Assessing the Impact of Cellular Coverage Areas on Distracted Driving, Crashes, and Injuries

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ABSTRACT

This study combines econometric and geospatial methods to analyze the impact of cellular coverage on distracted driving incidents, crashes, and injuries in Oregon from 2017 to 2020, focusing on cell phone-related crashes. Despite reduced travel in 2020, these crashes remained high. Geospatial tools identified urban hotspots like Portland and Salem. We used the mixed logit model to evaluate factors like driver demographics, vehicle characteristics, and environmental conditions, shedding light on the economic aspects of injury severity. Results highlight the crucial role of seatbelt use in reducing injury severity. The study underlines the need for comprehensive strategies to combat distracted driving in Oregon for better road safety and to lower economic costs associated with such incidents.

1. INTRODUCTION

Technological advancements in communication, coupled with the growing popularity of social media platforms like Instagram, Meta (formerly Facebook), and TikTok, have accelerated the use of cell phones in motor vehicles. As of now, the United States boasts over 300 million smartphone users, a figure projected to reach 360 million by 2040 (Statista, 2023). While smartphones serve as beneficial technological aids, offering everything from mapping directions to real-time traffic alerts, they pose significant distractions to drivers. The National Highway Traffic Safety Administration (NHTSA) defines "distraction" as a type of inattention occurring when drivers divert their attention from driving to another activity. NHTSA's (2021) report revealed that in the US in 2019, distraction-affected crashes accounted for 9% of fatal crashes, 15% of injury-related crashes, and 15% of all police-reported vehicle crashes. Additionally, 6% of drivers involved in fatal crashes were identified as distracted. Research indicates that 31.4% of individuals are distracted while on phone calls, and 16.6% while texting or dialing. Schroeder et al. (2018) conducted a comprehensive survey, finding that 56% of drivers engage in phone conversations, 9% send texts or emails, and 8% occasionally use apps while driving. Claveria et al. (2019) found that approximately 45% of truck drivers, from a sample of 515 respondents, used cell phones while driving in the Pacific Northwest Zone. Similarly, Gliklich et al. (2016) conducted a survey of 1,211 U.S. drivers, revealing that 43% frequently viewed maps. Notably, the highest percentage of distracted drivers involved in fatal crashes were those aged 15 to 20.

Between 2016 and 2020 in Oregon, distracted driving was a factor in over 15,000 crashes, resulting in 186 deaths and approximately 24,000 injuries, as ODOT (2023) reported. This trend is particularly alarming given the growing integration of social media into daily life. There's a notable correlation between the use of social media platforms and wireless connectivity availability. According to Hersh et al. (2019), in areas with wireless connectivity, the accident rate increases by 1.1%, with most injuries being non-severe. Huisingh et al. (2019) found that the risk of a severe crash is 3.79 times higher when using a cell phone compared to not using one at all. Teenagers, particularly prone to serious injuries while driving distracted, are often affected by distractions from other drivers or their cell phones (Neyens et al. 2008). Additionally, Klauer et al. (2014) discovered that even experienced drivers are significantly more likely to have crashes or near-crashes when making phone calls.

A number of studies have explored the effects of distracted driving on road safety using naturalistic data (Owens et al., 2018; Dingus et al., 2016; Lu et al., 2020) and these have often focused on the impacts of texting, calling, or engaging with passengers while driving. And other studies have also highlighted the consequences of distractions related to both on- and off-cellular service (Qin et al. 2019; Sundfør et al. 2019). Despite extensive research, the connections between distracted driving, crash factors, crash severity, and geographical location remain unclear. This study aims to investigate these relationships, particularly examining how cellular coverage influences distracted driving and crashes. Further this study will investigate the statistical and spatial risks associated with cellphone usage, including its impact on the severity of injuries in vehicle crashes. By analyzing various contributing factors, this study seeks to understand the broader implications of distracted driving. Key questions include: *How does cellular data coverage affect driver attention? What factors contribute to injury severity in distracted driving crashes in Oregon?*

To accomplish this, the research utilized crash data obtained from the Oregon Department of Transportation (ODOT), primarily focusing on the data related to crashes caused by distracted driving between the years 2017 and 2020. This study used a mixed logit modeling framework with heterogeneity in means and variance for the analysis (Alnawmasi and Mannering 2022). Recognizing that distracted driving is a complex issue intertwined with driver behavior, it was essential to consider unobserved individual characteristics in the statistical model. To our knowledge, this is the first study to investigate the impact of cellphone coverage on distracted driving and injury severity. This research makes a significant contribution to road safety, particularly in the context of distracted driving. It introduces a mixed logit model that accounts for variations in both means and variances, incorporating random factors affecting distraction. The findings offer valuable insights for stakeholders in transportation safety, law enforcement, public health, and emergency medical services. These insights could be instrumental in developing targeted interventions to combat distracted driving.

2. LITERATURE REVIEW

2.1 Injury Severity Studies

With the rise of technology, distracted driving has become a major road safety issue. To better understand injury severity in such crashes, researchers have applied various statistical and econometric models that account for unobserved factors (unobserved heterogeneity) like the mixed logit (Alnawmasi and Mannering 2022; Fatmi et al. 2019; Wu et al. 2022; Chen et al. 2021). For example, Fatmi et al., (2019) through there application of such a model found that environmental factors like rain and road alignment impact injury severity in distracted driving incidents, with some elements like sidewalk length reducing it. Similarly, Razi-Ardakani et al. (2019) determined that cognitive and passenger distractions decrease injury severity, while cell phone use increases it. Rain and curved roads also heighten injury risk, but morning peak hours reduce it. Islam (2023) focused on vehicle type in single-vehicle crashes, using random parameter multinomial logit models to account for heterogeneity. Restraint use emerged as a significant factor. Alnawmasi and Mannering (2022) noted a temporal decrease in injury severity, with daylight and high right shoulder indicators being significant factors in different years. Wu et al. (2022) observed a shift in significant factors like daytime and urban location in cell phone-related crashes in Pennsylvania. Meanwhile, Neyens and Boyle (2007) linked teenage drivers' rear-end collisions to cell phone distractions. García-Herrero et al. (2021) found that technological distractions almost double the risk of severe or fatal injuries in speeding scenarios. These studies emphasize the complexity of injury severity in distracted driving and the evolving use of econometric models that consider heterogeneity to better understand this issue.

2.2 Non-injury Severity Studies

This section provides a consolidated overview of various studies examining the impact of distracted driving on traffic safety and efficiency. It encompasses findings from Stavrinos et al. (2013) and Cooper et al. (2009), who identified that distracted driving leads to significant variations in lane positioning and speed, along with a tendency for riskier lane changes, adversely affecting traffic flow. Choudhary et al., (2017) and Xiao et al. (2016) further expand on this by noting behaviors such as reduced speeds and increased distances between vehicles, which contribute to lower traffic efficiency and more frequent overtaking incidents Xiao et al., (2015). Sherif et al., (2023) specifically focus on the impact of distracted driving at intersections, revealing a marked increase in the time interval between vehicles and a consequent reduction in intersection capacity.

Overall, these studies collectively illustrate the profound and varied ways in which driver distractions disrupt traffic dynamics, underscoring the critical need for continued research and targeted policy interventions to enhance road safety and maintain efficient traffic flow.

3. EMPIRICAL SETTING

For this study police-reported crash data sourced from ODOT's Crash Analysis and Reporting Unit, spanning 2017 to 2020, was collected (See Figure 1). Emphasis was placed on crash-level events specifically related to drivers' distractions. These events are characterized by several forms of distractions, including cell phone use, as documented on a Police Accident Report (PAR) or observed in use by the driver, instances where another party witnessed the driver's cell phone usage, distractions stemming from the operation of navigation systems or GPS devices, distractions attributed to other electronic devices, and incidents related to texting while driving. The comprehensive dataset identified a subset of 2,690 observations, each representing drivers involved in such distracting events. Each observation included information regarding driver, driver action, crash, roadway, temporal, environmental, and vehicle characteristics.

The study employed a modified version of the traditional KABCO injury scale to assess the severity of the outcomes stemming from these distractions. This scale was condensed into three primary categories for clarity: severe injury (comprising fatal and incapacitating outcomes, labeled as K+A), minor injury (including non-incapacitating and potential injuries, denoted as B+C), and cases where there was no injury sustained by the driver, resulting solely in property damage (categorized as O). As shown in Table 1, a closer examination of the 2,690 observations revealed a breakdown in injury outcomes: 32 crashes (or 1.19%) led to severe injuries; 960 cases (or 35.69%) ended in minor injuries; and the majority, accounting for 1,698 crashes or 63.12%, documented instances where no injury, with damages limited to properties. The following table illustrates the descriptive statistics of the significant variables in the three injury severity models.

Table 1: Injury Severity distribution of the final dataset

Year	Severe Injury (%)	Minor Injury (%)	No Injury (%)	Total (%)
2017	6(0.87)	236(34.10)	450(65.03)	**692(100)**
2018	11(1.38)	292(36.64)	494(61.98)	**797(100)**
2019	6(0.89)	265(39.32)	403(59.79)	**674(100)**
2020	9(1.71)	167(31.69)	351(66.60)	**527(100)**
2017-2020	**32(1.19)**	**960(35.69)**	**1698(63.12)**	**2690(100)**

Table 2 illustrates the descriptive statistics of the significant variables in each of the three injury severity models. Collision type (rear-end, fixed object), airbag deployment, seatbelt use, speed greater than 55 mph, female, and driver proximity within 25 miles to the residence were the variables found to be significant for different injury severity categories.

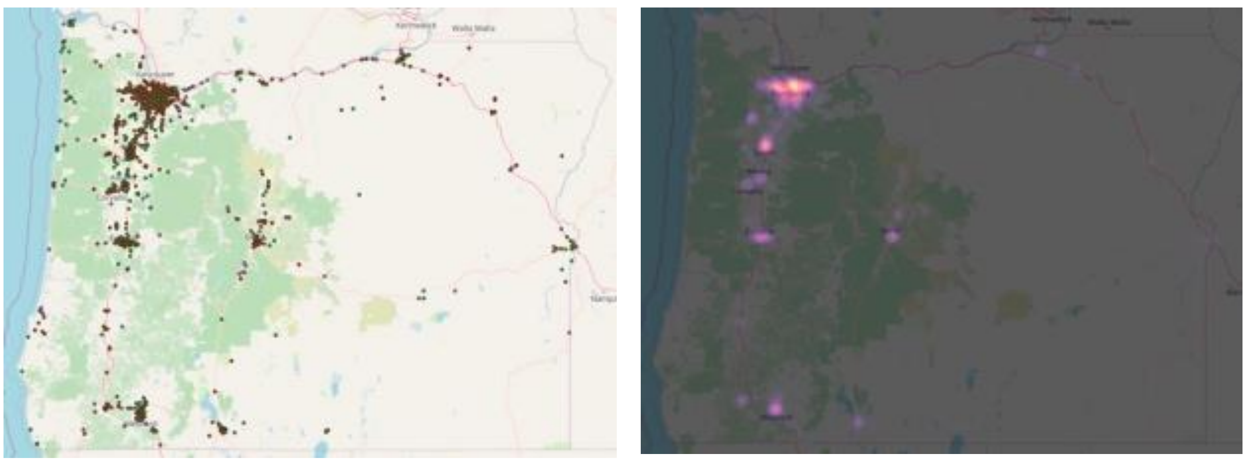
Table 2: Descriptive Statistics of Significant Variables by Injury Severity Category

Variable	Mean	Std Deviation
Mixed Logit Model		
Airbag (1 if the airbag deployed, 0 otherwise)	0.134572	0.341288
Collision Type (1 if rear-end, 0 otherwise)	0.562082	0.496162
High Speed (1 if was greater than 55 MPH, 0 otherwise)	0.178439	0.382905
Airbag (1 if the airbag deployed, 0 otherwise)	0.134572	0.341288
Collision Type (1 if fixed-object, 0 otherwise)	0.086245	0.280743
Safety Equipment (1 if seatbelt use, 0 otherwise)	0.549814	0.497543
Low Speed (1 if speed greater than 20 MPH but Less than 40 MPH, 0 otherwise)	0.302602	0.459413
Gender (1 if female, 0 otherwise)	0.30223	0.459253
Driver Proximity to Residence (1 if within 25 Miles, 0 otherwise)	0.521933	0.49955
Age (1 if driver age is less than 25 years old)	0.526766	0.499314

In addition, a pivotal aspect of this research aimed to ascertain whether cell phone coverage, or its absence, played a role in influencing the locations of distracted driving crash clusters (see Figure 1a). Figure 2a and Figure 2b present the mobile coverage maps for Verizon and AT&T, respectively, superimposed onto the recorded crash sites from the study period. The maps employ light-colored regions to depict areas devoid of coverage, while pink (in Figure 2a for Verizon) and yellow (for AT&T in Figure 2b) shades signify areas with cellular service. Upon close examination, a notable pattern emerges: most crashes appear to be concentrated within the cell service zones for both carriers. This suggests a potential correlation between areas with active mobile service and the incidence of distracted driving crashes, underscoring the need for further investigation into the underlying factors and drivers' behaviors in these regions.

Furthermore, central to this research was the utilization of heatmaps/hotspots within QGIS—a geospatial tool renowned for its adeptness at visualizing spatial data distributions (See Figure 1b). Through the heatmaps/hotspots, the analysis transformed discrete data points into continuous visual narratives, delineating regions experiencing elevated instances of cell phone-induced/related crashes. The subsequent urban analyses illustrated that Portland and Salem, highlighted the distracted driving scenario in Oregon (see Figure 1b).

Hence, the relationship between cell phone use, connectivity, and distracted driving crashes is both complicated and multifaceted. While regions with pronounced cell service witness a concentration of such crashes, sporadic connectivity zones present their own set of challenges, potentially diverting driver attention (this was confirmed from hot spot analysis). As this study reveals the overarching patterns in Oregon, it also underscores the importance of further research and strategic interventions to address this pressing concern. As such, this study proposes an econometric to uncovers the complex interactions.

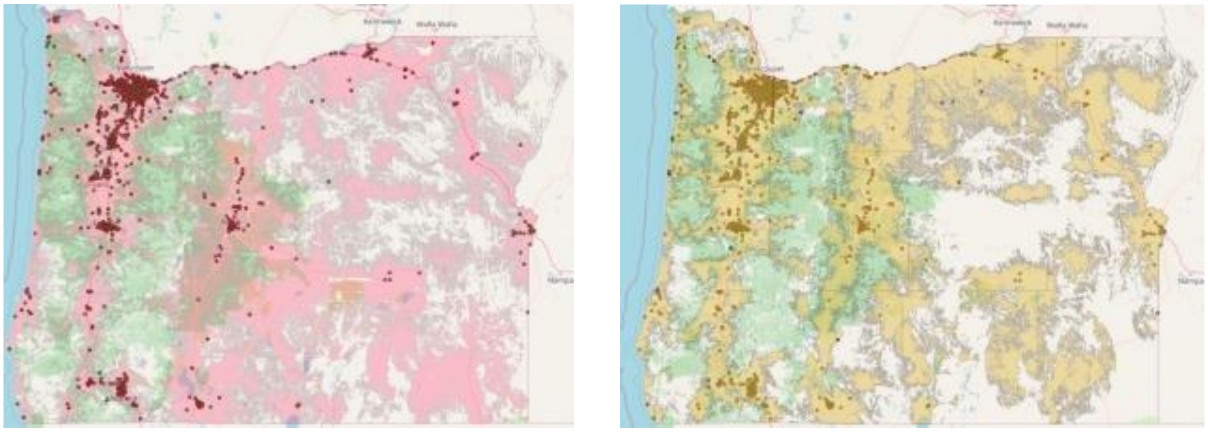


(a) (b)

Figure 1. (a) Spatial Distribution of Distracted Driving Crashes in Oregon (2017-2020): A GIS visualization highlighting the geolocations of reported incidents over the four-year study period; (b) Heatmap of Oregon: Delineating Concentrations of Distracted Driving Crashes with Dominant Clusters in Major Urban Centers like Portland, Salem, Eugene, Medford, and Bend.

4. METHODOLOGY

In the present research, while police-reported crash data offer extensive insights, they need to capture certain details. Aspects such as the driver's physical characteristics (e.g., height, weight) or nuanced environmental conditions at the exact moment of the crash (e.g., subtle shifts in weather or lighting) remain to be determined. Such factors can introduce unobserved variations across the dataset, termed as "unobserved heterogeneity." If not addressed, this heterogeneity can skew the model's estimations, potentially leading to biased outcomes, as highlighted by (Mannering et al., 2016).



(a) (b)

Figure 2. (a) Verizon Mobile Cell Coverage Map Superimposed onto the Recorded Crash Sites from the Study Period (2017-2020); (b) AT&T Mobile Coverage Map Superimposed onto the Recorded Crash Sites from the Study Period (2017-2020).

Current research employed the mixed logit model with possible heterogeneity in the means and variance of random parameters to mitigate the impact of this unobserved heterogeneity. This methodology stands as a cutting-edge statistical and econometric tool, with its application evident in a myriad of recent studies focused on injury severity (Alnawmasi and Mannering 2022; Al-Bdairi et al. 2020; Behnood and Mannering 2017; Islam 2021; Zubaidi et al. 2021). Further, this econometric modeling method treats injury severity outcomes as discrete choices, enabling insights into the probability of each injury severity outcome. Using this approach, the estimated parameters of the mixed logit model highlight statistically significant factors that either elevate or reduce the likelihood of specific injury severity outcomes.

The mixed logit model starts with a linear function. Each linear function corresponds to a particular injury severity resulting from a distracted driving crash and can be represented as:

$$U_{in} = \beta_i X_{in} + \varepsilon_{in} \tag{1}$$

Where U_{in} is a linear function for injury severity i and distracted driving crash n; i represents injury severities of no injury, minor injury and severe injury; X_{in} represents the vector of explanatory variables (roadway characteristics, driver actions, driver characteristics, roadway characteristics, demographic characteristics, environment characteristics) that lead to the discrete outcome of crash due to distracted driving n; β_i represents the vector of estimated parameters for injury severity i and ε_{in} is the error term that attempts to capture the unobserved factors within the model (Washington et al. 2011); but ε_{in} is unable to capture all the unobserved factors. Police-reported crash data often lacks certain essential variables, and the variability within the available variables can lead to unobserved heterogeneity. If this heterogeneity is overlooked, it may produce biased estimates and lead to incorrect conclusions (Mannering et al., 2016). Therefore, the mixed logit model captures this heterogeneity by allowing varying parameters. In addition, the mixed logit model (if variables are found to be random) eliminates the independence from irrelevant alternatives (IIA) property. In essence, by accounting for variables identified as random, unobserved factors are addressed, allowing for the categorization of injury severities into three distinct groups (Geedipally et al., 2011). The mixed logit model is then formulated as follows (McFadden and Train 2000; Washington et al. 2011).

$$P_n(i|\varphi) = \int \frac{e^{(\beta_i X_{in})}}{\sum_{\forall I} e^{(\beta_i X_{in})}} k(\beta_i|\varphi)\, d\beta_i \tag{2}$$

where $P_n(i|\varphi)$ is the weighted outcome probability of injury severity i (severe, minor and no injury) conditional on $k(\beta_i|\varphi)$, where $k(\beta_i|\varphi)$ is the density function of β_i and φ with distribution specified by the analyst —the density function is what allows the parameters to vary and is regularly specified to be normally distributed. All other variables have the same definition as the ordinary multinomial logit model (Washington et al. 2011).

To account the unobserved heterogeneity in distracted driving by incorporating heterogeneity in the means and variances of random parameters, β_{in} is modeled to be a function of additional explanatory variables that influence its mean and variance as demonstrated (Seraneeprakarn et al. 2017; Behnood and Mannering 2017)

$$\beta_{in} = \beta + \delta_{in} Z_{in} + \sigma_{in} EXP(\omega_{in} W_{in}) v_{in} \tag{3}$$

Where, β is the mean parameter estimate across all distracted driving crashes, Z_{in} is a vector of explanatory variables that captures heterogeneity in the mean that affect drivers injury-severity level *i* (severe, minor and no injury), δ_{in} is a corresponding vector of estimable parameters, W_{in} is a vector of explanatory variables that captures heterogeneity in the standard deviation σ_{in} with corresponding parameter vector ω_{in}, and v_{in} represents a disturbance term.

A total of 200 Halton drawings were employed in this simulation approach due to its higher effectiveness and preference over random draws (Bhat 2003). This study estimates the marginal effect for all significant explanatory variables, which enables the assessment of how individual variable estimations influence the likelihood of distracted driving injury severity outcomes. The marginal effect quantifies the effect of a one-unit change in the chosen explanatory variable on the probability of injury severity outcomes while holding all other variables constant. The marginal effect for the kth indicator variable associated with injury severity level i for driver n (X_{ikn}) can be calculated by:

$$ME_{X_{ikn}}^{P_n(i)} = [P_n(i) = 1 \mid X_{ikn} = 1] - [P_n(i) = 1 \mid X_{ikn} = 0] \tag{4}$$

5. DISCUSSION OF ESTIMATED RESULTS

From the analysis, as shown in Table 3, ten unique variables were identified as significant across three injury severity categories (severe, minor, and no injury). Notably, the variable 'airbag deployment' was significant in both the 'No injury' and 'Minor injury' categories. Out of these ten variables, two were found to be random parameters with statistically significant means and standard deviations. Specifically, as per Table 3, the random parameters were 'Airbag deployment' for the 'Minor Injury' category and 'Driver Proximity to Residence' (within 25 miles of their home) for the 'No Injury' category.

Table 3: Estimated results of injury severity for mixed logit model

Variable	**Coefficient**	**T-Statistic**	**Marginal effects**		
			Severe Injury	**Minor Injury**	**No Injury**
Constant [SI]	-7.04763	-13.39***			
Constant [MI]	-2.64681	-10.11***			
Driver Characteristics					
Gender (1 if female, 0 otherwise) [NI]	-0.84311	-3.43***	0.0007	0.0205	-0.0212
Age (1 if driver age is less than 25 years old) [NI]	1.77923	7.17	-0.0010	-0.0347	0.0358
Crash Characteristics					
Collision Type (1 if rear-end, 0 otherwise) [SI]	-1.59146	-3.41***	-0.0049	0.0038	0.0011
Airbag (1 if the airbag deployed, 0 otherwise) [SI]	2.35322	4.15***	0.0124	-0.0092	-0.0032
Collision Type (1 if fixed-object, 0 otherwise) [MI]	1.76798	3.88***	-0.0012	0.0107	-0.0096
Airbag (1 if the airbag deployed, 0 otherwise) [MI]	1.91106	4.18***	0.0008	0.0130	-0.0122
(Standard Deviation of Parameter, Normally Distributed)	*(1.94798)*	*(2.18)* **			
Safety Equipment (1 if seatbelt use, 0 otherwise) [NI]	-2.58226	-9.25***	0.0052	0.1256	-0.1308
Accident-Specific Characteristics					
High Speed (1 if speed was greater than 55 MPH, 0 otherwise) [SI]	2.62176	4.97***	0.0139	-0.0102	-0.0036
Low Speed (1 if speed greater than 20 MPH but Less than 40 MPH, 0 otherwise) [NI]	0.73945	3.12***	-0.0002	-0.0124	0.0127
Driver Proximity to Residence (1 if within 25 Miles, 0 otherwise) [NI]	-2.12281	-4.82***	0.0008	0.0217	-0.0225
(Standard Deviation of Parameter, Normally Distributed)	*(3.01796)*	*(4.48)*			
Heterogeneity in the means of random parameter					
Airbag [MI]: Age greater or equal to 35 and less than 45	-1.57362	-2.22**	-	-	-
Driver Proximity to Residence [NI]: Male	1.31031	2.48**	-	-	-
Heterogeneity in the variance of random parameter					
Driver Proximity to Residence [NI]: Rear-end crash	0.74355	3.38***	-	-	-
Model Statistics					
Number of Observations	2690				
Restricted Log-Likelihood	-2955.267				
Log-Likelihood at Convergence	-1246.0096				
McFadden pseudo-*R*-squared (ρ^2)	0.5784				

Note: *Italic* value: Random parameter. [SI]: Severe injury, [MI]: Minor injury, [NI]: No injury. ***, **, * denotes significance at 1%, 5%, 10% level.

5.1 Random Parameters

The variable 'airbag deployment' in the 'Minor injury' category was found to be a random parameter that followed a normal distribution with a mean of 1.91106 and a standard deviation of 1.94798 (see Table 3). This indicates that in approximately 16.33% of the cases where airbags were activated during distracted driving events, the average effect of the parameter was negative. Conversely, the average effect was positive for 83.67% of the cases. Therefore, for 16.33% of drivers, airbag deployment reduced the likelihood of incurring a minor injury during distracted driving incidents. However, for the remaining 83.67%, airbag deployment had the inverse effect.

Similarly, the variable 'Driver Proximity to Residence' (within 25 miles of their home) in the 'No Injury' category exhibited characteristics of a random parameter. It was found to be random and normally distributed, with a mean of -2.12281 and a standard deviation of 3.01796. This distribution suggests that in cases where drivers were within 25 miles of their residence during distracted driving crashes, the average effect of the parameter was positive for a certain percentage of observations and harmful for the rest. Specifically, for approximately 24.09% of such cases, being close to one's residence increased the likelihood of sustaining no injuries during distracted driving events. Conversely, for the remaining 75.91%, being near one's home had the opposite effect, suggesting these drivers were more prone to sustaining injuries (the negative sign).

5.2 Heterogeneity in Means and Variance

The data in Table 3 reveals interesting insights into the impact of various explanatory variables on the mean and variance of random parameters in distracted driving crashes. Specifically, it was noted that individuals aged 35 to 45 and males had a sequential effect on the mean values of the Airbag and Driver Proximity to Residence random parameters. The variable “Age 35 to less than 45” was associated with a decrease in the mean of the airbag variable for minor injuries. This may indicate a correlation where drivers in this age group are less likely to sustain minor injuries in such events. The variable 'Male' was observed to be positively associated with the 'Driver Proximity to Residence' variable in instances of no-injury crashes, suggesting a correlation where male drivers are more often involved in no-injury crashes when these occur closer to their residence. However, it's important to note that this association does not imply causality. This could be capturing driving behaviors associated with male drivers especially in closer distances to their residence in comparison to female drivers.

The "Rear-end" variable was the only explanatory factor found to be significant in accounting for the variability in the variance of the random parameter related to the driver's proximity to residence in no-injury scenarios. This variable contributes to an increased variability of the 'Driver's Proximity to Residence' parameter. Specifically, this suggests a correlation where the likelihood of a driver avoiding injury in a rear-end collision seems to increase when the incident occurs closer to their residence. This could be capturing the risk taking behaviors of drivers close to home which is consistent with Burdett, Starkey, and Charlton (2017).

5.3 Driver Characteristics

The data reveals a negative correlation (-0.84311) between the presence of female drivers (Gender Variable) and the occurrence of no-injury crashes, suggesting a tendency for female drivers to be less frequently involved in crashes that do not result in injuries. However, the same data shows that female drivers have a higher likelihood of being involved in crashes resulting in severe or minor injuries. As indicated by the marginal effects (See Table 3), being a female driver increases the probability of experiencing serious injuries by 0.0007 and minor injuries by 0.0205. These findings, particularly concerning the context of cell phone use during driving, align with the results reported by Russo et al. (2014), although it's crucial to consider the differences in study design, population, and variables when making such comparisons. The observed trends warrant a cautious interpretation and highlight the need for a more in-depth understanding of the underlying factors that contribute to these gender differences in crash outcomes, especially in the context of distracted driving.

Conversely, for drivers under 25 years old, there is a positive correlation (1.77923) with no-injury crashes. This implies that the likelihood of these younger drivers not sustaining injuries in an accident increases by 0.0358, while the chances of incurring minor and severe injuries decrease. Factors contributing to this trend may include a lack of driving experience and a tendency for reduced risk-taking due to lower confidence. Additionally, greater physical resilience in younger individuals might lead to a higher incidence of non-injury outcomes compared to severe or minor injuries.

5.4 Crash Characteristics

Rear-end collisions are associated with a decrease in the probability of severe injuries but show an increase in the likelihood of minor and no injuries. This indicates that while rear-end collisions are common, they often result in less severe injuries. This is likely because such crashes typically occur in congested conditions where vehicles maintain lower speeds, leading to less severe impacts.

In contrast, collisions with fixed objects, increase the likelihood of minor injuries while reducing the chances of severe injuries and no injuries. This finding is consistent with Alnawmasi and Mannering (2022) who similarly identified the significance of fixed object collisions in causing minor injuries.

When an airbag is deployed during a distracted driving crash, the probability of severe injuries increases as indicated for the severe injury category (see Table 3). However, this same deployment slightly reduces the chances of minor injuries and no injuries, respectively.

Additionally, for the minor injury category, airbag deployment is associated with slight increase in minor injuries and a decrease in no-injury crashes. These findings imply that while airbag deployment can mitigate some injuries, it is also linked to a notable increase in severe injuries. The airbag's effect appears to have a degree of randomness, which can lead to minor injuries, as evidenced by the significant variation in the standard deviation of this parameter, suggesting it follows a normal distribution (See Table 3).

Wearing a seatbelt significantly reduces the risk of sustaining severe injuries in a crash and increases the likelihood of surviving without any injuries. This underscores the critical role of seatbelts in enhancing passenger and driver safety during vehicular accidents. However, there is a possibility that some drivers might develop a false sense of security when wearing a seatbelt, potentially leading to more aggressive driving behaviors. This could inadvertently result in more severe collisions as seen from the marginal effects.

5.5 Accident-Specific Characteristics

Driving at speeds greater than the posted speed limit of 55 MPH is associated with a higher probability of severe injuries, while it slightly decreases the likelihood of minor and no injuries (see marginal effects). This correlation between higher speeds and more severe outcomes is consistent with expectations, as higher velocities can worsen the impact and consequences of a crash. Conversely, adhering to posted speed limits, especially in zones with limits between 20 to 40 MPH, increases the probability of emerging from a crash without injuries and decreases the likelihood of severe and minor injuries. This outcome aligns with general traffic safety principles, as driving at lower, regulated speeds typically reduces the force of impact and the potential for injury severity in the event of an accident.

Being within 25 miles of one's residence slightly diminishes the probability of no injuries, yet it increases the odds for minor and severe injuries. Nevertheless, it is essential to acknowledge that this variable produced unpredictable parameters for the model, suggesting the presence of substantial variations in its effects on distracted driving crashes, as shown earlier.

6. CONCLUSION

This study investigated crash factors linked to distractions like cell phone use, utilizing data from the Oregon Department of Transportation from 2017 to 2020. It reviewed 2,690 distracted driving crashes and found 1.19% led to severe injuries, 35.69% to minor injuries, and 63.12% resulted in property damage only. Hot spot analysis was conducted and confirmed the visual inspection of crashes to cell coverage. In addition, the study acknowledges certain limitations, such as the absence of detailed information on the driver's physical condition or minor environmental variations at the time of the crash, which introduces "unobserved heterogeneity." To mitigate this, a mixed logit model for injury severity was estimated. The analysis shed light on several interesting findings. For instance, airbag deployment during a distracted driving incident heightens the chance of severe injuries by 0.99%. Conversely, rear-end collisions, despite being frequent, often culminate in less severe injuries. Safety equipment usage, particularly seatbelts, substantially mitigates injury, emphasizing their critical importance. Furthermore, younger drivers, those below 25 years, exhibited a higher likelihood of less severe injuries. These insights offer a comprehensive view of distraction-induced crashes, highlighting the need for targeted safety interventions.

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