

**PREDICTING TRUCK DRIVERS' CRITICAL EVENTS: EFFICIENT
BAYESIAN HIERARCHICAL MODELS**

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Dedication

I dedicate this dissertation to my parents, Zhimin Cai and Guizhen Xu, who believe in the power of higher education, hard work, and always support me.

Acknowledgement

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Chapter 1

INTRODUCTION

1.1 Transportation safety

Traffic safety is a pressing public health issue that involves huge lives losses and financial burden across the world and in the United States (US). As reported by the World Health Organization (WHO [2018b](#)), road injury was the eighth cause of death globally in 2016, killing approximately 1.4 million people, which consisted of about 2.5% of all deaths in the world. If no sustained action is taken, road injuries are predicted to be the seventh leading cause of death across the world by 2030 (WHO [2018a](#)). Compared to the victims who were claimed lives by diseases, people killed in traffic are mostly early- or middle-aged, particularly those aged 4 to 44 years old (Litman [2013](#); Evans [2014](#)). Without traffic accidents, these victims could have much longer lives with normal health.

Apart from fatal deaths, road traffic injuries were also reported to be the cause of 50 million non-fatal life injuries and approximately 75.5 million disability-adjusted life years globally (Staton et al. [2016](#)). In high-income countries, the majority of non-death costs were attributable to non-fatal crashes, with 2% of non-fatal events leading to over 40% of life-time medical costs (Ameratunga, Hajar, and Norton [2006](#)). Besides non-fatal injuries, traffic safety is a major economic burden. The global economic losses attributable to transportation safety were estimated to be 518 billion the United States Dollars (USD), which accounted for 1%

the gross domestic product (GDP) in low-income countries, 1.5% in middle-income countries, and 2% in high-income countries (Peden et al. 2004; Dalal et al. 2013).

Specifically in the United States, transportation contributed to the highest number of fatal occupational injuries, leading to 2,077 deaths and accounting for over 40% of all fatal occupational injuries in 2017 (The United States, Bureau of Labor Statistics 2017). The National Safety Council reported that the number of deaths attributable to car crashes will be at least 40,000 in 2018, which is the third straight year that this number is over 40,000 (The National Safety Council 2018). A comparison study of 26 developed countries revealed that 20 to 60 traffic deaths per billion kilometers were reduced from 2011 (Evans 2014). Despite the fact that fatality rates attributable to road traffic in the US were reduced by 40% during that period, the rates declined more rapidly in all other 25 countries. Given the large amounts of investments in roads, improved vehicle protection and traffic policy implementation, and advanced emergency and trauma care, the reduction in traffic associated fatality rates is nominal (Litman 2013). If the change of traffic fatality rates match those in other unremarkable countries, 20,000 traffic deaths could have been prevented each year (Evans 2014).

The impact of road injuries are even more impactful in developing countries than in developed countries (Goonewardene et al. 2010). Although low- and middle-income countries own only 48% of the registered vehicles in the world, 90% of road traffic fatalities and injuries were estimated to occur in these countries, which continue to be escalating due to rapid urbanization and motorization (Dalal et al. 2013; Staton et al. 2016). Ten developing countries, including Brazil, Cambodia, China, Egypt, India, Kenya, Mexico, Russia, Turkey, and Vietnam, account for almost half of all the road traffic in the world (Hyder et al. 2012). For example, China has around 100,000 traffic-related fatalities each year (Zhang et al. 2010), accounting for around 80% of all accidental deaths, with 87% of them were caused by motor vehicles in 2015 (Jiang et al. 2017). In comparison, 148,707 lives were claimed by road collisions in India in 2015, with the road fatality rate similar to the global average level of

17.4 deaths per 100,000 people (National Crime Records Bureau, Government of India 2015).

1.2 Trucking safety

In the US, large commercial trucks . approximately 70% of freight is delivered via a truck at some point of their transporation (Olson et al. 2016). Illustrate the importance of trucks

However, among all vehicles, large trucks are the primary concern of traffic safety since they are associated with more catastrophic accidents. In 2016, the Federal Motor Carrier Safety Administration (FMCSA) reported that 27% fatal crashes in work zones involved large trucks (FMCSA 2018). Among all 4,079 crashes involving large trucks or buses in 2016, 4,564 lives (1.12 lives per crash) were claimed in the accidents (FMCSA 2016). The economic losses associated with large truck crashes are also higher than those with passenger vehicles, with an estimated average cost of 91,000 US dollars per crash (Zaloshnja, Miller, and others 2008).

The high risk of large trucks is attributed to two aspects of reasons (Huang et al. 2013). First, large truck drivers generally need to drive alone for long routes, under on-time demands, challenging weather and traffic conditions. the severe outcomes of fatigue driving.

On the other hand, trucks are huge weighted and potentially carrying hazardous cargoes.

1.3 Crashes and critical events

To reduce the lives and economic losses associated with trucks, numerous studies attempted to screen the risk factors for truck-related traffic crashes or predict the crashes. The most common study design is a case-control study, matching a crash with one to up to ten non-crashes, and use statistical models such as logistic regressions to explain the causes or predict the crashes (Braver et al. 1997; C. Chen and Xie 2014; Meuleners et al. 2015; Née et al. 2019). This widespread case-control design is due to the fact that large truck crashes are very rare compared to the amount of time on road. However, a case-control study is limited in estimating the incidence data and may be contentious in selecting the control groups (Grimes

and Schulz 2005; Sedgwick 2014).

Past truck safety literature almost exclusively focused on crashes, while ignoring the precursors to crashes. A precursor, or critical event, is a pattern or signature associated with an increasing chance of truck crash (Saleh et al. 2013; Janakiraman, Matthews, and Oza 2016). Truck critical events deserve more attention since they occur more frequently than crashes, suggest fatigue and a lapse in performance, and they can lead to giant crashes (Dingus et al. 2006). Although critical events do not always result in an accident, they could be used as an early warning system to mitigate or prevent truck crashes (Kusano and Gabler 2012).

Rome et al. (2018)

1.4 Proposal

I propose using real-time truck ping data provided by the J.B. Hunt to

- 1) **quantify the association between truck crashes and critical events;**
- 2) **construct predictive models for truck critical events;**
- 3) **establish scalable Bayesian hierarchical models for large truck data.**

I believe that this work will contribute to statistical theories in constructing scalable Bayesian hierarchical statistical and reliability models using modern Markov Chain Monte Carlo methods. Realistically, these predictive models will inform policy-makers the functional relationship between driver characteristics, traffic, weather, and other real-time driving environment. These predictive models can be further used to provide data-driven justification to optimize trucking routes and minimize unsafe driving behaviors.

Chapter 2

LITERATURE REVIEW

2.1 Precursors to crashes

2.2 Risk factors

2.2.1 Fatigue

Among all driver-related safety critical events, fatigue has become the most pressing problem of traffic accidents. It is estimated by National Sleep Foundation that approximately 32% of drivers in U.S drive with fatigue over twice a month (National Sleep Foundation [2008](#)). The American Automobile Association Foundation for Traffic Safety claimed that 16.5% of fatal traffic accidents and 12.5% of collisions related to injuries in the US in 2010 were associated with driving with fatigue (American Automobile Association Foundation for Traffic Safety [2010](#)).

Drowsy driving is an especially common practice in less-developed countries because of cost control and tight schedule. Surveys of commercial and public road transportation companies in less-developed countries showed that employers were frequently forcing their employees to drive for longer hours and keep working even when they were exhausted (Zhang et al. [2016](#); Odero, Khayesi, and Heda [2003](#); Nantulya and Reich [2002](#)). High proportions of

drowsy driving have been found among Brazilian (22%) (Canani et al. 2005), Argentinean (44%) (Pérez-Chada et al. 2005), Pakistani (54%) (Azam et al. 2014), and Thai (75%) (Leechawengwongs et al. 2006) truck or bus drivers. The mechanism of fatigue leading to safety critical events is that a driver's capability to stay alert to ambient traffic and pedestrians will be largely impaired. The reaction time is subsequently prolonged in that situation (Zhang et al. 2014). It is estimated that 17 hours of continuous working lead to a deterioration of driving performance equivalent to a blood alcohol level of 0.05% (MacLean, Davies, and Thiele 2003). What makes the outcomes worse is that fatigue driving is more likely to happen on expressways and major highways where the speed limit is over 55 miles per hour (Knipling and Wang 1994). This is especially concerning because fatigue driving safety critical events are more likely to result in serious injuries and fatalities, compared with non-fatigue driving safety critical events.

Stern et al. (2018) reviewed the research related to fatigue of commercial motor vehicle drivers. Because of the difficulty of running a controlled experiment by imposing treatments, most research designs are observational studies, that is, they compare the effects of variables that are observed, not imposed. One exception to this is a *randomized encouragement design* where drivers are randomized to receive some sort of incentive to apply some treatment, but are not forced to do so. If an effect is observed, we would conclude that it is due to the incentive, not necessarily to the actual treatment. Many studies use a cohort design or a case-control study. In a cohort design, a number of drivers is identified and studied across time. In a case-control study, a number of cases (e.g., crashes, or some other safety measure) are identified and are matched with controls; focus is then placed on the differences between the cases and controls. Both cohort studies and case-control studies can be useful in assessing safety.

2.2.2 Fatigue measurement

The reason why little has been done about drowsy driving is there is no simple way to objectively measure fatigue driving (Dement [1997](#)).

2.2.3 Driver characteristics

A study by Pack et al. ([1995](#)) revealed that the drivers were 25 years of age or younger in over a half of the 5,000 highway crashes in which they fell asleep whiling driving.

Another driver-related risk factor of driving safety critical events is drivers' age. In many developing countries, to meet the huge demand services and supply chain management, it is very common to extend the retirement age or reemploy retired workers (Popkin et al. [2008](#)). Aging drivers increase the chance of the safety critical events in three aspects: impaired eyesight, prolonged reaction time to exogenous stimuli, and vulnerability to fatigue (Di Milia et al. [2011](#)). Aged drivers are associated with eyesight diseases or functionality impairment, such as cataracts, narrowed peripheral vision and decreasing visual acuity (Di Milia et al. [2011](#)). In addition, working for truck companies often means irregular shifts and taking the night schedules, which disrupt the circadian time-keeping systems, especially for the aged workers (Moneta et al. [1996](#)).

Aged drivers may find it much more difficult to adjust for the sleep-wake cycle to keep pace with the schedule required by the employer company. Therefore, this disruption of the circadian systems, in turn, increases the chances to feel sleepy or fatigue for workers. It is indicated by research that the “critical age” of shiftwork intolerance is about 45 to 50 years, at which sleep disorder, persisting fatigue and digestive problems become the most obvious (Di Milia et al. [2011](#)). Young drivers are much better in the sense of physical health and resistance to fatigue compared with aged drivers, however, they are more vulnerable regarding the experience of driving. A study conducted by Clarke suggested that young drivers (17 – 19 years old), especially males, have significantly more accidents than other drivers during the hours of darkness, on rural curves, and rear-end shunts compared with male drivers aged

20 -25 years (Clarke et al. 2006). The reasons for these young driver accidents were not fully explained, but could largely be attributed to inexperience.

One more risk factor that could explain driving safety critical events is drivers' gender. Gender has been suggested to be related with outcomes in medical treatment, education, sports and other fields, and there is no exception for truck drivers' safety. In the first place, women are more likely to suffer from fatigue compared with men. A study found that women in general have 1.4 times higher chance of complaining of fatigue than men (Fjell et al. 2008). However, females are found to have longer sleeping hours than their male counterparts of the same race (Lauderdale et al. 2006). In that study, it was found that the mean sleep hours for white females was 6.7 hours compared with 6.1 hours for white males, and 5.9 hours for black female compared with 5.1 hours for black males even after adjusting for socioeconomic status, lifestyle and sleep apnea (Lauderdale et al. 2006). Gender differences are huge in terms of working conditions. Females had significantly fewer working hours per week, with 47 hours versus 52 hours per week (Rotenberg et al. 2008). In general, women tend to work fewer hours within a week but are more prone to feel fatigue and have a higher risk of traffic incidences.

2.2.4 Traffic

2.2.5 Weather

Weather has both direct and indirect effects on drivers' safety critical events. On one hand, the increase of ambient temperature places risks on drivers' occupational safety, and possibly leads to cognition loss, heat stroke, and impairment of wakefulness. Evidence showed that the risk of mistakes and safety critical events increase in hot weather (Kjellstrom et al. 2009; Basagaña et al. 2015). Leard and Roth found that for a day with temperature above 80F there is a 9.5% increase in fatality rates compared with a day at 50-60 F (Leard, Roth, and others 2015). A literature review found that 11 out of 13 studies indicated an increase in unintentional injuries associated with high temperatures (Kampe, Kovats, and Hajat 2016).

On the other hand, real-time extreme weather conditions such as heavy rain, fog, storm, and snow can either impair the driver's visual capability or reduce the safety of driving on the road (Chang and Chen 2005; Al-Ghamdi 2007; Baker and Reynolds 1992). It is to noted that the cumulative time of driving in such extreme weather conditions could increase the chances of safety critical events. Studies that explore the association between precipitation and driving safety critical events consistently find a negative relationship. The positive linear relationship between precipitation and traffic accidents can be observed in both driver accidents and pedestrian accidents (Al-Ghamdi 2007; Graham and Glaister 2003). Abdel-Aty et al. used detector and sensor data to successfully predict more than 70% of accidents with low visibility conditions (Abdel-Aty et al. 2012). The common problem for the literature exploring the relationship between ambient weather and safety driving critical events is the failure to include the cumulative effect of weather conditions. Instead, they all use an indicator variable to represent whether extreme weather happened during the trip or not, which could lead to potential bias in prediction models.

2.2.6 Time of the day

Pack et al. (1995)'s analysis reported the crashes in which the drivers fell asleep occurred primarily from mid-night to 7 a.m. and from 2 p.m. to 4 p.m.

2.3 Predictive models

2.3.1 Bayesian models

2.3.2 Hierarchical models

2.4 Scalable Bayesian models

An introduction to MCMC methods (Metropolis-Hasting Algorithm, Gibbs sampler), limitation of these traditional methods. (Quiroz [2015](#))

2.4.1 Hamiltonian Monte Carlo

(Betancourt [2017](#); Neal and others [2011](#))

2.4.2 Integrated Laplace Approximation (INLA)

(Rue, Martino, and Chopin [2009](#); Lindgren, Rue, and Lindström [2011](#); Martins et al. [2013](#); De Coninck et al. [2016](#); Rue et al. [2017](#); Verbosio et al. [2017](#); Kourounis, Fuchs, and Schenk [2018](#))

2.4.3 Subsampling MCMC

Stochastic Gradient HMC

(Quiroz et al., [n.d.](#), [2016](#); Gunawan et al. [2018](#); Quiroz, Tran, et al. [2018](#); Quiroz, Kohn, et al. [2018](#); Dang et al. [2017](#); Quiroz [2015](#))

T. Chen, Fox, and Guestrin ([2014](#))

2.5 Conceptual framework

Cantor et al. (2010) suggested three factors that cause truck crashes: driver factors, vehicle factors (type and condition), and environmental factors.

Roshandel, Zheng, and Washington (2015) proposed five factors that affect traffic safety: (a) behavioral characteristics of the driver, e.g., impairment, fatigue, distractions; (b) vehicle — the condition of the vehicle; (c) traffic — the traffic conditions; (d) geometry — geometric characteristics of the road, e.g. curve, hill, ramps, etc.; and (e) environmental — characteristics of the surrounding environment, such as weather conditions (rain, snow, night-time driving, etc.). Traffic conditions are the most studied of these and we focus on discussing them in this subsection.

2.6 Gaps in literature

- A focus on crashes instead of precursors of crashes
- A focus on road segments rather than drivers
- A focus on case-control comparison given the rareness of truck crashes rather than rates

2.7 Research aims

Aim1: Explore the association between truck crashes and critical events.

Aim2: Predict critical events using hierarchical statistical models.

Aim3: scalable hierarchical Bayesian models using subsampling MCMC.

Chapter 3

METHODS

3.1 Data source

3.1.1 Real-time ping data

The 496 over-the-road drivers

3.1.2 Weather data

The DarkSky API.

3.2 Study design

3.3 Analytical Plan for Aim 1

3.4 Analytical Plan for Aim 2

3.5 Analytical Plan for Aim 3

Chapter 4

The Probable Content

This dissertation will be completed according to the three-paper model. The expected chapter headings are as follows:

Chapter 1: Introduction: The problem

A. Epidemiology of head and neck squamous cell carcinoma and its association with second primary malignancies

1. Cancer
2. Head and neck squamous cell carcinoma
3. Definition of second primary malignancies
4. second primary malignancies and Head and neck squamous cell carcinoma

B. Risk factors for second primary malignancies

1. Tobacco use
2. Excessive alcohol use
3. Human papillomavirus infection

C. Existing literature and gaps that exist in the area of second primary malignancies in patients with head and neck squamous cell carcinoma

Chapter 2: Literature review

A. Introduction

B. Methods

1. Source of data and eligibility/exclusion criteria
2. Definitions of primary and secondary outcomes and covariates
3. Statistical analysis

C. Results

1. Description of studies included in the study
2. Primary outcome results
3. Secondary outcome results
4. Publication bias and study quality assessment

D. Discussion/Conclusions

1. Implications
2. Strengths and limitations
3. Future research

Chapter 3: Aim 1 - Truck crashes and critical events

A. Introduction

B. Methods

1. Source of data and eligibility/exclusion criteria
2. Definitions of primary and secondary outcomes and covariates
3. Statistical analysis

C. Results

1. Demographics of study population

CHAPTER 4. THE PROBABLE CONTENT

2. Primary outcome results
3. Secondary outcome results

D. Discussion/Conclusions

1. Implications
2. Strengths and limitations
3. Future research

Chapter 4: Aim 2 - Statistical models predicting truck critical events

A. Introduction

B. Methods

1. Source of data and eligibility/exclusion criteria
2. Definitions of primary and secondary outcomes and covariates
3. Statistical analysis

C. Results

1. Demographics of study population
2. Primary outcome results
3. Secondary outcome results

D. Discussion/Conclusions

1. Implications
2. Strengths and limitations
3. Future research

Chapter 5: Aim 3 - Subsampling Markov Chain Monte Carlo methods

Chapter 6: DISCUSSION

A. Conclusion

B. Strengths and limitation

C. Future research

Chapter 5

TRUCK CRASHES AND CRITICAL EVENTS

Chapter 6

THREE STATISTICAL MODELS PREDICTING TRUCK CRITICAL EVENTS

6.1 Hierarchical logistic model

6.1.1 Model set up

6.1.2 Bayesian estimation based on simulated data

6.2 Hierarchical Poisson model

6.3 Hierarchical power law process

*Mean function of a point process**:

$$\Lambda(t) = E(N(t))$$

$\Lambda(t)$ is the expected number of failures through time t .

Rate of Occurrence of Failures (ROCOF): When Λ is differentiable, the ROCOF is:

$$\mu(t) = \frac{d}{dt}\Lambda(t)$$

The ROCOF can be interpreted as the instantaneous rate of change in the expected number of failures.

Intensity function: The intensity function of a point process is

$$\lambda(t) = \lim_{\Delta t \rightarrow 0} \frac{P(N(t, t + \Delta t] \geq 1)}{\Delta t}$$

When there is no simultaneous events, ROCOF is the same as intensity function.

Nonhomogeneous Poisson Process (NHPP): The NHPP is a Poisson process whose intensity function is non-constant.

Power law process (PLP): When the intensity function of a NHPP is:

$$\lambda(t) = \frac{\beta}{\theta} \left(\frac{t}{\theta} \right)^{\beta-1}$$

Where $\beta > 0$ and $\theta > 0$, the process is called the power law process (PLP).

Therefore, the mean function $\Lambda(t)$ is the integral of the intensity function:

$$\Lambda(t) = \int_0^t \lambda(t) dt = \int_0^t \frac{\beta}{\theta} \left(\frac{t}{\theta} \right)^{\beta-1} = \left(\frac{t}{\theta} \right)^{\beta}$$

6.3.1

6.3.2 Bayesian estimation based on simulated data

Chapter 7

HIERARCHICAL BAYESIAN MODELS USING SUBSAMPLING MARKOVE CHAIN MONTE CARLO METHODS

- Comparison with results given by frequentist models using REML (`lmer4`)
- Comparison with results given by Bayesian models using HMC (`rstan`)
- Comparison with results given Bayesian models using INLA (`INLA`)

Chapter 8

DISCUSSION

APPENDIX

R code

Another appendix

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CHAPTER 8. DISCUSSION

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