost twice in the senior male group (OR = 6.10) than the all-population risk estimate, and teen females (OR = 0.99) and senior males (OR = 0.80) did not seem to be as affected by the IVIS distraction as the other groups did. Analyzing the risks of distracted driving by age-gender group shows that specific activities can be riskier for a certain population.

Among specific age groups, Gershon et al., used naturalistic driving data of teenage drivers from the Supervised Practice Driving cohort study and analyzed similar distraction types as those of this study but without fault determination (a limitation the author pointed out); their analysis found similarly increased risk associated with manual cellphone use (OR = 2.7) and reaching/handling objects (OR = 6.9), but not with External and IVIS distractions, which this study did. This study found mild significance (0.01 <= P < 0.05) associated with IVIS among teen males, but not among teen females, so it is possible that the distraction effects were attenuated when combining genders. This study reported mild significance (0.01 <=P < 0.05) on the association between External Scenes and at-fault crashes, but not all-cause crashes, which suggests the effects of distraction may be overlooked without fault determination.

For older drivers, Huisingh et al., using the SHPR2 dataset reported increased risks associated with cell phone use (OR = 3.79) and "other glances into the interior of the vehicle" (similar to In-Cabin Objects and IVIS) (OR = 2.55). However, external distraction was found to be associated with a decreased risk of crash involvement (Huisingh et al., 2019), contrary to the elevated crash risk found in this study. The

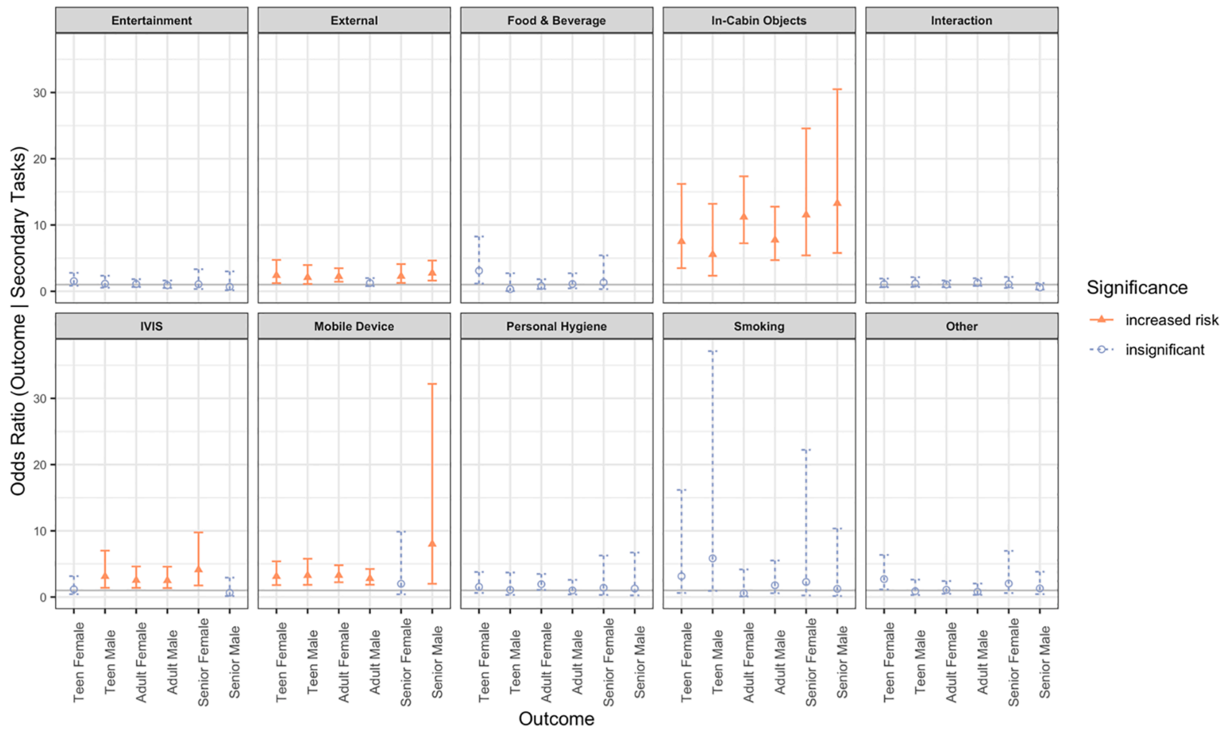

Fig. 1. The association between distraction types and at-fault crashes.

authors explained that the analysis did not control for driving environment, road type, time of day, and weather, which this study did and may explain the difference.

While much attention has focused on assessing the danger of using cell phones (Gariazzo et al., 2018; Pöysti et al., 2005; Truong and Nguyen, 2019), our research identifies detrimental distraction types previously understudied. For example, although looking at road signs, a form of External Scenes distraction, is a socially acceptable distraction (Patel et al., 2008), it can be dangerous. Coupled with its high prevalence, External Scenes distraction is both common and contributes significant risk. In-vehicle technologies prove to be as hazardous as mobile devices, although current legislation has not taken a stance against in-vehicle technology use (Parnell et al., 2017). In-cabin Objects universally elevated the odds of at-fault crashes, but has not been extensively studied.

This study has several limitations. The fault determination is based on the manual assessment of human experts. Some could argue that this process is subjective or arbitrary, however other ways of determining fault are limited. Another limitation is the generalizability of the study as the study population was sampled from six cities in the United States, however our findings on in-cabin objects and external distraction are similar to one study conducted in France (Bakiri et al., 2013). Lastly, this study did not explain why certain distraction types contribute significant risk. To address this question, further research will focus on how drivers adapt their driving behaviors while engaging in secondary tasks.

5. Conclusions

A better understanding of at-fault crashes is much needed. In this study, we compared the at-fault crash risk of distractions among six age-gender groups using mixed-effect logistic regression and controlling for environment factors and driver heterogeneity. Analyzing the risks of distracted driving by age-gender group shows that specific activities can be riskier for a certain population. This study provides evidence that the detrimental effect of distraction may be underestimated without distinguishing at-fault crashes from all-cause crashes.

CRediT authorship contribution statement

Ou Stella Liang: Data curation, Formal analysis, Methodology, Software, Validation, Visualization, Writing – original draft, Writing – review & editing. **Christopher C. Yang:** Conceptualization, Funding acquisition, Investigation, Methodology, Project administration, Resources, Supervision, Validation, Writing – original draft, Writing – review & editing.

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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Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.aap.2021.106505.

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