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Understanding truck driver behavior with respect to cell phone use and vehicle operation

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ABSTRACT

Distracted driving continues to pose threats to transportation safety as it impairs driver performance and increases crash risk. In recent years, cell phone use while driving has become the primary research interest regarding distracted driving. However, the majority of this research has focused on the prevalence and risks of such behavior in passenger car drivers and few have investigated its effect on the performance of drivers of large trucks. Due to the inherent job responsibilities, truck drivers are more susceptible to use a cell phone, or other communication devices (e.g., CB radio), while driving to coordinate delivery logistics. The purpose of this study is to further understand distracted driving in the context of large trucks by identifying the factors that contribute to large truck drivers' decision to report using a cell phone while operating a commercial motor vehicle. Through survey data collected in 2017 from drivers of large trucks who either pick-up or deliver goods in the Pacific Northwest (Oregon, Washington, Idaho, British Columbia), a random parameters binary logit model is used to identify these factors. Of the 515 respondents, 234 (45%) indicated that they use a cell phone while driving. Through the random parameters binary logit model, unobserved heterogeneity is captured, and specific driver behaviors, demographic, work, temporal, and management characteristics are found to affect the likelihood of truck drivers reporting to use their cell phone while driving. Of particular interest, are carrier management characteristics and safety training. Carriers who manage fatigue by imposing schedules to make it easier to take breaks result in a decrease in probability of drivers reporting cell phone use, while carriers who restrict the number of hours worked decreased the probability of reporting cell phone use for the majority of drivers. In addition, having participated in road safety driving resulted in a decrease in probability of reporting cell phone use for the majority of drivers. Such findings have the potential to aid government agencies and commercial motor vehicle carriers in understanding the factors influencing cell phone use while driving among truck drivers. Understanding these motives can aid in the development of programs and policy initiatives that are intended to mitigate distracted driving among truck drivers.

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1. Introduction

As technology continues to penetrate and transform all aspects of society, there has been an increasing interest in understanding the effects of distracted driving, particularly due to cell phone use, on transportation safety (Farmer, Braitman, & Lund, 2010; Haigney, Taylor, & Westerman, 2000; Klauer, Dingus, Neale, Sudweeks, & Ramsey, 2006; Oviedo-Trespalacios, Haque, King, & Washington, 2017a; Stavrinos et al., 2013). This interest stems from an increase in distracted driving related crashes. In 2015, fatalities involving cell phone use throughout the United States increased from 385 in 2011 to 476, or 23.6 percent (National Center for Statistics and Analysis, 2017a). These values are grossly underreported due to a lack of methods and/or procedures to assess the culpability of a crash due to cell phone use while driving. Furthermore, traffic fatalities that were attributed to distracted driving had the largest percentage increase (8.8 percent) from 2014 than alcohol-impaired or speed-related fatalities (National Center for Statistics and Analysis, 2017a). Of special interest are fatalities involving large trucks crashes (vehicle weighting greater than 10,000 lb) which have continued to increase since 2009. In 2015, there were 4067 killed in crashes involving large trucks compared to 3380 in 2009; a 20% increase (National Center for Statistics and Analysis, 2017b).

Regarding economic impacts, distracted driving related crashes are quite significant. In 2010, distracted driving fatalities accounted for roughly $40 billion in economic costs and $123 billion in societal costs, which equate to 16 and 15 percent, respectively, of the total economic impacts and societal harm caused by motor vehicle crashes in 2010 (Blincoe, Miller, Zaloshnja, & Lawrence, 2015). With regard to large trucks, Zaloshnja and Miller (2007) estimated the average cost of (in 2005 USD) property damage only (PDO), non-fatal, and fatal crashes involving large trucks to be approximately $15,114, $195,258, and $3,604,518, respectively. In 2017 dollars, these values equate to about $19,500, $252,500, and $4,700,000, respectively (Bureau of Labor Statistics, 2017). These statistical and economic findings indicate a need for distracted driving research especially for cases where cell phone use while driving could be a leading factor, particularly for crashes involving large trucks.

Although there have been several efforts to understand large truck-involved crashes (Al-Bdairi & Hernandez, 2017; Al-Bdairi, Hernandez, & Anderson, 2018; Anderson & Hernandez, 2017; Pahukula, Hernandez, & Unnikrishnan, 2015), the relationship between cell phone use, distracted driving and large truck-involved crashes are not completely understood. This may be caused by the fact that in most distracted driving studies, data is derived from either naturalistic or simulator studies, which are both time and cost intensive, or crash data, which are retroactive in nature and typically results in significant amounts of unknown or missing information (Regan, Lee, & Young, 2008). Further, the majority of the efforts in understanding distracted driving have only been applied to passenger vehicles (Dingus et al., 2016; Klauer et al., 2006). Few studies, however, examined the prevalence and associated crash risk of distracted driving among commercial motor vehicles by combining and assessing naturalistic observation data sets on large truck drivers (Hickman & Hanowski, 2012; Olson, Hanowski, Hickman, & Bocanegra, 2009). While studies conducted by Hickman and Hanowski (2012) and Olson et al. (2009) provide insight into the frequency and crash risk of distracted driving among commercial motor vehicle drivers, they do not assess the contributing factors that influence truck drivers' decisions to use a cell phone, or participate in a secondary task, while driving.

Therefore, the objective of this study is to identify factors that influence truck drivers' decisions to report using electronic mobile devices while driving. To accomplish this, a stated-preference survey distributed in 2017 to drivers of large trucks who originate, are destined to, or pass through the Pacific Northwest (Washington, Oregon, Idaho, and British Colombia) is utilized. A random parameters binary logit modeling framework is then used and estimated to gain insights into the complex interactions between the factors captured through the survey and those unobserved factors (i.e., unobserved heterogeneity) that may be influencing cell phone use while driving. In doing so, this study seeks to provide additional insight into the prevalence of cell phone use by drivers of large trucks to aid government agencies and private carriers in identifying and/or developing potential countermeasures that can then be used to mitigate electronic device use while driving.

2. Literature review

Previous research on distracted driving has concluded that a consistent definition of the term has yet to be achieved. Still, multiple authors have determined that distracted driving is a result of attention being diverted away from the driving task to a competing activity that is not related to safe driving (Lee, Young, & Regan, 2008; Ranney, Mazzae, Garrott, & Goodman, 2000; Regan, Hallett, & Gordon, 2011; Young & Regan, 2007). Regan et al. (2011) developed a taxonomy of driver distraction that includes five sub-categories: restrictive, mis-prioritized, neglected, cursory, and diverted attention. These sub-categories consider driver inattention due to both driving and non-driving related activities, such as using a cell phone while driving, being consumed in internal thoughts, or reading a road information sign. Since driver distraction is a vast problem resulting from diverted attention, cell phone use while driving is a subset of a larger distraction problem; however, understanding its effects and the factors that lead individuals, or drivers of large trucks, to use cell phones while driving will significantly improve roadway safety.

While research on distracted driving by drivers of large trucks is scarce, the effects of cell phone use and driving have been widely studied in the context of passenger cars (Beanland, Fitzharris, Young, & Lenné, 2013; Caird, Willness, Steel, & Scialfa, 2008; Dingus et al., 2006, 2016; Haigney et al., 2000; McEvoy & Stevenson, 2007; Regan et al., 2008). In two naturalistic studies, cell phone use was present in about 23% of all crashes and near-crashes, and at least one form of driver inattention in as much as 78% of all safety critical events for passenger vehicles (Klauer et al., 2006; Regan et al., 2008). Although there is an association between crash occurrence and cell phone use, some studies have shown that talking or listening on a cell phone, either handheld or hands free, does not significantly increase the odds of being involved in a safety critical event (Hickman & Hanowski, 2012; Klauer et al., 2006). Still, subtasks of cell phone use, such as texting, emailing, or operating the phone, increases crash risk odds by at least 3.5 times and as high as 164 times (Hickman & Hanowski, 2012; Klauer et al., 2006). The increased association with cell phone use and safety critical events may be due to increased cognitive load caused by cell phone use while driving. These studies prove that driver distraction, particularly cell phone use, is a common occurrence on roadways and increases the chances of being involved in a safety critical event.

Turning to large trucks, naturalistic study data on drivers of large trucks had consistent findings with the results from passenger car studies in that 60% of all crashes and near-crashes in which the driver of the large truck was at-fault involved one secondary task (Olson et al., 2009). Data from the Large Truck Crash and Causation Study (LTCCS), which used police reports and interview information, is consistent with this finding and reports that 35% of truck-involved crashes involved some form of driver recognition error (this includes internal and external distractions) (Administration, 2005). Specifically, 12% of crashes where the large truck was assigned the critical reason for the crash was due to either internal or external distraction, or inattention (Administration, 2005). As mentioned previously, talking or listening on a cell phone, either handheld or hands free, does not significantly increase the likelihood of being involved in a safety critical event. However, among drivers of large trucks, complex cell phone tasks, such as texting or emailing, increases the odds of being involved in a crash or near-crash by 164 times. Further, engaging in either a complex tertiary task (interacting with dispatch device, dialing cell phone) or moderate tertiary task (use other electronic device, talk/listen to CB radio) increases the chances of being involved in a safety critical event by 10.34 and 1.30 times, respectively (Olson et al., 2009). The significant increase in crash risk for drivers of large trucks, prompts needed research to understand and reduce the effects of cell phone use on truck-involved crashes. Combined with the understanding that large truck-involved crashes are more severe than passenger car only crashes, and that truck drivers need to engage more frequently with electronic devices to perform their jobs, research in this area is needed to improve roadway safety.

Previous findings on distracted driving, for both passenger cars and truck drivers, are vital contributions to engineering safety, but their findings are limited. Data sources that derive from police crash reports are subjected to bias and significant amounts of unknown or missing information (Gordon, 2009). While naturalistic data observes drivers in real-time driving conditions, they are often time, cost, and data intensive. Additionally, the statistical measures used in these studies are limited and do not account for any unobserved heterogeneity in the data collection process or contributing factors to critical safety events. The results from these studies utilize simple statistical measures to determine either odds ratios of being involved in safety critical events or prevalence and frequency of driver distraction in vehicle crashes (Asbridge, Brubacher, & Chan, 2012; Dingus, Klauer, Neale, Petersen, Lee, Sudweeks, Perez, Hankey, Ramsey, & Gupta, 2006; Hanowski, Perez, & Dingus, 2005; Olson et al., 2009).

To overcome these shortcomings, few studies have ventured away from traditional distracted driving study methods to assess personal and behavioral information that influence cell phone use while driving (Kidd, Tison, Chaudhary, McCartt, & Casanova-Powell, 2016; Márquez, Cantillo, & Arellana, 2015; Oviedo-Trespalacios et al., 2017a). Márquez et al. (2015) and Oviedo-Trespalacios, King, Haque, and Washington (2017b) collected survey data regarding cell phone use while driving and used an integrated choice latent variable model, a mixed logit model, and a binary logit model to identify parameters influencing cell phone use while driving. Factors found in these studies, from the perspective of passenger car drivers' decisions to use a cell phone while driving, included age, driving experience, risk perception, and urgency of call. (Márquez et al., 2015; Oviedo-Trespalacios et al., 2017a). Additionally, Kidd et al. (2016) conducted roadside observations of motorists at different roadway characteristics, such as free-flow traffic, time-of-day, and at controlled intersections. The results of this study identified roadway and driver characteristics that affect the prevalence of any secondary behavior (Kidd et al., 2016). These studies are instrumental for improving roadway safety as they identify the contributing factors influencing cell phone use while driving and agencies can use this information to mitigate the occurrence of distracted driving by tailoring outreach initiatives to specific groups. Despite providing useful information, these studies have been limited to passenger car drivers and statistical models that do not account for unobserved heterogeneity.

One study, however, investigated the demographic and occupational characteristics of heavy-vehicle drivers that influence the likelihood of using a cell phone while driving. Troglauer, Hels, and Christens (2006) collected survey data from 1153 professional truck drivers in Denmark to determine the extent of phone use among heavy-vehicle drivers through an ordinal logistic regression model. Through this methodology, the study determined the odds of different demographic and occupational characteristics that lead to a higher prevalence of phone use among heavy-vehicle drivers. Additionally, this study reports that 99% of the respondents indicated that they use their cell phone while driving (Troglauer et al., 2006). Coupled with the fact that large truck-involved crashes are more severe than passenger car only crashes, this finding is disturbing being that cell phone use while driving has been proven to significantly increase crash risk (Chang & Mannering, 1999; Klauer et al., 2006). Although this study identifies certain driver characteristics that are more likely to use a cell phone while operating a heavy-vehicle, the statistical procedure used does not account for unobserved heterogeneity that is inherent in any survey data, which in turn results in erroneous estimates and corresponding inferences (Mannering, Shankar, & Bhat, 2016).

The present study will expand upon the work conducted by Oviedo-Trespalacios et al. (2017b), Márquez et al. (2015), and Troglauer et al. (2006) by collecting survey data distributed to drivers of large trucks who originate, are destined to, or pass through the Pacific Northwest (Washington, Oregon, Idaho, and British Colombia). By using a random parameters binary logit model to identify the factors that influence the likelihood that truck drivers' would report using a cell phone while driving, the present study will overcome the limitations of previous studies by accounting for unobserved heterogeneity (unobserved factors) present in the data collection process. By identifying the factors that lead to truck drivers using a cell phone while driving, commercial motor carriers and government entities can implement mitigation strategies tailored to specific groups that may reduce the occurrence of cell phone use while driving amongst large truck drivers. To the authors' knowledge, this study would be one of the first to use a random parameters methodology to determine the contributing factors that influence cell phone use among drivers of large trucks.

3. Data description

To determine the factors that influence a truck driver's decision to use a cell phone while driving, a stated-preference survey is developed and distributed to drivers of large trucks in 2017. This survey includes a total of 64 questions divided into eight parts: socioeconomic, business, driver, driving and accident characteristics, time of day operations, driving management, and truck configuration. In order to be considered for this study, truck drivers must have either originated in, or delivered goods, to the Pacific Northwest. Drivers who passed through the Pacific Northwest were also considered for this study. The survey was administered through Oregon State University and utilized the Qualtrics survey platform, an online electronic survey program. The survey, prior to distribution, obtained approval from the Institutional Review Board (IRB).

All respondents voluntarily completed the survey, were at least 18 years of age, and held a Commercial Driver's license (CDL). A total of 1919 individuals received the survey, but just 515 met the survey requirements and completed the survey. To determine the level of confidence that inferences can be made, the following equation is used (Smith, 2013):

$$n = \frac{z^2 \times p \times (1 - p)}{MoE^2} \tag{1}$$

where n is the sample size needed for desired level of precision; p is an estimated value of proportion; MoE is the desired margin of sampling error; and z is the critical value for the desired level of confidence. As a conservative estimate, which assumes half of the population will answer positively and negatively to a posed question, a p value of 0.5 is used in this study (Dillman, Smyth, & Christian, 2014). Further, a value of 4.5 was assumed as the desired margin of error. In most studies, it is desired to achieve a 95% confidence level. The corresponding z value for this level of confidence is 1.96. Applying these values to Eq. (1), it is determined that 475 responses are needed to ensure 95% confidence. With 515 valid and completed responses, this study exceeds this minimum requirement. In other words, parameter estimates and inferences can be made with well over 95% confidence.

Of specific interest to this study is the following question:

Do you use a cell phone while driving? (Either handheld or hands-free)

This question presented a binary choice to respondents as they were required to respond with either *yes* or *no.* Fig. 1a shows the frequency of respondents that responded *yes* or *no* to using a cell phone while driving. This finding is consistent with past studies that determined about 50% of surveyed respondents use a cell phone while driving (Nurullah, Thomas, & Vakilian, 2013; Schroeder, Meyers, & Kostyniuk, 2013).

To corroborate on the increased crash risk associated with cell phone use while driving, self-reported crash history was disaggregated based on cell-phone use. In the survey, respondents were asked, *"During the last 5 years how many accidents have you had in which the police had to attend?"* Respondents had to respond with either one, two, three, four or more, or none. The initial survey analysis, as shown in Fig. 1b, revealed that 24% of respondents indicated that they were involved in at least one crash in the past five years in which the police had to attend. Of these respondents who indicated being involved in at least one crash in the past 5 years, 57% also reported that they use their cell phone while driving. As shown in Fig. 1c, the number of crashes reported by those who use their cell phone while driving is about 31% more than those who were involved in a crash and did not report cell phone use while driving. A t-test was conducted between these two groups and determined a statistically significant difference at the 99th percentile. Since the question was posed to the general use of cell phones while driving, this initial data comparison compliments the findings of Olson et al. (2009) and Klauer et al. (2006) that using a cell phone while driving leads to higher crash involvement.

Descriptive statistics of these 22 significant variables, as well as the dependent variable, are shown in Table 1.

4. Methodology

As mentioned previously, the binary logit modelling framework has been applied in various areas of transportation engineering (Lee & Abdel-Aty, 2008; Moudon, Lin, Jiao, Hurvitz, & Reeves, 2011; Oviedo-Trespalacios et al., 2017a; Young & Liesman, 2007), in which Anderson, Hernandez, Jessup, and North (2018) have recently and successfully applied this

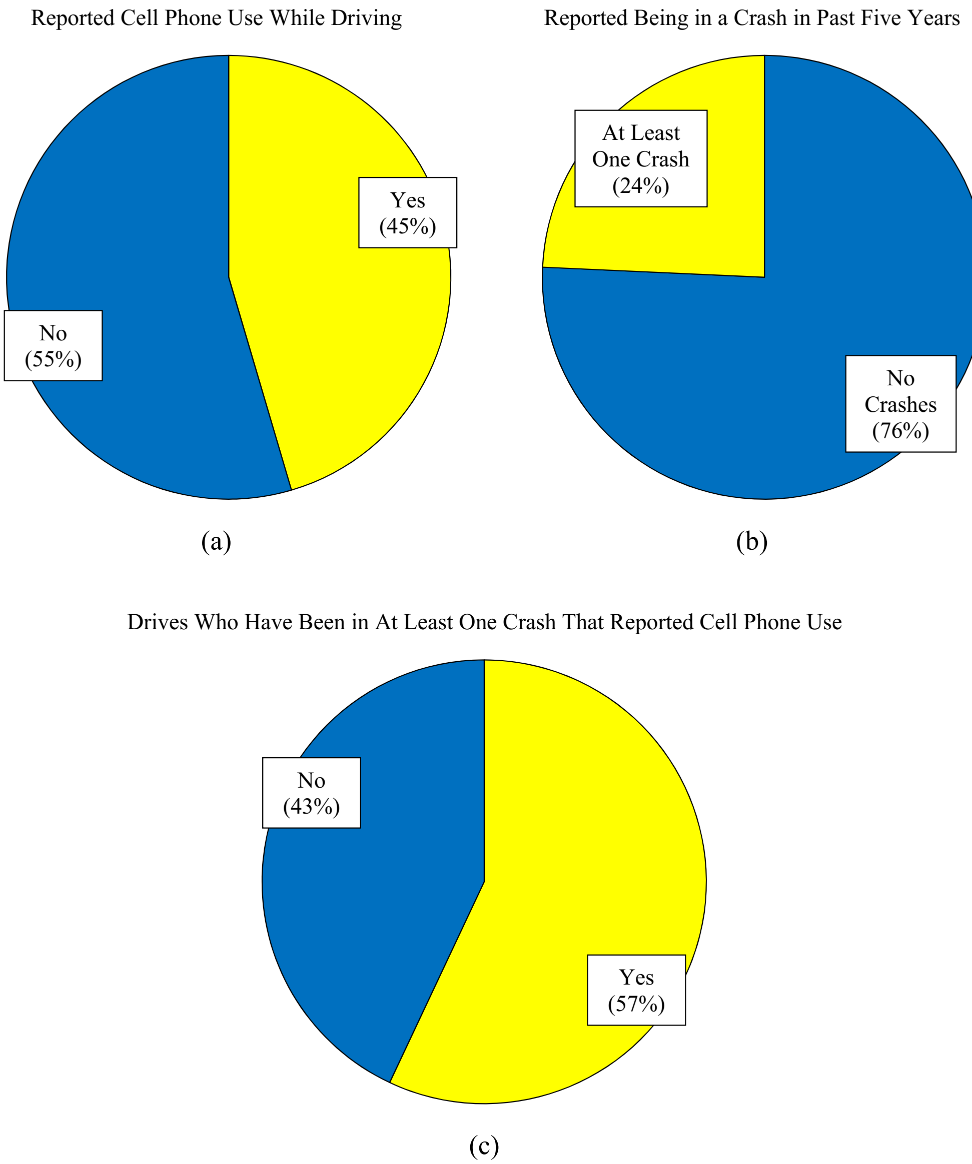

Fig. 1. (a) Proportion of truck drivers who reported using their cell phone while driving, (b) proportion of truck driver who reported being in crashes in the past five years where the police had to attend, and (c) proportion of truck drivers who reported being involved in at least one crash in the past five years that reported cell phone use.

framework to truck driver survey data. Further, studies have expanded on the traditional logit modelling framework by utilizing a random parameters, or mixed logit, methodology to account for unobserved heterogeneity in the data (Anderson & Hernandez, 2017; Islam, Jones, & Dye, 2014; Milton, Shankar, & Mannering, 2008; Morgan & Mannering, 2011; Pahukula et al., 2015). In this study, the use of a cell phone while driving is a binary choice; either the driver used a cell phone while driving or the driver did not. Finally, since the survey data has inherent unobserved heterogeneity, a random parameters binary choice modelling framework is an appropriate technique for assessing drivers' decisions on using a cell phone while driving.

Due to the binary nature of the selected response variable, a binary logistic regression model is applied. The two possible outcomes for the response variable are represented by the following: 1 if a driver reports using a cell phone while driving, and 0 otherwise (driver does not report using their cell phone while driving). The following binary logit formulation is used to estimate the probability that the outcome takes the value of 1 (using cell phone while driving) as a function of covariates (McFadden, 1973; Washington, Karlaftis, & Mannering, 2011):

Table 1
Descriptive statistics of significant variables.

Variable	Mean	Standard deviation
Dependent variable		
Cell phone use (1 if driver reports using a cell phone - either handheld or hands-free - while driving, 0 otherwise)	0.45	0.50
Driver characteristics		
Age (1 if between 18 and 25, 0 otherwise)	0.16	0.36
Marital status (1 if single, 0 otherwise)	0.26	0.44
Income (1 if between $50,000 and $60,000, 0 otherwise)	0.28	0.45
Crash history (1 if involved in at least one crash in the past 5 years, 0 otherwise)	0.24	0.43
Safety training (1 if participated in road safety training, 0 otherwise)	0.87	0.33
Work characteristics		
Private carriage (1 if present employer is operated under private carriage, 0 otherwise)	0.35	0.48
Start work (1 if work starts between 12:00 a.m. and 6:00 a.m., 0 otherwise)	0.11	0.32
Start work (1 if work starts between 10:00 a.m. and 4:00p.m., 0 otherwise)	0.26	0.44
Rural roads[1] (1 if routes are usually driven on rural roads, 0 otherwise)	0.05	0.22
City roads[1] (1 if routes are usually driven on city roads, 0 otherwise)	0.05	0.22
Truck parking (1 if driver decides parking location, 0 otherwise)	0.78	0.41
Trailer (1 if truck is driven very often with two trailers, 0 otherwise)	0.10	0.31
Temporal characteristics		
Most difficult hour finding safe truck parking (1 if afternoon, 0 otherwise)	0.15	0.36
Driving behavior		
Driving while tired (1 if often, 0 otherwise)	0.47	0.50
Never change lanes to avoid travelling with passenger vehicle behind (1 if yes, 0 otherwise)	0.33	0.47
Driving break (1 if a stop is made every 4–6 h on a longer trip, 0 otherwise)	0.33	0.47
Truck inspection (1 if driver inspects truck before starting each trip, 0 otherwise)	0.46	0.50
Management characteristics		
Fatigue management (1 if schedule imposed by carrier makes it easier to take a break, 0 otherwise)	0.29	0.45
Driving hours management (1 if carrier restricts the number of hours worked per week, 0 otherwise)	0.49	0.50

[1] Note: Drivers were asked about four routes, in which two were found to be significant.

$$P_n(i) = \frac{e^{(\widehat{\beta})}}{1+e^{(\widehat{\beta})}} \text{where} \widehat{\beta} = \beta_0 + \beta_1 X_{1,n} + \cdots + \beta_i X_{i,n} \tag{2}$$

where $P_n(i)$ is the probability that a truck driver uses their cell phone while driving (i.e., the outcome takes on the value 1); $\widehat{\beta}$is a vector of estimated parameters; and, X is a vector of explanatory variables (i.e., indicator variables coded from the survey data).

One shortfall of survey data is that responses can potentially have unobserved heterogeneity, or variation, across drivers. Within the data, there exists a significant amount of information that affects the likelihood of using a cell phone while driving and is not capable of being measured for analysis. Information, such as type of driver behavior (i.e., aggressive vs. passive), forgetfulness, and reporting false information (i.e., indicate no cell phone use while driving to comply with laws and policies) are possible unobserved factors that can affect model results for cell phone use while driving. However, these unobserved factors are not captured in the data through the survey responses. This inherent limitation of survey data will result in erroneous model estimates and, therefore, inferences if this unobserved heterogeneity is not accounted for in the model (Mannering et al., 2016). To account for potential heterogeneity within the data, a random parameters methodology is applied to allow estimated parameters to vary across observations. Eq. (1) can now be written as (Washington et al., 2011):

$$P_n(i|\varphi) = \int_X \frac{e^{(\widehat{\beta})}}{1+e^{(\widehat{\beta})}} f\left(\widehat{\beta}|\varphi\right) d\widehat{\beta} \tag{3}$$

where $P_n(i|\varphi)$ is the weighted average of $P_n(i)$ taking on the value of 1 determined by the density function, $f\left(\widehat{\beta}|\varphi\right)$. The density function, $f\left(\widehat{\beta}|\varphi\right)$, is a given distribution determined by the analyst (i.e., normal, uniform, triangular, etc.) that enables β to account for driver-specific variations of the effects of X on outcome probabilities, $P_n(i|\varphi)$ (Washington et al., 2011). Although the density function $f\left(\widehat{\beta}|\varphi\right)$ can utilize different distributions, only the normal distribution is found to be statistically significant (based on significance of the standard deviations) and used in the current study. To simulate maximum likelihood estimation of the random parameters binary logit model, 200 Halton draws are used, as they have been proven to be computationally efficient and preferred over purely random draws (Bhat, 2003; Halton, 1960; Train, 2000).

Lastly, marginal effects are used to measure variable impact on the use of cell phone while driving. Marginal effects measure the change in outcome probability due to a one-unit increase in an explanatory variable while holding all variables constant (equal to their means). This provides the analyst with an absolute change in probability on the outcome due to an explanatory variable. In this study, only indicator variables are found to be significant. As such, marginal effects are computed as the difference in probability as indicator variable X_k changes from zero to one while all other variables remain equal to their means (Greene, 2012):

$$ME_{X_k}^{P_n(i)} = \text{Prob}[P_n(i) = 1|X_k = 1] - \text{Prob}[P_n(i) = 1|X_k = 0] \tag{4}$$

4.1. Test for model significance

A likelihood ratio test (LRT) was utilized in this study to determine if the random parameter binary logit model is of more significance than the fixed parameter binary logit model.. The log-likelihood ratio test is defined as (Washington et al., 2011):

$$\chi^2 = -2\left[LL_{fix}\left(\beta^{fix}\right) - LL_{ran}(\beta^{ran})\right] \tag{5}$$

where

χ^2 :chi-square statistic with degrees of freedom equal to the number of random parameters
$LL_{fix}\left(\beta^{fix}\right)$: log-likelihood at convergence of fixed parameter binary logit model
$LL_{ran}(\beta^{ran})$: log-likelihood at convergence for random parameter binary logit model.

The LRT is used in this study to test the hypothesis that the random parameters logit model is statistically more significant than the fixed parameters logit model.

5. Results and discussion

To estimate the random parameter binary logit model, only variables that were significant at the 95% confidence level were retained. Computed log-likelihood and Akaike information criteria (AIC) values were used to assess model improvement. With these criteria, the final model included 16 fixed parameters (i.e., the variables are homogeneous across drivers) and seven random parameters (i.e., the variables are heterogeneous across drivers). Results of this final model are shown in Table 2, which include model specifications and corresponding marginal effects

5.1. Model significance

Results of the LRT, Eq. (5), determined that the random parameters binary logit model is statistically superior over its fixed parameters counterpart with over 90% confidence. The log-likelihood at convergence of the fixed and random parameters binary logit models were -304.53 and -298.47, respectively. The resulting chi-square statistic is 12.12, with seven degrees of freedom, which is equal to the number of random parameters. The associated p-value for this statistic is 0.0967, which suggests that, with over 90% confidence, the null hypothesis can be rejected and the random parameters model is statistically preferred over the fixed parameters model. Further, this result indicates that there is indeed variation across drivers regarding specific characteristics that impact a driver reporting to use a cell phone (or not). In addition, the McFadden Pseudo R-Squared value of 0.16 indicates the presented model is of adequate fit (McFadden, 1973, 1977, 1981).

5.2. Variable discussion

The best fitted random parameter binary logit model determined that driver, work, temporal, and management characteristics, as well as driver behavior, all influenced the probability of a truck driver's decision to report using a cell phone while driving. Understanding these factors can assist transportation agencies and carriers in identifying and developing policies and programs that aim to mitigate distracted driving among truck drivers.

5.2.1. Driver characteristics

Younger truck drivers, drivers between the ages of 18 and 25, were found to have a random and normally distributed parameter based on the statistical significance of the standard deviation. With a mean of -1.52 and a standard deviation of 5.20, 38.5% of drivers in this age group have an estimated parameter mean greater than zero and 61.5% this driver demographic have an estimated parameter mean less than zero. In regards to the 38.5% of drivers that are more likely to report using their cell phone while driving, this finding is consistent with passenger car research that finds younger passenger car drivers more likely to uses their cell phones while driving than other age groups (Farmer et al., 2010; Gliklich, Guo, & Bergmark, 2016; Oviedo-Trespalacios et al., 2017a; Young & Lenné, 2010). On the other hand, 61.5% of drivers between 18 and 25 are less likely to report using their cell phone while operating a truck. The heterogeneous nature of this variable may be capturing differences in job experience among younger truck drivers. For instance, if a truck driver falls within this age demographic and has minimal truck driving experience, they might be less likely to use their cell phone while driving because they are still learning to operate their truck. Contrarily, a small portion of drivers within this age group might have slightly more experience operating a truck and are more likely to report using their cell phone while driving.

Table 2
Final binary logit specifications and marginal effects.

Variable	Coefficient	Std. error	Marginal effect
Constant	-4.18^{***}	0.78	
Driver characteristics			
Age (1 if between 18 and 25, 0 otherwise)	-1.84^{***}	0.51	−0.357
(Standard Deviation of Parameter, Normally Distributed)	*(1.41)* **	*(0.59)*	
Marital status (1 if single, 0 otherwise)	-3.79^{***}	0.63	−0.735
(Standard Deviation of Parameter, Normally Distributed)	*(10.86)* ***	*(1.51)*	
Income (1 if between $50,000 and $60,000, 0 otherwise)	0.69^{**}	0.35	0.133
(Standard Deviation of Parameter, Normally Distributed)	*(5.83)* ***	*(0.82)*	
Education (1 if completed trade school or technical certificate, 0 otherwise)	-0.68^{**}	0.35	−0.133
Crash history (1 if involved in at least one crash in past 5 years, 0 otherwise)	1.10^{***}	0.35	0.212
Safety training (1 if participated in road safety training, 0 otherwise)	2.08^{***}	0.48	0.403
(Standard Deviation of Parameter, Normally Distributed)	*(0.94)* ***	*(0.23)*	
Work characteristics			
Private carriage (1 if present employer is operated under private carriage, 0 otherwise)	-0.69^{**}	0.30	−0.134
Start work (1 if work starts between 10:00 a.m. and 4:00 p.m., 0 otherwise)	2.29^{***}	0.55	0.444
Start drive (1 if drive starts between 12:00 a.m. and 6:00 a.m., 0 otherwise)	0.74^{**}	0.34	0.144
(Standard Deviation of Parameter, Normally Distributed)	*(2.76)* ***	*(0.52)*	
Rural roads (1 if routes are usually driven on rural roads, 0 otherwise)	3.99^{***}	0.81	0.773
City roads (1 if routes are usually driven on city roads, 0 otherwise)	1.91^{***}	0.73	0.369
Truck parking (1 if driver decides parking location, 0 otherwise)	2.06^{***}	0.42	0.398
(Standard Deviation of Parameter, Normally Distributed)	*(2.83)* ***	*(0.38)*	
Trailer (1 if truck is driven very often with two trailers, 0 otherwise)	2.45^{***}	0.56	0.475
Temporal characteristics			
Most Difficult Day of the Week Finding Safe Parking (1 if Tuesday, 0 otherwise)	1.48^{***}	0.36	0.287
Most Difficult Hour Finding Safe Truck Parking (1 if afternoon, 0 otherwise)	1.52^{***}	0.46	0.294
Driving behavior			
Driving while tired (1 if often, 0 otherwise)	1.41^{***}	0.31	0.274
Never change lanes to avoid travelling with passenger vehicle behind (1 if yes, 0 otherwise)	1.07^{***}	0.33	0.207
Driving break (1 if a stop is made every 4 h to 6 h on a longer trip, 0 otherwise)	1.54^{***}	0.34	0.299
Truck Inspection (1 if driver inspects truck before starting each trip, 0 otherwise)	0.94^{***}	0.29	0.182
Management characteristics			
Fatigue management (1 if schedule imposed by carrier makes it easier to take a break, 0 otherwise)	-2.07^{***}	0.39	−0.401
Driving hours management (1 if carrier restricts the number of hours worked per week, 0 otherwise)	-1.98^{***}	0.36	−0.384
(Standard Deviation of Parameter, Normally Distributed)	*(5.10)* ***	*(0.66)*	
Model summary			
Number of observations	515		
Log-likelihood at zero	−354.82		
Log-likelihood at convergence (fixed)	−304.09		
Log-likelihood at convergence (random)	−298.47		
McFadden pseudo R^2	0.16		

The bold italics represent the catergory under which the proceeding variables fall under.

Single marital status was another variable found to have a random and normally distributed parameter. The mean for this parameter was −3.65 with a standard deviation of 8.97 resulting in the estimated parameter mean being greater than zero for 34.2% of drivers and less than zero for 65.8% of the drivers. In other words, 34.2% of single truck drivers are more likely to report using their cell phone while driving and 65.8% behave differently (i.e., less likely to self-report). One possible explanation for this non-homogenous nature is that the random parameter might be capturing unobserved differences for the need to use a cell phone while driving. According to Sarkisian and Gerstel (2015), single individuals are more likely to socialize and exchange help with friends/neighbors and exchange more support with their parents than individuals that are married. In this study, a proportion of single respondents may be more socially active than others, which prompts the need, or desire, to use a cell phone while driving a large truck, despite the inherent risks and associated fines if caught.

The next driver characteristic found to be significant is driver income, particularly those who reported earning between $50,000 and $59,999. This estimated parameter was found to be random and normally distributed with a mean and standard deviation of 0.75 and 7.63, respectively. This finding suggests that the estimated parameter mean is less than zero for 46.1% of drivers and greater than zero for 53.9% of drivers. The latter finding is consistent with past studies, in which participants in higher income brackets were more likely to use their cell phone while driving (Nurullah et al., 2013). The heterogeneity in this variable might be explained by the difference in perception of possible fines due to using a cell phone while driving. Some drivers within this income range may not be affected by the financial impact of a fine, whereas others are attempting to minimize any unnecessary costs.

The last driver characteristic found to be significant, also with a significant random and normally distributed parameter, was safety training. With a mean of 1.72 and a standard deviation of 1.13, the estimated parameter mean for drivers who previously had some form of safety training is less than zero for 6.4% of drivers and greater than zero for 93.6% of drivers.

That is to say, just 6.4% of drivers who received some form of safety training are less likely to report using their cell phones while driving. As studied by Gregersen (1996), there is a relationship between training strategies and overestimation of driving skill among young drivers. This notion of overestimating one's driving ability due to the training received may explain why almost all drivers (93.6%) have an increased outcome probability of self-reporting cell phone use while driving. For instance, in a driving safety course, a driver might be taught to improve their skills, which leads them to believe that they can handle driving situations better than expected (Gregersen, 1996). This is supported by past research that self-efficacy of driving is a significant predictor of distracted driving (Hill et al., 2015). If the goal is to eliminate cell phone use among truck drivers, this finding suggests that training programs should focus on more than just developing driver skills (i.e., source and consequences of distracted driving) as it may result in an overestimation of their driving abilities. The remaining proportion of drivers who have a decreased outcome probability of reporting cell phone use may not be affected by safety trainings and continue to limit their exposure to risky driving behaviors.

Regarding the driver, crash history was the final factor found to be significant in the model, where crash history decreases the likelihood of self-reporting cell phone usage while driving. Marginal effects show that those who indicated being involved in at least one crash in the past 5 years have a 0.214 increase in self-reporting probability of using a cell phone while driving. This finding is consistent with past research that found drivers who have been involved in a crash are more likely to self-report texting while driving (Jashami, Abadi, & Hurwitz, 2017). Being involved in a crash may be considered as a form of reckless driving and explain why this parameter increases the self-reported likelihood of using a cell phone while driving.

5.2.2. Work characteristics

Of the work characteristics found to be significant, the estimated parameters for truck parking decisions and the time the driver reported staring work are found to be random and normally distributed. With a mean of 2.27 and a standard deviation of 2.87, the estimated parameter mean for drivers who make their own parking decisions is less than zero for 21.5% of drivers and greater than zero for 78.5% of drivers. In other words, 21.5% of drivers who make their own parking decisions are less likely to report using their cell phone while driving and 78.5% are more likely. A proportion of drivers (78.5%) who make their own parking decisions may not be familiar with safe and adequate parking locations along their route and must use their cell phone to identify possible locations (e.g., call employer, call information services, check truck parking applications/websites). In opposition, a proportion of drivers (21.5%) may be familiar with safe and adequate parking facilities along their route; therefore, these drivers are less likely to use their cell phone for such purposes.

In regards to starting work early in the morning (between 12:00 a.m. and 6:00 a.m.), the estimated parameter mean is less than zero for 33.6% of drivers and greater than zero for 66.4% of drivers and. That is to say, 33.6% of drivers who start work in the early morning are less likely to report using their cell phone, but 66.4% are more likely to report engagement in the secondary task. This variation among drivers may be attributed to the variation in traffic flow and density at various times and locations during the morning that defer cell phone use while driving. For example, if traffic volumes are high and require full driver attention, the driver is less likely to use their cell phone. However, if traffic volumes are low, this may lead to cell phone usage for some drivers. This finding is consistent with past research that suggests engagement in secondary tasks while driving is influenced by low driving hazards, such as traffic volume (Oviedo-Trespalacios et al., 2017a).

Although not found to be random, drivers who begin work midday (between 10:00 a.m. and 4:00 p.m.) were found to be statistically significant and increase the self-reporting probability of using a cell phone while driving. Marginal effects suggest a 0.503 increase in probability in reporting using a cell phone while driving for those who start work midday. This finding is plausible, as traffic during midday is typically less congested than morning commute times (i.e., 7:00 a.m. to 9:00 a.m.) or afternoon peak hour times (5:00 p.m. to 7:00 p.m.). During these times, driving tasks are less demanding due to lower traffic volumes and fewer interactions between other vehicles. This result compliments past research on cell phone usage among passenger car drivers, where Kidd et al. (2016) showed that drivers are at increased odds of engaging in any secondary behavior during the afternoon.

Drivers who report primarily using city roads or rural roads for their routes are found to have an increased probability of reporting cell phone use while driving. For city and rural roads, marginal effects show a 0.451 and 0.765 increase in probability, respectively. roads and rural roads, compared to highways or interstates, experience lower traffic volumes and drivers may feel more comfortable using their cell phones in these roadway environments. As mentioned previously, engagement with secondary tasks are influenced by the roadway environment (Oviedo-Trespalacios et al., 2017a). In addition, drivers who primarily use city roads or rural roads are likely to be near their destination (e.g., retail business or warehouse distribution center) and may need to communicate with the recipient of the delivered goods.

Regarding truck configuration, drivers who report driving a truck with two trailers often were found to have an increase in probability of self-reporting cell phone use. Marginal effects indicate that the probability of reporting cell phone use increases by 0.489. One possible explanation for this finding is that two-trailer trucks are intended to carry a higher volume of goods and this increased amount may require drivers to coordinate the delivery with one or more recipients.

Lastly, drivers working for a private carriage are found to have a 0.181 probability decrease in self-reporting cell phone use according to marginal effects. Private carriers may impose strict safety policies that discourage risky driving behaviors among their operators so that they can maintain a high safety rating. A high safety rating would expand these carriers' client base.

5.2.3. Temporal characteristics

Drivers who reported having difficulty finding safe and adequate truck parking in the afternoon have an increase in probability of reporting using their cell phones while driving. Marginal effects for these drivers show a 0.326 increase in probability for reporting cell phone use. This finding is plausible as parking difficulties, especially when nearing hours of service limitations, may force drivers to use their phones to communicate with their employer or access an application/website to identify other safe parking locations along their route. This notion is supported by Anderson et al. (2018) who find that receiving real-time information lowers the probability of encountering trouble when locating safe and adequate truck parking. Using a cell phone while driving may be a way to receive such information and counteract truck parking difficulties.

5.2.4. Driving behavior

Regarding truck driver behavior and its influence on cell phone use while driving, several characteristics were found to be significant and increase the outcome probability of a driver reporting using a cell phone while driving. The probability of drivers who report using their cell phones while driving increases by 0.310, according to marginal effects, for those who often drive while tired. Driving while tired, or fatigued, has been proven to increase crash risk and result in higher levels of injury severities (Bunn, Slavova, Struttmann, & Browning, 2005). Because of these safety risks, truck drivers may adopt strategies to combat the effects of fatigue, such as using a cell phone. According to Gershon, Shinar, Oron-Gilad, Parmet, and Ronen (2011), professional drivers perceive talking on a cell phone while driving as an effective countermeasure to driver fatigue. This may explain why the surveyed respondents who often drive while tired are more likely to report using a cell phone while driving.

Similarly, drivers who take a break every four hours to six hours on a longer haul are more probable to report using their cell phones while driving. Marginal effects for this variable indicate a 0.276 increase in probability of reporting cell phone use. This finding is consistent with Oviedo-Trespalacios et al. (2017b) who determined that, among passenger car drivers, every additional hour driven per day increases the likelihood of reporting using a cell phone while driving. Truck drivers may exhibit similar driving behavior and this might explain why those who take breaks every four hours to six hours are more likely to report using their cell phone while driving.

Further, drivers who never change lanes when a passenger vehicle is behind them were found to have an increased probability of reporting cell phone use while driving, as marginal effects show a 0.193 increase in probability. Studies have shown that when drivers use their cell phones while driving, they adopt compensatory driving behaviors, such as decreased speed or increased headway, to account for the added cognitive demand from the cell phone (Oviedo-Trespalacios et al., 2017; Young & Lenné, 2010; Zhou, Yu, & Wang, 2016). With passenger cars behind the truck, truck drivers are more capable of dictating their speed and headway than when following other vehicles. This driving situation can allow drivers to use their cell phones and perform compensatory driving behaviors.

Lastly, those who inspect their trucks before starting each trip were found to have a higher probability of reporting using their cell phone while driving. As measured by marginal effects, these drivers have a 0.162 increase in probability of reporting cell phone use. Drivers who inspect their trucks before every trip may feel that their vehicle is safe and mechanically sound and overestimate their ability to avoid being involved in safety critical events even when using a cell phone while driving.

5.2.5. Management characteristics

Two carrier management characteristics, particularly those aimed at fatigue and hours of service, were found to be significant and decrease the probability of reporting cell phone usage while driving. One variable, carriers who restrict the number of hours worked per week, was found to have a random and normally distributed parameter. With a mean of -1.90 and standard deviation of 4.97, the estimated parameter mean is greater than zero for 35.1% of drivers and less than zero for 64.9% of drivers. This discrepancy among drivers may be capturing the ineffectiveness of such policies in mitigating fatigue. For instance, because weekly hours are restricted, some drivers may elect to drive for 8 consecutive hours before taking a break, which is allowed under the FHWA's HOS regulations; but, this may increase the likelihood of feeling fatigue effects. As mentioned previously, professional drivers perceive that talking on a cell phone is an effective countermeasure to driver fatigue (Gershon et al., 2011). On the other hand, some drivers may only drive for a short period before taking a break, which minimizes the likelihood of feeling fatigued. This may explain the heterogeneity in reporting cell phone usage while driving among drivers who work under weekly hour restrictions. This may suggest that more specific regulations, such as restricting the number of consecutive hours driven, may be more effective in reducing distracted driving among truck drivers.

Similarly, drivers who operate under carriers that manage fatigue by creating schedules that allow drivers to take breaks easily were found to have a decreased probability of reporting cell phone use while driving. Marginal effects show a 0.467 decrease in probability of reporting cell phone use. Because professional drivers perceive talking on a cell phone while driving mitigates the effects of driver fatigue, easily taking breaks when fatigued may explain why drivers are less likely to report using their cell phones while driving (Gershon et al., 2011). If drivers can easily take breaks when fatigued, they do not have to rely on using their cell phones while driving to combat the effects of driver fatigue. Additionally, being able to take breaks easily allows drivers to pull over at a rest stop, or other safe location (e.g., private truck stop), when they need to use their cell phone.

6. Conclusion and future work

Literature regarding the relationship between cell phone use and large truck crashes is sparse. As such, the current study is one of the first attempts at understanding this critical relationship. Unlike traditional studies that investigate the relationship between passenger car crashes and cell phone use, this study collected data through a stated-preference survey distributed to truck drivers who deliver goods in the Pacific Northwest (Oregon, Washington, Idaho, and British Columbia) to investigate the relationship of drivers of large trucks and cell phone use. The survey solicited information regarding driver socioeconomic characteristics, crash history, driver behavior, and management strategies. From this data, a random parameters binary logit model was utilized to determine contributing factors that influence a driver's decision on whether or not to report using a cell phone while driving. The influential factors that have been determined to either increase or decrease cell phone use probability among truck drivers can be leveraged to reduce the frequency of distracted driving and, as such, improve roadway safety for all users.

Contributing factors to truck drivers' decisions to report cell phone use while driving include: driver, work, temporal, and management characteristics, as well as driving behaviors. More specifically, age, single marital status, education, crash history, fatigue management, and driving hours management were all found to decrease the probability of truck drivers' decisions on reporting cell phone use while operating their large vehicle. From a policy standpoint, policies can be enacted at the strategic operating level of private carriers to address factors that influence cell phone use among truck drivers. For instance, this study shows that factors related to fatigue and driving hours management, such as restricting the number of hours worked or schedules that enable drivers to easily take breaks when fatigued, are effective methods to reduce the likelihood that a truck driver would use their cell phone while driving. As shown, carriers that restrict the number of hours worked per work is an ineffective policy in mitigating cell phone use while driving. This finding can support other means of restricting driving hours, such as the amount of consecutive hours driven before taking a break. Carriers can develop and enforce similar policies within their company to reduce the occurrence of distracted driving among their truck drivers.

Further, income level, safety training, difficulty finding safe parking, and various driving behaviors (driving while tired, frequency of breaks) were found to increase the probability of truck drivers reporting cell phone use while driving. As mentioned, safety training programs may cause an overestimation of drivers' ability to operate a large truck and lead to increased self-efficacy of driving (Gregersen, 1996; Hill et al., 2015). In addition to developing driving skills, future safety training programs can include topics that highlight the sources and safety implications of distracted driving. Additionally, government agencies can reduce the likelihood that truck drivers would use their cell phone while driving by addressing truck parking shortages. In 2012, the Federal Highway Administration determined that there is a severe and widespread truck parking shortage in the U.S. (Administration, 2012). Considering this shortage, Anderson et al. (2018) found that receiving real-time information, through GPS or other smartphone applications, would help truck drivers find safe and adequate parking. If truck drivers can find truck parking locations without difficulty, they may be less inclined to use their cell phone while driving and reduce their crash risk.

Although this study provides new insights into the relationship between cell phone use and truck driver behavior, there are some inherent limitations. Because this study assesses self-reported cell phone use while driving, it is subjected to the possibility of inaccurate responses by truck drivers. Respondents may not have truthfully reported if they use a cell phone and thus may lead to inaccurate responses. However, the results from this study provide significant insight into possible factors that influence cell phone use while driving among truck drivers and investigates the relationship between truck drivers and distracted driving. Additionally, the results from this study cannot be extrapolated beyond drivers who deliver or pick up freight in the Pacific Northwest. Future studies can use the same methodology but to a larger region via a random sampling process to generalize results. Additionally, there may be other driver and environmental factors that influence the probability of a truck driver using a cell phone while driving that were neither captured in this survey nor found to be significant in these results. Future studies should tailor survey questions around the idea of distracted driving among truck drivers that examines their interactions with all varieties of electronic mobile devices within the cab of a truck (ELD, CB Radio, GPS devices, etc.). These additional survey questions can further expand the understanding of distracted driving and large-truck drivers.

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Appendix A. Supplementary material

Supplementary data to this article can be found online at https://doi.org/10.1016/j.trf.2019.07.010.

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