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AN INVESTIGATION OF MOTOR VEHICLE DRIVER INATTENTION AND ITS EFFECTS AT HIGHWAY-RAIL GRADE CROSSINGS

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AN INVESTIGATION OF MOTOR VEHICLE DRIVER INATTENTION AND ITS EFFECTS AT HIGHWAY-RAIL GRADE CROSSINGS

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AN INVESTIGATION OF MOTOR VEHICLE DRIVER INATTENTION AND ITS EFFECTS AT HIGHWAY-RAIL GRADE CROSSINGS

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The relationship between accident injury severity and drivers' inattentive behavior requires an in-depth investigation – this is especially needed in the case of motor vehicle drivers at highway-rail grade crossings (HRGCs). The relationship between drivers' personality/ socioeconomic characteristics and inattentive behavior at HRGCs is another topic requiring research. Past educational programs about safe driving at HRGCs have often not been designed to target people who may be in urgent need of such information, which may limit the effectiveness of those programs.

This dissertation thus focuses on the following four objectives: to investigate the association between motor vehicle inattentive driving and the severity of drivers' injuries sustained in crashes reported at or near HRGCs; to investigate the association between drivers' self-reported inattentive driving experience and a series of factors such as drivers' knowledge of safe driving, attitudes towards safe driving, etc.; to identify driver groups that have lower or higher levels of knowledge of correct rail crossing negotiation; and to investigate the direct and indirect effects between drivers' characteristics and their knowledge level as well as their involvement with inattentive driving behavior at HRGCs. The research obtained 12 years of police-reported crash data from the Nebraska Department of Roads and collected data in a statewide random-sample mail questionnaire survey. Statistical analysis methods, including random parameters binary logit model, confirmatory factor analysis, robust linear regression, multinomial logit model, and structural equation models were utilized in this research.

Conclusions are that inattentive driving plays a significant role in contributing to more severe injuries in accidents reported in proximity of HRGCs in Nebraska; Nebraska motor vehicle drivers’ personality traits, knowledge levels of negotiating HRGCs and driving experience are associated with inattentive driving; drivers with lower levels of knowledge of correct HRGC negotiation are: drivers who drive vehicles other than passenger cars, have received less safety information, have a shorter driving history, are older, have lower household income, and have higher intent to violate rules at rail crossings; inattentive driving behavior at HRGCs is directly and indirectly affected by their personality traits while drivers’ knowledge of correct HRGC negotiation appears to only have an indirect effect.

DEDICATION

This dissertation is dedicated to my father Xiangfa Zhao, my mother Jicui Zhang, my husband Hanghang Zhao, and my son Aaron.

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CHAPTER 1 INTRODUCTION

1.1 Background

The U.S. Department of Transportation (DOT) initiated the Rail-Highway Crossing Safety Action Plan in 1994 and set a goal of reducing crossing collisions and fatalities by 50% over ten years. Incidents among trains and highway users and the corresponding fatalities were reduced significantly–40.4% and 45.9% reduction from 1994 to 2003, respectively (Ngamdung and DaSilva, 2013). Figures 1-3 show trends in the total number of annual incidents, deaths, and injuries at highway-rail grade crossings (HRGCs, also called “rail crossings”) in the U.S. from 2001 to 2012, based on the Federal Railroad Administration (FRA) Office of Safety Analysis (OSA) (accessed on June 2, 2015). The number of highway-rail incidents and corresponding casualties has seen a general decrease although some years show increases when compared to years immediately preceding them (e.g., year 2010 in **Figures 1.1-1.3**).

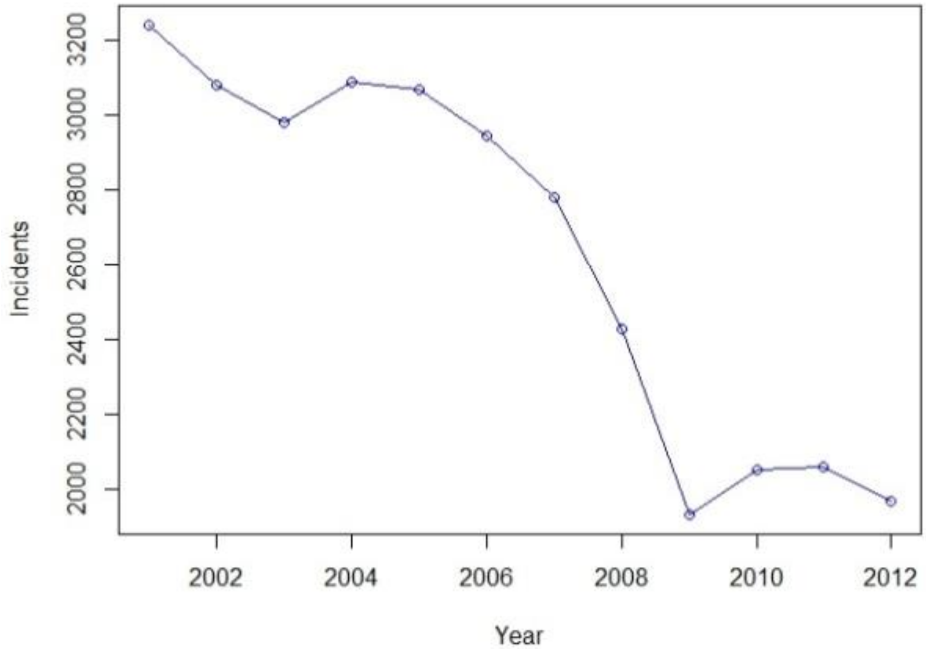


Figure 1.1 National HRGC incidents from 2002 to 2012

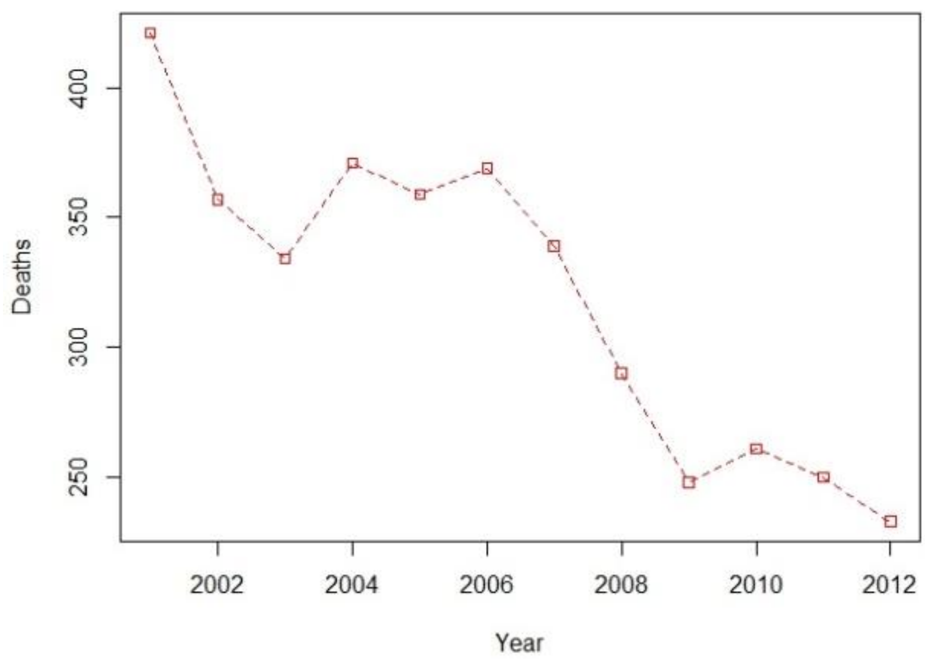


Figure 1.2 National HRGC deaths from 2002 to 2012

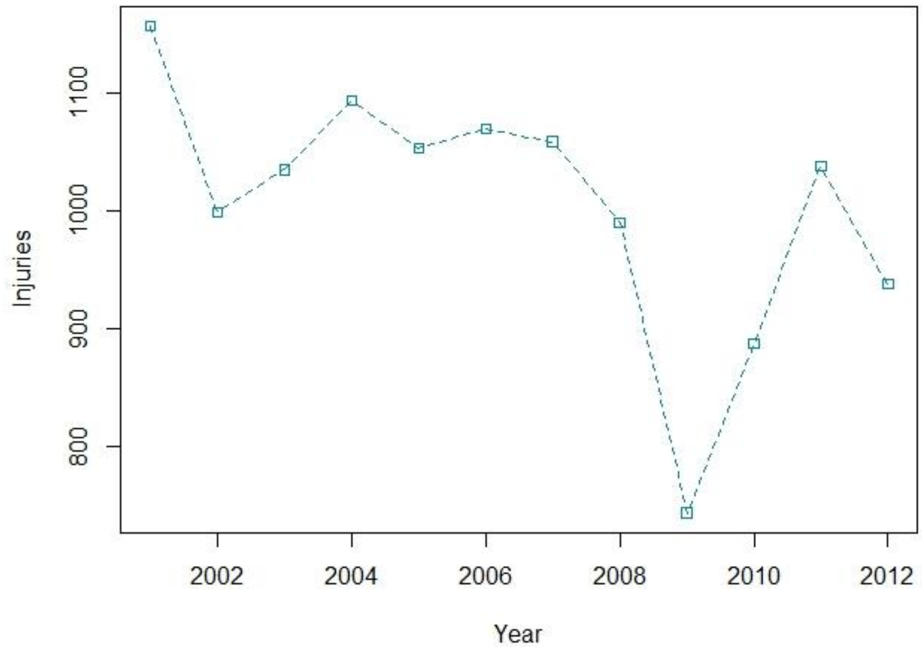


Figure 1.3 National HRGC injuries from 2002 to 2012

In spite of this generally decreasing trend, safety at HRGCs is still a significant concern because the severity of accidents at these locations is usually higher than those reported at non- HRGC locations and potential for disruption of two different modes of transportation. According to police-reported accident data from the Nebraska Department of Roads (NDOR) (Office of Highway Safety), from 2008 to 2013 there were a total of 305,160 highway traffic accidents reported in Nebraska, with 304,042 (99.63%) reported on highways and the remaining 1,118 (0.37%) reported at HRGCs. **Table 1.1** presents a comparison of total accidents, fatal accidents, and disabling injury accidents at HRGC and non-HRGC locations. The percentage of fatal and disabling injury accidents was much greater for accidents reported at HRGCs compared to accidents reported at non-HRGC locations, indicating that accidents at HRGCs tend to be more severe.

Table 1.1 Accidents reported at HRGCs and non-HRGCs

	Total Accidents	Fatal Accidents	Disabling Injury Accidents
HRGC	1,118	19 (1.70%)	54 (4.83%)
Non-HRGC	304,042	1,113 (0.37%)	8,686 (2.86%)

Motor vehicle driver inattention is a major factor in highway traffic accidents. Driver inattention means, “insufficient or no attention to activities critical for safe driving” (Regan et al., 2011). Inattentive driving is dangerous and increases the risk of roadway accidents. Motor vehicle driver inattention is a major factor in serious traffic crashes and accounted for 22.7% of total roadway crashes based on 1996-1997 data (NHTSA 2001). Driver inattention is even more critical at highway-rail grade crossings (HRGC) because train-involved motor vehicle accidents are usually more severe compared to other motor vehicle accidents. Investigation of motor vehicle inattentive driving at HRGCs is therefore important for public safety.

The current research will investigate motor vehicle driver inattentive behavior at HRGCs utilizing two data sources and the following aspects of inattentive driving at rail crossings will be investigated: the association between accident injury severities and driver inattentive behavior based on Nebraska Department of Roads (NDOR) motor vehicle crash data and the relationship between drivers’ attitudes and knowledge of safe driving at rail crossings and their non-compliance and inattentive driving behavior at HRGCs, based on data collected from Nebraska residents through a mail survey.

The concepts of driver inattention and driver distraction in this research are clarified as follows. Regan et al. (2011) argued that driver distraction is a form of driver inattention and the research presented herein is based on the same idea. Drivers at rail crossings may be mentally distracted in situations where they are not distracted by objects or events in or outside of their vehicles. Such mental distractions will be taken into account in this research because "inattention" is often listed as a primary cause leading to accidents in the vicinity of rail crossings in the Nebraska motor vehicle crash reports. Driving under the influence (DUI)/driving while intoxicated (DWI)/operating under influence (OUI) is another unsafe driving behavior. DUI is usually defined as driving while impaired by alcohol or other legal or illegal substances. All states now have DUI laws that deem a driver with a blood alcohol concentration (BAC) of 0.08% or higher "per se intoxicated" regardless of whether the driving task was actually impaired or not. Certain types of DUIs can be charged as felonies, which is a serious crime that can result in a prison sentence (Brown; Stim). Some states (e.g., Colorado) also include a lesser charge of driving with a BAC of 0.05%. For commercial vehicle drivers, the general BAC level is 0.04%. All states in the U.S. have zero tolerance laws that specify suspension of driving licenses for drivers under the legal drinking age (e.g., age of 21) when any trace of alcohol in is found in their systems (BAC of 0.0%) or negligible BAC levels (e.g., 0.01% or 0.02% in some states) will be suspended (FindLaw, 2013). DUI may cause drivers' cognitive distractions during driving and thus lead to driver inattention. However, in this research instances of DUI are not considered as driver inattention but discussed as a separate factor.

Driver inattention is a broad idea that includes drivers engaging in and being distracted by secondary tasks, internal thoughts, drowsiness, fatigue, daydreaming, etc.

The reviewed literature presented in the next chapter shows that some researchers used a narrower definition of distraction (i.e., those involved in secondary tasks) while others used a broader notion of it (i.e., also including cognitive distractions). In this research, the concept of inattention is used to assimilate these differences and introduce the broadest idea of inattentive driving that can be caused by any reason (DUI is studied as a separate factor).

In conclusion, this research will investigate motor vehicle inattentive driving behavior at HRGCs and answer the following three questions. Does inattentive driving lead to more severe accidents? Which factors affect drivers' inattentive behavior at HRGCs? Which groups of drivers have lower or higher levels of knowledge of safely negotiating HRGCs?

1.2 Problem Statement

When considering the issue of drivers' inattentive driving behavior at HRGCs, three correlating aspects are apparent – the consequences of such behavior, the drivers' personality and socioeconomic characteristics associated with such behavior, and the corresponding safety improvement strategies. Regarding consequences, the impact of inattention on driver injury severities in crashes reported at HRGCs has not been reported in published literature. On the associated factors side, drivers' personality and socioeconomic characteristics that might be associated with their behavior (i.e., inattention) when approaching HRGCs have not been investigated thoroughly. Finally, relating to the improvement strategy, groups of drivers that may have lower levels of knowledge of correctly maneuvering HRGCs and higher propensity of inattentive driving have not been identified, which may enable targeted educational programs on rail crossing safety. **Figures 1.4-1.5** present the conceptualization model of the current research and the role of this dissertation under the umbrella of literature about safety at HRGCs.

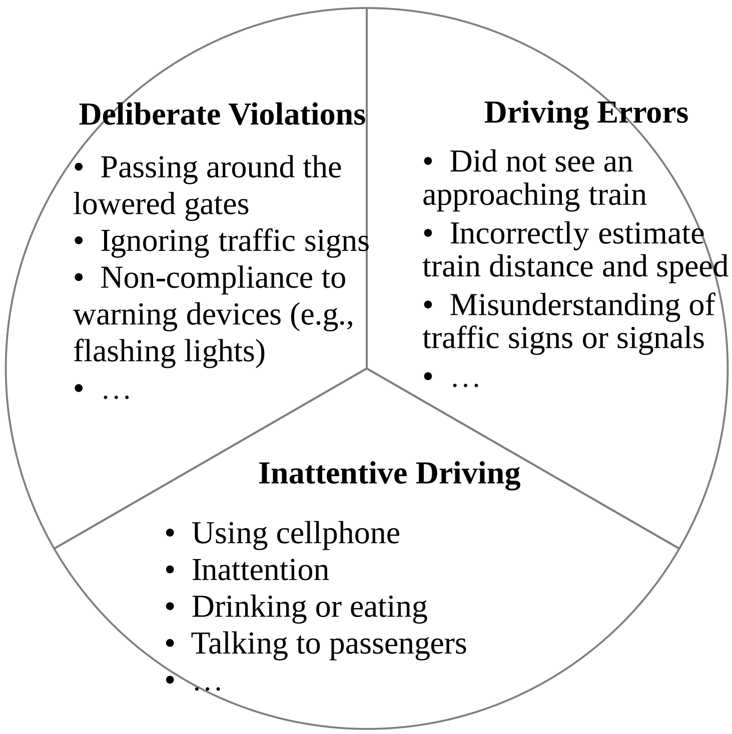


Figure 1.4 Safety at HRGCs and categories of drivers' contributing factors

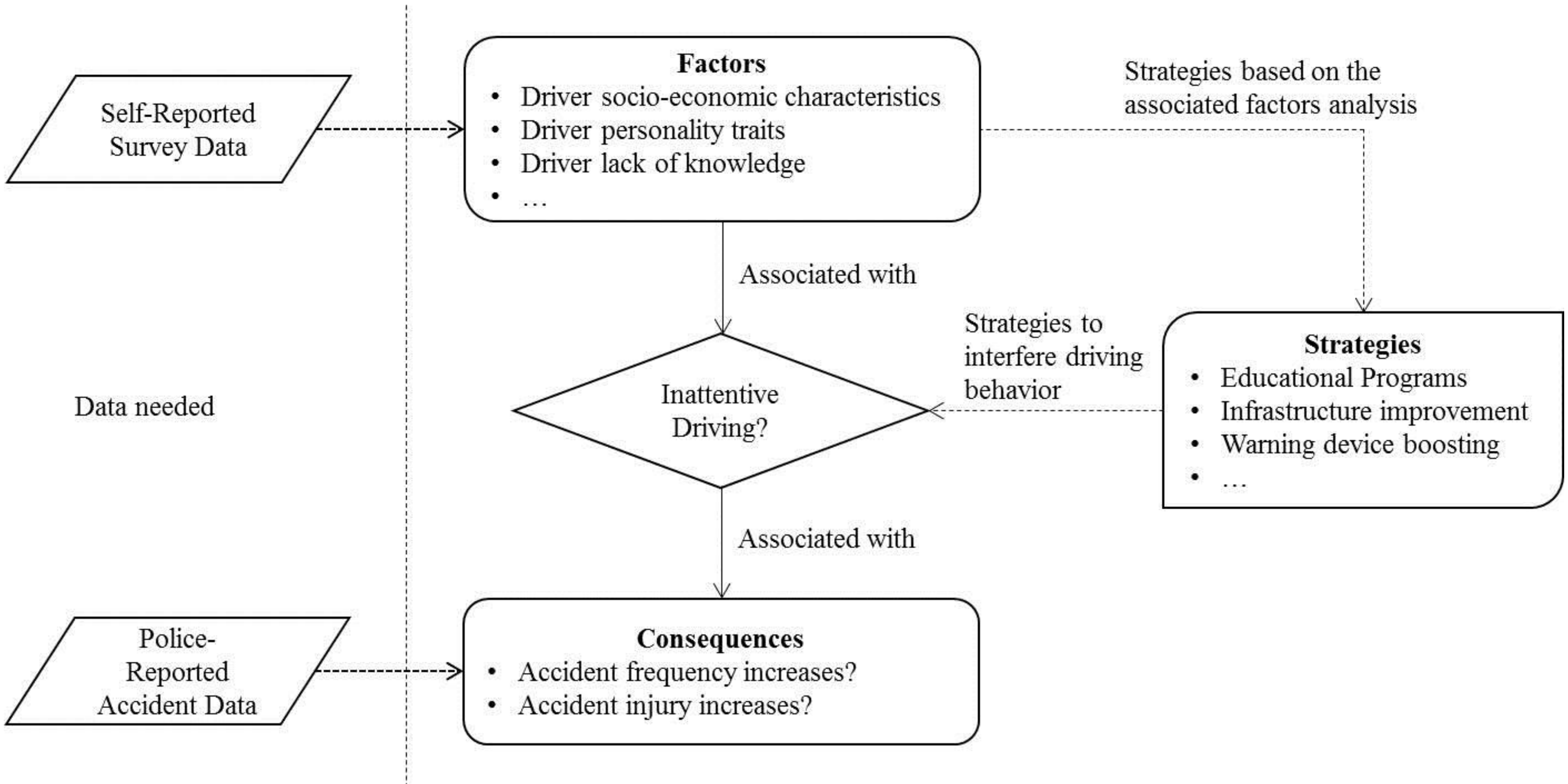


Figure 1.5 Conceptualization of the study

Pertaining to these problems, a series of hypotheses will be statistically tested in this research:

(1) Motor vehicle driver inattention at HRGCs increases the likelihood of more severe accidents.

(2) Inattentive driving behavior at HRGCs is associated with drivers' socioeconomic and personality characteristics (e.g., knowledge of driving rules, expectation of train presence, familiarity with crossings, indifference or overconfidence with safety at rail crossings, etc) and rail crossing configuration factors (e.g., presence of highway intersections in vicinity of HRGCs, location in urban/commercial areas, etc.).

(3) Certain groups of drivers lack driving safety knowledge at HRGCs.

1.3 Research Objectives

There are four objectives for the research:

(1) To investigate the association between motor vehicle inattentive driving and the severity of drivers' injuries sustained in crashes reported at or near HRGCs. Differentiation will be made between accidents that were train-involved and accidents that were rail crossing related but did not involve trains. Factors such as rail crossing warning devices, nearby highway intersections, seatbelt usage, driver characteristics, etc., will be considered. Different types of accidents (e.g., a single vehicle involved, two vehicles involved, more than two vehicles involved, etc.) will be included in the discussion.

(2) To investigate the association between drivers' self-reported inattentive driving experience and a series of factors such as drivers' usage of rail crossings, knowledge of safe driving, attitudes towards safe driving, expectations of encountering trains at rail crossings, previous noncompliance behavior, etc.

(3) To identify driver groups that have lower or higher levels of driving knowledge of correct rail crossing negotiation so future dissemination of information on safe driving at rail crossings can be targeted.

(4) To investigate the direct and indirect effects between drivers' characteristics and their knowledge level as well as their involvement with inattentive driving behavior at HRGCs. The fourth objective is a derivative of the previous two objectives. The rationale behind this objective is that the statistical regression models used in the previous two objectives may identify driver factors associated in one way or another with drivers' inattentive behavior and their levels of knowledge of safely negotiating at HRGCs; however, the regressions do not reveal the direct and indirect causal relationships between the outcomes (e.g., involvement of inattentive behavior and levels of knowledge) and driver factors. The direct or indirect relationships, the sharing of the same independent variables, and the correlations between the dependent variables could be assessed using the structural equation modeling (SEM) technique.

1.4 Dissertation Organization

This dissertation consists of seven chapters. Chapter 1 introduces the study background, states the research problem, and outlines the structure of the dissertation.

Chapter 2 presents a comprehensive review of published literature and open-accessed research reports. Reviewed topics include driver inattention in general highway settings, driver behavior at HRGCs, and injury severity studies at HRGCs. The chapter ends with identification of gaps in existing research. Chapter 3 describes the process of data collection and reduction, provides descriptive statistics for the two datasets, and introduces the statistical methodology for data analysis. This covers random parameters logistic regression, confirmatory factor analysis, robust linear regression, and structural equation modeling. Chapter 4 presents analysis of driver inattention and injury severity in crashes reported at HRGCs. Investigations of single-vehicle-single-driver crashes, two-vehicle-two-drivers crashes, and more-than-two-vehicle crashes are presented. Chapter 5 studies drivers' personality and socioeconomic characteristics associated with inattentive driving when approaching HRGCs.

Chapter 6 investigates driver knowledge of safely maneuvering rail crossings and groups of drivers that may be at a higher risk of crash involvement. Also included in Chapter 6 is a direct and indirect effects investigation in the relationships between drivers' demographic characteristics, drivers' inattentive driving behavior, drivers' knowledge, and latent variables that reflect drivers' perceptions or intents. Chapter 7 summarizes the dissertation work, presents conclusions from the analysis, provides recommendations for safety improvements at HRGCs, and proposes future research.

CHAPTER 2 LITERATURE REVIEW

2.1 Driver Inattention in General Highway Settings

2.1.1 General Statistics

Inattentive driving, such as driver distraction, drowsiness, or daydreaming, is a risky behavior that has been studied widely in roadway safety. Driver inattention was a contributing factor to 78% of accidents and 65% of near-accidents, according to the naturalistic study of 100 instrumented vehicles conducted by the Virginia Tech Transportation Institute (Klauer et al., 2006). Drowsiness and tasks with greater than 1.0 second eye glances away from the forward roadway or operating instrument control buttons could significantly increase the risk of accidents or near-accidents.

An important aspect of inattentive driving is driver distraction. Motor vehicle drivers were found engaged in secondary tasks 23.5% of the time when they drove (Klauer et al., 2010). Distractions may be classified as visual, mutual, and cognitive. The impact of distraction is not only determined by the types, but also by the duration and frequency of the distractions (NHTSA, 2010).

2.1.2 Distraction and Driving Errors

Distraction can easily lead to driving errors. Young et al. (2012) reviewed extensive literature on distracted driving and investigated the association between distraction and driving errors. They concluded that distraction led to action errors by disrupting natural driving performance variation, led to observation errors by disrupting visual scanning behavior and situation awareness, led to information encoding and retrieval errors by disrupting cognitive processing, and led to cognitive and decision-making errors by disrupting decision making. Among these effects between distraction and driving errors, the disruption of visual scanning behavior is especially dangerous to situations at rail crossings as motor vehicle drivers may not be able to sufficiently scan for the presence of a train.

By asking participants driving in an instrumented vehicle, Young et al. (2013a) found that drivers tend to make more driving errors when visually distracted than not distracted, but the nature of these errors is the same. Young et al. (2013b) also examined driving errors caused by distractions at intersections and on roadways. A total of 39 different types of errors were made by participants, with speeding being the most common error. Drivers made more errors at intersections than at mid-blocks and made more errors at fully (protected) signalized intersections than at partially (permissive) signalized intersections. Young et al. (2013b) concluded that distracted driving did not alter the structure of drivers' situation awareness, but decreased the contents of their awareness and limited their visual scanning abilities. Drivers seemed to have a decreased ability to deal with complicated situations when distracted. These finding are pertinent to rail crossing safety as well.

A driver's cognitive distraction can be as risky as visual and manual distractions. Harbluck et al. (2007) carried out an on-road experiment in which 21 drivers were asked to drive a city route in an experimental vehicle under three conditions: no task, easy task, and difficult task. Math problems with varied difficulties were given as cognitive tasks.

The authors reported that when cognitively distracted, drivers spent more time looking ahead and less time looking peripherally. Also, when engaging in cognitive tasks drivers made fewer inspections of the instruments and mirrors inside the vehicle and less attention was paid to traffic lights outside of the vehicle. These consequences of distracted driving can be especially dangerous at rail crossings where conscientious scanning for a train and watching out for the crossing warning signals are crucial to the driving task.

2.1.3 Norms with Inattentive Driving

Atchley et al. (2012) discussed the importance of understanding social norms in conducting successful campaigns for safe driving among young people. They conducted two experiments in which young drivers were asked to read crash scenarios, rate drivers' responsibilities, and levy fines and jail time on drivers involved in inattentive, drinking, or distracted driving. Their results showed that young drivers generally knew that inattentive and distracted driving was a risky behavior, but they perceived it as a normative behavior. Anti-drunk campaigns from the 1970s have changed young people's attitudes towards drunk driving, but the norms towards distracted driving have not been stressed enough (Atchley et al., 2012).

2.1.4 Inattentive Driving and Injury Severity

Inattentive driving may increase accident injury severity. Nofallah (2003) reported that 38% of all motor vehicle accidents resulted in an injury or fatality to the driver, a number that rose to 75% in distraction-involved accidents. Compared to attentive drivers, distracted drivers are 50% more likely to be seriously injured or killed in their accidents, while drivers who have fallen asleep are 2.3 times more likely to be seriously injured or killed (Stutts et al., 2005). However, only a very limited number of studies have investigated the relationship between injury severity and driver inattention. Liu and Donmez (2011) studied police-involved accidents and investigated the association between injury severity and police driver distraction using the U.S. General Estimates System (GES). They found that cognitive distraction (such as lost in thought and looked but did not see) decreased injury severity while in-vehicle distraction increased injury severity. Liu (Liu, 2012) took into account all ages of drivers and assessed the association between age-distraction interaction and crash injury severities using GES data from 2003 to 2008. The author concluded that dialing, texting, and drowsiness were extremely dangerous to young (16 to 24 yrs) and old drivers (65 yrs and above). Some other in-vehicle distractions such as eating and using entertainment also increased the likelihood of more severe injuries. Inattention and distractions outside of the vehicle were associated with reduced injury severity across all age groups. Talking on the phone while driving seemed to be associated with less severe injuries to the young, but more severe injuries to the old. Neyens and Boyle (2008) used 2003 national GES data to focus on teenage drivers. The results revealed that teenage drivers had an increased likelihood of more severe injuries if distracted by a cell phone or passengers than if inattention or other in-vehicle distractions were involved. Passengers of distracted teenage drivers also suffered more severe injuries in accidents compared to accidents when teenage drivers were not distracted.

In summary, motor vehicle driver inattention can lead to traffic crashes, but whether it causes more severe crashes still requires investigation. The studies mentioned above that focused on highways showed that some distractions (e.g., cell-phone usage) could lead to more severe crashes, but other distractions (e.g., cognitive inattention or distractions outside of the vehicle) were associated with less severe crashes on highways.

2.2 Driver Behavior at Highway-Rail Grade Crossings

2.2.1 General Statistics

Highway users are usually at fault in accidents reported at HRGCs because trains have the right of way. From 1994 to 2003, about 94% of the motor vehicle accidents reported at rail crossings were associated with motor vehicle drivers' risky behavior or poor judgement (Ngamdung and DaSilva, 2013; U.S. DOT Office of Inspector General, 2004). In 2005, 82% of the U.S. rail crossing accidents were attributed to highway users, and motor vehicle driver inattentiveness attributed to 41% of all the reported accidents (Federal Railroad Administration, 2006; Searle et al., 2011). Many times highway user behavior at rail crossings is different from that at other road locations: they may seek excitement in passing around gates before train arrival, display lack of patience, or display low expectations of train encounters, misjudge train speed, or otherwise underestimate the risks of non-compliance at rail crossings.

2.2.2 Behavior at Different Rail Crossings

Freeman et al. (2013) found greater HRGC accident frequency at passive crossings than at active crossings. Berg et al. (1982) examined contributing factors of rail crossing accidents at flashing light and crossbuck crossings. A total of 79 train-vehicle accidents were reconstructed and analyzed for patterns of motor vehicle driver errors and other factors. They reported that the credibility of the warning devices was an important issue at crossings equipped with flashing lights. At crossings equipped with crossbuck signs, the principle contributing factor was drivers' failure to detect a crossing or an approaching train, which they attributed to drivers' possible low expectancy of hazards, inadequate sight distances, or inattentive driving.

Yeh and Multer (2008) also emphasized credibility of warning devices and the conspicuity of crossings. They concluded that noncompliance at crossings equipped with active warning devices was quite often likely caused by drivers' failure to detect the crossing or an approaching train. According to their study, the situation may be improved by installing barriers or four-quadrant gates to increase the level of protection, or by improving the credibility of warning devices.

Åberg (1988) conducted an observational study of 2000 drivers at 16 rail crossings with drivers' head movements as the major variable of interest. Results showed that many drivers turned their heads to look for trains, even at crossings equipped with flashing lights. Fewer drivers looked when their lines of sight were restricted and when significant effort on part of the driver was needed for head movements. Drivers' previous experience of trains' absence at crossings affected their motivation to acquire information at the crossing and the impulse to look for trains increased as the number of trains at the crossing increased.

The impact of stop signs at rail crossings is somewhat controversial (Yeh and Multer, 2008). Compliance with stop signs at passive rail crossings is relatively low and this noncompliance can potentially increase drivers' disrespect of stops signs at other locations (e.g., roadway intersections). The Federal Highway Administration (FHWA) recommends the use of yield signs at passive rail crossings while the use of stop signs is limited to unusual situations and subject to engineering studies. Lenné et al. (2011) conducted a driving simulator study and compared driver behavior at rail crossings with different warning devices such as flashing red lights, traffic signals, and stop-signs. They found that vehicle speed reduced more rapidly in response to flashing lights than to traffic signals. Stop-sign crossings had the lowest speed but also had the highest number of noncompliance drivers.

2.2.3 Roots of Noncompliance

Highway user noncompliance behavior at HRGCs can be due to a variety of reasons, such as restricted sight of crossings or trains, highway users' distraction and inattention, lack of knowledge, inaccurate risk perception, deliberate risk-taking behavior, etc. (Searle et al., 2011). Except in rare cases when there are problems with the rail crossing design or warning devices are malfunctioning, most of the noncompliance is due to highway users (Ngamdung and DaSilva, 2012). The noncompliance is either deliberate or by mistake (Freeman and Rakotonirainy, 2015). It is not uncommon for drivers to be unfamiliar with rail crossing safety. Drivers generally recognize the advanced warning and crossbuck signs, but some did not fully understand the signs in relation to crossings and which actions were required (Yeh and Multer, 2008).

Through a survey that investigated the origin of pedestrians' rule violation behavior at railroad crossings in Australia, Freeman and Rakotonirainy (2015) reported that pedestrians were more likely to deliberately violate rules rather than make errors. In their study, 24.52% of the participants reported having intentional violations and only 3.46% of the participants made errors at crossings. The most common reason for the deliberate violations was being in a hurry. Males, minors (<18 years), frequent crossing users, and risk-prone people are more inclined to make deliberate violations. Similar results were reported by Edquist et al. (2011), who did a literature review and conducted field observations in Australia. They concluded that typical non-compliant crossing users were adult, males, crossing alone, and in a hurry. Distraction was not found as a common reason for trespassing pedestrians. Based on the findings, the authors recommended improving warnings and physical barriers, and designing good education and enforcement campaigns along with changing the crossing layout.

Motor vehicle drivers were generally considered more likely to get involved in railroad crossing violations as a result of judgment errors or failure to detect the crossing or the train (Freeman and Rakotonirainy, 2015). By analyzing data from detailed police reports at rail crossings in Victoria, Australia, Wigglesworth (2001) concluded that the majority of accidents were due to driver distraction, inattention, and cognitive overload rather than deliberate violations.

Many studies differentiated intentional and unintentional violations at railroad crossings (Salmon et al., 2013a, 2013b). Intentional violations at rail crossings may result from sensation seeking or risk taking behavior (Witte and Donohue, 2000), low perceptions of risks (Davey et al., 2008), being in a hurry (Freeman and Rakotonirainy, 2015), etc. Unintentional violations are due to drivers' failure to detect the train, crossing or signals, misunderstanding the meaning of signals and proper actions to take, etc. Unintentional violations account for about half of all accidents at rail crossings in Australia (Young et al., 2015). Motor vehicle driver inattention and low awareness of risks are potential key factors leading to unintentional violations (Caird et al., 2002; Freeman and Rakotonirainy, 2015; Salmon et al., 2013b; Young et al., 2015).

Driving skill and driving style are two driver aspects that explain drivers' behavior at rail crossings (Yeh and Multer, 2008). Driving skill is the ability to conduct correct and safe driving. It may be affected by age, experience, or distractions. Driving style is more about a driver's decision: how a driver perceives the danger at a rail crossing and whether a driver decides to comply or not. Driving skill may be related to unintentional violations while a risky driving style can lead to intentional noncompliance. Yeh and Multer (2008) concluded that alcohol consumption and drug use, fatigue, and distraction decreased drivers' driving skills. Drivers' expectations, gender, and age affected their driving styles. Drivers tended to underestimate the dangers at rail crossings, did not expect to encounter a train, and sometimes did not even look for a train. Those who were familiar with the crossings were more likely be involved in an accident. Male and young drivers were found to be more aggressive in their driving styles.

Driver age and vehicle type may play a role in explaining the differences in the type of noncompliance. Older people may suffer from the degeneration of critical judgment abilities while young drivers may be more risk-prone. Wallace (2008) investigated motorist behavior at rail grade crossings and the effectiveness of educational interventions for improving safety. The investigation included three studies. The first study identified three user groups with the highest risks -- older, younger, and heavy vehicle drivers. Each of the three groups has unique issues: older drivers may make judgment errors while younger drivers may be more prone to risk. Drivers of heavy vehicles may intentionally take risks and the length of heavy vehicles may also be a major concern. The second study examined the characteristics of each risk group. The third study developed targeted interventions for each group, investigated the present context of unsafe driving behavior at rail crossings, and piloted a safety radio advertisement campaign as an intervention. The main methods of data collection in Wallace's study were expert and train driver panels, focus group discussions, and non-sampling interviews.

2.2.4 Driver Inattention and Distraction

Significant research has addressed drivers' inattention and distraction in general highway settings, but research regarding the contribution of these factors to rail crossing safety is limited (Yeh and Multer, 2008). Although some research on highway-rail grade crossing investigated distracted driving behavior (Ngamdung and DaSilva, 2012, 2013), reasons for driver distractions and inattention at HRGCs are not clear.

Naturalistic driving studies have been used for data collection in research that focused on distracted driving behavior at rail crossings. The FRA conducted research on driver behavior at or on approach to HRGCs aimed at identifying potential driver education/awareness strategies that would best mitigate risky driver behavior at these locations (Ngamdung and DaSilva, 2012, 2013). A total of 4,215 grade crossing events involving light vehicle drivers and a total of 3,171 involving heavy vehicle drivers were collected from a field operational test of vehicle safety systems. The collected information included drivers' activities, driver and vehicle performances, driving environments, and vehicle locations at the crossings. The study found that on average light vehicle and heavy vehicle drivers engaged in secondary tasks 46.7% and 21% of the driving time, respectively. The most common secondary tasks conducted by light vehicle drivers were talking to or looking at passengers (15.5%) and using cellphones (6.6%). Comparisons for heavy vehicle drivers included using cellphones (6.5%) and smoking or lighting cigarettes (4.9%). The studies also examined drivers' looking behavior and found that on approach to passive rail crossings, 35% of the light vehicle drivers failed to look either left or right for trains, while the percentage among heavy vehicle drivers was 41%. At active crossings, 68.8% of the light vehicle drivers and 39.3% of the heavy vehicle drivers failed to look for trains.

At passive crossings where train and highway traffic is usually low, motorists may be more inattentive and thus fail to notice approaching or passing trains (Searle et al., 2012; Edquist et al., 2009). The US National Transportation Safety Board (NTSB) investigated 60 crash cases at passive grade crossings (NTSB, 1998). Of these cases, driver distraction was as a primary cause in 10 cases and cited as a contributing factor two additional cases; this accounted for 20% of all the cases (Yeh and Multer, 2008). In-vehicle distraction sources included stereo systems and passengers, while highway traffic was the external distraction most frequently cited.

Caird et al. (2002) developed a taxonomy of factors that contributed to the HRGC crashes that included unsafe actions such as distraction and risk taking behavior, low train visibility, etc. The analysis of crash narratives revealed that intentional risk actions (e.g., drove around lowered gates or descending gates) and distraction were crash contributors. In the 3,990 crash narratives that Caird et al. queried, 86 indicated intentional actions as a contributing factor and 39 of them found driver distraction was a contributing factor. Identified distractors included cellular phone usage, cognitive distraction, interacting/talking with passengers, distraction from outside of vehicles, and adjusting in-vehicle equipment.

A survey of 4,402 participants in Australia revealed that 25% of the respondents had engaged in risky behavior at rail level crossings (Searle et al., 2012). Amongst the respondents, 22% did not notice a level crossing until they had driven through it and the study identified motor vehicle driver inattentiveness and impatience as the most significant risk factors.

Driver inattention can also be a result of drivers' low expectation of a train. Drivers seem to underestimate the number of trains passing a crossing (NTSB, 1998). All 18 drivers interviewed in this study underestimated the frequency of train crossings per day; the number of actual train crossings is typically two to three times higher than the drivers' expect, and sometimes 10 times higher than expected. This low expectancy gets reinforced each time the driver passes the crossing without seeing a train.

Traffic outside of the vehicle or highway signals can become a distraction to a driver at a rail crossing that may make the driver unable to detect an approaching train (NTSB, 1998). Young et al. (Young et al., 2015) examined driver attention on approach to urban railroad crossings by using on-board monitoring equipment. They found rail crossings were not the key focus of drivers' attention; drivers were over-dependent on warning signals and surrounding vehicles' behavior to alert them of the presence of crossings and trains rather than relying on their own scanning activities and judgment. Behavior was also found to be different between experienced drivers and novice drivers. A train itself can sometimes become a distraction to roadway users because they may focus their attention on one approaching or stationary train while a second train is coming from another direction (Caird et al., 2002; Wallace, 2008). This can occur at active crossings where highway users may think the activation is only due to the first train. Mental inattention, which means the driver is not distracted by an obvious outside or inside object or event, can also be detrimental and sometimes results in drivers "looking but not seeing" (Salmon et al., 2013b).

Tung and Khattak (2015) investigated motor vehicle driving distraction in the vicinity of HRGCs using data collected with video recordings. They found about 1/3 of the drivers were distracted. The presence of an intersecting highway near the HRGC and the presence of front-seat passengers in vehicles increased distracted driving, while drivers in multiunit trucks were less often distracted.

2.2.5 Method and Data

A naturalistic driving study is an effective method to investigate driver behavior such as inattention. The Second Strategic Highway Research Program (SHRP2) is the largest and most comprehensive naturalistic driving database to date and contains information on driver pre-crash and pre-near-crash behavior. The database has 3,900 vehicle-years and 12,500 roadway centerline miles. A previous well-known naturalistic study is the 100-Car naturalistic driving study, the data for which was collected in North Virginia with 100 vehicles in one year. The advantages of using naturalistic driving data to study driver inattentive behavior include allowing researchers to directly observe the subjects in a natural setting, see exactly what drivers were doing (any distraction or inattention) before accidents or near-accidents, etc. There are some disadvantages as well, including: data collection through instrumented vehicles is costly, participants are usually voluntary and not randomly chosen, drivers may behave differently when they know they are being watched, different observers may draw different conclusions from the same witnessed behavior, etc. Also, due to a limited number of accidents observed in naturalist data, it is difficult to use naturalistic data to investigate the association between injury severity and inattentive driving behavior. Studies of driver behavior at HRGCs using field observational test data for light and heavy vehicles are naturalistic studies (Ngamdung and DaSilva, 2012, 2013). As mentioned earlier, these studies found that vehicle drivers engaged in secondary tasks 21% - 46.7% of the time when driving at HRGCs.

The fixed-site observational data collection method is used to observe driver behavior at selected rail crossings. It can utilize direct observation (Åberg, 1988) or video-based observations (Khattak and Luo, 2011; Khattak et al., 2012; Ko et al., 2003; Tung, 2015). Fixed-site observation can usually collect data such as driver distraction behavior, head movements, drivers' looking behavior, the presence of passengers in the vehicle, etc. Compared to naturalistic data, fixed-site observational data is confined to a "fixed site" and the accuracy of the observations or resolution of the cameras, and cannot provide as much detailed information as naturalistic data. However, fixed-site data collection is much less costly and more feasible; can exactly pertain to driver behavior at HRGCs; can have a large sample size; normally does not influence drivers; and has a better control of location selection.

Crash reports are also used to investigate driver behavior such as distractions. NHTSA (2010) currently has three major sources of data to assess the effects of distraction. The first is the Fatality Analysis Reporting System (FARS), which contains fatal crash data. The second is the National Automotive Sampling Systems (NASS) General Estimate System (GES) that provides a sample of all police-reported accidents of varying severities. Crash data showed that 17% of all police-reported accidents involved some distraction (NHTSA, 2012). The third NHTSA data source is the National Motor Vehicle Crash Causation Survey (NMVCCS, accessed on July 5, 2015), which is a national representative database that contains in-depth investigations of 6,949 accidents reported between 2005 and 2007. This data indicated that 11% of the accidents involved in-vehicle distraction as a primary reason. The first two data sources are all police accident report-based. One potential problem of using this type of crash data to evaluate the role of distraction is that there is a wide range of variability in the data because of the collection and reporting differences from different states. Driver inattention may be underestimated among these police-reported accidents (Abay, 2015; Neyens and Boyle, 2008), especially in fatal accidents. People may not always honestly report their actual behavior (such as distracted by a cellphone) or psychology at the time of the accident (Salmon et al., 2013b) and this can lead to significant bias in evaluating the impact of inattentive driving on injury severities. There is a consensus that underestimation exists in police-reported data, but there are few detailed analyses of the extent of underreporting and its effects on analysis. On the other hand, police-reported accident data is often the only source of accurate and comprehensive crash data. In traffic accident studies, for example, those focused on injury severities at rail crossings, police-reported data is the only available source that is comprehensive enough to include adequate sample sizes for every injury level.

Questionnaire surveys or focus group interviews are other methods that can be used to collect information on driving behavior at rail crossings. Davey et al. (2008) conducted semi-structured focused group interviews with 53 young drivers from regional and metropolitan settings. Motorists' self-reported behavior, attitudes, and knowledge about highway-rail grade crossings were explored. Freeman and Rakotonirainy (2015) conducted a survey for pedestrians using rail crossings and examined the origins of pedestrian rule breaking behavior. Roy Morgan Research (2008) surveyed 4,402 drivers and identified the significant role of inattentiveness in increasing rail crossing risks. A survey of 891 randomly selected residents in Michigan was conducted by Witte and Donohue (2000), who reported that male drivers with strong sensation seeking tendencies were risk-takers at rail crossings. Overall, many studies conducted surveys or interviews that investigated highway users' knowledge, risk-taking attitudes, and behavior at rail crossings, but surveys particularly focusing on driver inattention and distraction are sparse.

Besides discussions on different data sources, researchers also investigated the improvement of analysis methods. Read et al. (2013) indicated that current studies of user behavior at railway crossings are mostly from individual perspectives instead of a systemic perspective. They advocated a systems approach and discussed the key concepts and criteria for this approach. Previous research that focused on individuals usually only considered one user group, no relations or limited relations between components of the system, established unidirectional cause and effect relationships, etc. A systems approach, on the contrary, treats safety as an emergent property, considers the variability of the system and the performance of all components, and notes the system is dynamic and has a hierarchical structure. Salmon et al. (2013b) used a system analysis framework and an individual psychological schema theory explained an accident between a semi-trailer truck and a passenger train. In that accident, the truck driver refused to be interviewed by the investigators for the reason that he did not react properly to the crossing warning devices. The authors utilized other information obtained from the Office of Chief Investigator (OCI) investigation report and selected court transcripts and concluded that the primary cause of the accident was that the driver looked but failed to see.

2.3 Injury Severity at Highway-Rail Grade Crossings

Multiple studies have investigated factors associated with crash injury severity at HRGCs (Eluru et al., 2012; Hao and Daniel, 2014; Russo and Savolainen, 2013; Fan and Haile, 2014; Zhao and Khattak, 2015). Commonly employed models for analysis included the logit, multinomial logit, probit, and ordered logit/probit models. The US based research on crash injury severity at HRGCs mostly utilized the FRA crash and the national rail crossing inventory data (FRA, 2015). Factors increasing crash injury severity included greater train and highway traffic (especially heavy vehicles), higher train and vehicle speeds, the presence of highway separation, adverse weather conditions, low visibility, freight-train involvement, truck and truck-trailer involvement, older drivers, females, and higher daily temperature. The following summarizes some previous research on the severity of injuries at HRGCs.

Hu et al. (2010) formulated a generalized logit model using data from 592 highway railway crossings in Taiwan. Railway, highway, crossing, traffic control, and land use features were considered in their research. Results showed that an increase in the number of daily trains and daily trucks increased the likelihood of more severe crash injuries. The presence of highway separation and obstacle detection devices were also associated with more severe accident injuries.

Eluru et al. (2012) developed a latent segmentation-based ordered logit model using FRA crash data from 1997-2006. The crossings were first assigned probabilistically to different segments based on their attributes. Attributes such as a higher number of trains, the existence of pavement markings for stop signs, and lower maximum posted train speed limits were associated with low-risk crossing segments. Within each segment, an OL model was applied to analyze crash-related attributes. A comparison of the results across different segments showed different variables associated with crash injury severities.

Hao and Daniel (2013) used FRA crash data from 2002-2011 and an OP model to determine factors influencing drivers' injury severity levels at HRGCs. The factors found to relate to higher injury severities included: accidents reported during peak-hour traffic, adverse weather (e.g., cloudy, rain, fog, sleet, and snow), low visibility, vehicular speed greater than 50 mph, highway average annual daily traffic (AADT) of over 10,000, train speed greater than 50 mph, trucks and truck-trailers, and accidents reported in open areas.

Using FRA HRGC crash data from 2011, Russo and Savolainen (2013) assessed the effects of rail, highway, traffic, and driver characteristics on the frequency and severity of HRGC collisions. An injury severity analysis was investigated using an OL model. The factors that increased the likelihood of fatal injuries included train speeds greater than 60 mph, driver age over 60 years, females, and motorists who did not stop at crossings.

Fan and Haile (2014) used 2005-2012 FRA HRGC crash data and a MNL model to explore the impacts of various explanatory variables on crash injury severity levels.

Results showed that chances of fatalities increased when rail equipment at high speeds struck a vehicle and when accidents were reported at higher air temperatures. Male vehicle drivers 25 years of age and above, pickup trucks, and concrete and rubber crossing surfaces were associated with more severe crash injuries; while truck-trailers, foggy and snowy weather conditions, certain land development types, and higher daily vehicle traffic volumes were associated with less severe crash injuries.

Zhao and Khattak (2015) also utilized the FRA accident and crossing inventory data and compared different models while studying motorist injury severity at rail crossings. The comparison revealed that the random parameter logit model and multinomial logit model were more suitable for injury severity analysis at HRGCs. Factors that increased the likelihood of severe accidents included higher train and vehicle speeds, freight trains, older and female drivers, etc.

There are at least two potential limitations among these previous injury severity studies at HRGCs. First, the aforementioned studies at HRGCs using FRA data were limited to train-involved crashes and ignored other crashes reported near HRGCs. This is a limitation because, for example, considerable speed variation exists amongst highway traffic at HRGCs, which is responsible for many rear-end crashes near rail crossings (Mortimer, 1988). These crashes could potentially block the crossing, thus disrupting traffic or causing secondary crashes. Secondly, studies on the effects of inattentive driving on the severity of accidents near rail crossings are sparse.

2.4 Gaps in the Literature

Distracted motor vehicle driving on highways has been studied extensively. Motor vehicle inattentive driving and its consequences at highway-rail grade crossings, however, has not been explored to the same extent. Motor vehicle driver inattention leads to traffic accidents, but its role in accident severity is unclear. Some studies on highways show that distractions such as cell-phone usage can lead to more severe accidents but other distractions such as cognitive inattention are associated with less severe accidents. There is a research gap regarding the association between inattentive driving and injury severity at HRGCs. Therefore, a comprehensive study of this association, which takes into consideration different types of accidents (e.g., single-vehicle, multi-vehicle, train-involved, etc.) and varied types of inattentive driving behavior (e.g., cell phone use, inattention, etc.) at HRGCs is needed.

Previous studies on inattentive driving explored how inattention affects safe driving; how distraction influences drivers' visual, manual, and cognitive performances; how distraction introduces driving errors; etc. The reason behind drivers' inattentive driving behavior at HRGCs has not been widely discussed by previous research. A survey questionnaire that asks motor vehicle drivers about their inattentive driving experiences, knowledge, attitudes, and expectations towards safety at HRGCs can provide information useful in explaining inattentive driving behavior.

Previous programs of educating drivers about safe behavior at HRGCs may have improved safe driver behavior at HRGCs but information on which groups of people are in urgent need of such information and identification of safe driving knowledge that drivers may be lacking is needed. In this case, a study is needed to identify groups of drivers that have lower or higher levels of knowledge about correct rail crossing negotiation, higher risks of inattentive driving, and higher chances of being involved in accidents. Again, information gathered from a survey questionnaire that includes information on motor vehicle drivers' knowledge and experiences at HRGCs and an analysis in this area can hopefully fill this gap.

CHAPTER 3 DATA COLLECTION AND METHODOLOGY

3.1 Data Collection

Two datasets are used in this research.

(1) Dataset 1: Nebraska motor vehicle crash reports. This is a Nebraska-based police-reported accident database. Accidents reported at HRGCs in Nebraska from 2002 to 2013 will be extracted and included in this research. The accident database includes a wide range of useful information, such as accident data case summaries, driver information, injured occupant information, and vehicle information. This database will be used to complete the first objective. The available data fields are presented in Appendix A.

(2) Dataset 2: Questionnaire survey. A survey questionnaire was designed to solicit information from Nebraska drivers on their experience at HRGCs and mailed to randomly selected respondents across Nebraska in July and August 2015. The survey prototype is attached in Appendix B. The survey asked for a motor vehicle driver's perceptions of safety at HRGCs, usage and knowledge of HRGCs, noncompliance and inattentive driving experiences at HRGCs, attitudes towards safety at HRGCs, accident history at HRGCs, and general information about the driver. This database will be used to complete the second, third and fourth objectives of this research. The datasets are described in more detail below.

3.1.1 Dataset 1

Dataset 1 was Nebraska motor vehicle crashes reported in proximity to HRGCs from 2002-2013, acquired from the Nebraska Department of Roads (NDOR) Office of Highway Safety. The dataset contained a field called "Railroad Involved," which was used to extract motor vehicle crashes reported at or near HRGCs. This field indicates the involvement of a train, a rail crossing, or other railroad property in a crash. Thus, the extracted dataset consisted of all motor vehicle crashes that were reported at, or adjacent to, railroad crossings within the state of Nebraska from 2002 to 2013. Another field called "Impact Point with Railroad" allowed identification of train-involved crashes. The final dataset consisted of 2,303 crashes. Amongst the crashes reported at or near HRGCs in Nebraska during the study period, 25.0% involved at least one person injured and 2.6% of the crashes reported at least one fatality. The average injury rate and fatality rate per thousand crashes were 365 and 30, respectively. These numbers are higher than crash numbers reported at non-HRGC highway locations. For example, there were 654,065 crashes reported at non-HRGC locations in Nebraska from 2002 to 2013. Amongst these crashes, 24.1 % crashes had at least one injury and 0.4% of the crashes involved at least one fatality. The injury and fatality rates per thousand crashes reported at non-HRGC locations were 349 and 4, respectively. This comparison strengthens the need to investigate crash injury severity at HRGCs and relevant associated factors.

In the final dataset that consisted of 2,303 crashes reported at or near HRGCs, 133 did not have any driver or vehicle information recorded and were thus excluded from the analysis. The remaining 2,170 crashes consisted of 1,171 single-driver crashes, 897 two-driver crashes, 90 three-driver crashes, 10 four-driver crashes, one five-driver crash, and one six-driver crash. **Table 3.1** presents a cross tabulation of the number of drivers and number of vehicles in the dataset.

Table 3.1 Crash distribution based on number of vehicles and number of drivers

		Number of vehicles						
		1	2	3	4	5	6	total
Number of drivers	1	1,138	33	0	0	0	0	1,171
	2	0	890	7	0	0	0	897
	3	0	0	90	0	0	0	90
	4	0	0	0	10	0	0	10
	5	0	0	0	0	1	0	1
	6	0	0	0	0	0	1	1
	total	1,138	923	97	10	1	1	2,170

The study focused on driver injury severity instead of overall crash severity because that allowed the use of variables such as driver age, gender, use of seatbelt, etc., in the estimated models. Driver injury severity was measured on the KABCO scale: K = fatal injury, A-type = incapacitating injury, B-type = non-incapacitating (evident) injury, C-type = possible injury, and O-type = property damage only. Categorization of crash injury severity using the KABCO scale is common practice in the US. Other variables in the dataset that were of interest are summarized in Appendix A.

3.1.2 Dataset 2

A survey questionnaire was designed to solicit information from Nebraska drivers on their experiences at HRGCs and mailed to randomly selected respondents across

Nebraska in July and August 2015. The Bureau of Sociological Research (BOSR) of the University of Nebraska-Lincoln helped administer the survey (i.e. mail-out survey questionnaire, send reminders to non-responders, and receive and code completed questionnaires).

Survey development

The questionnaire consisted of eight sections: Section 1 (Question 1 a-e) used five single choice questions to acquire drivers' perceptions of HRGC delays, safety, whether the traffic signs and pavement markings are confusing at HRGCs, the reliability of train warning devices at local HRGCs in their cities, as well as perception of information from HRGC safety outreach. All five questions were measured on a five-point Likert scale, which allows individuals to expresses how much they agree or disagree with a particular statement.

Section 2 (Question 3, 5, 7) included one single choice question asking drivers what motor vehicle types were used for personal purposes as well as two questions asking drivers' their frequency of using HRGCs and perceived number of daily train passages at the HRGCs they use the most often.

Section 3 (Question 8 to 16) included nine questions testing drivers' knowledge of safe driving at HRGCs and proper actions under emergency situations. There were six single choice questions and three multiple choice questions. Specifically, knowledge tested included understanding of crossbuck signs, use of railway 1-800 phone number, proper actions when lights are flashing, proper actions when lights start flashing while crossing, the meaning of "No Train Horn," proper actions when stalled on tracks, actions that are considered violations at gated rail crossings, proper actions when gates do not ascend immediately after a train has passed, and what types of vehicles must stop at rail crossings.

Section 4 (Question 17 a-n) had 14 questions asking about drivers' attentive or inattentive driving behaviors at HRGCs. All questions were single choice questions based on the five-point Likert scale (from "always" to "never"). These behaviors included looking left and right to check for trains; crossing when warning devices are activated; crossing when gates are descending, ascending, or leveled; stopping at STOP signs at HRGCs; talking to passengers; eating or drinking; talking on a phone; texting or using apps; reaching for objects inside the vehicle; adjusting in-vehicle equipment; being distracted by an outside person or object; being involved in mental distraction; smoking cigarettes; or any other form of inattention.

Section 5 (Question 18 a-m) contained 13 questions asking about drivers' attitudes towards safety, safety reinforcement strategies, and intent to break the rules at HRGCs. All questions were single choice questions based on the five-point Likert scale (from "strongly agree" to "strongly disagree"). The questions included whether they agree or disagree that safety at HRGCs is a significant issue, whether they like to wait for trains to pass, whether they like to accelerate to cross through when warning devices are activated, whether they routinely stop when warning devices are activated even if there is a chance to cross, whether they regret stopping for trains when there is a chance to cross, whether they like to cross after train passage but warning devices are still active, whether they ensure warning devices are off before crossing, whether they like to drive around fully lowered gates, whether they support technology that blocks cell phone signals at HRGCs (except for emergencies), whether they support stronger law enforcement, whether they are familiar with Operation Lifesaver, whether they would like to receive information on rail crossing safety, and whether they feel it is fun to play “chicken” (intentionally stopping a vehicle on a rail crossing in front of an oncoming train) at HRGCs.

Section 7 (Question 23 to 30) was a collection of general demographic information that included asking participants their years of residency in their current city, household size, years of driving, gender, age, education, occupation, and household income level.

Survey implementation

As stated before, the mail survey was administrated by the BOSR of the University of Nebraska-Lincoln. The survey was aimed at obtaining a general population sample of motor vehicle drivers in Nebraska. To reach this goal, the survey used a postal delivery sequence-based sample of household addresses (Address-Based Sample, or ABS). To randomize responding household members, instructions in both cover letters and the postcard reminder were included to have the licensed driver 19 years of age or older living in the household, who has the next upcoming birthday, complete and return the questionnaire.

A sample of 2,500 households was purchased from Survey Sampling International, LLC (SSI). The household addresses were drawn from Nebraska with equal probability of selection. A total of 980 households completed the survey during the survey study period. The overall response rate for this survey was 39.2%. It should be noted, however, that due to the mode of data collection (mail), it is uncertain if surveys reached the entire sample. From the original 2,500 households, 210 surveys were returned as undeliverable with no forwarding address available.

Participants demographics

A total of 980 respondents completed and returned the survey questionnaire. However, some returned questionnaires included missing values; the treatment of missing values in this dataset is discussed later. The average years of residency in the participants' current city ranged from one month to 83 years, with an average of 24.7 years and a standard deviation of 20.6 years. Considering household size, there were 299 (30.5%) households with fewer than two adults, 539 (55.0%) with two adults, and the remaining 106 (10.8%) with more than two adults (36 missing). Except for the 26 missing values, 889 (90.7%) participants have been a licensed driver for more than 10 years.

With 544 (55.5%) female participants and 406 (41.4%) male participants (30 missing values), when compared to 50.2% females in Nebraska's total population in 2014 (U.S. Census Bureau, 2014), female respondents were slightly overrepresented in this sample. The participants' age distribution showed 96 (9.8%) were under 30 years old, another 438 (44.7%) were under 60 years old, and the remaining 420 (42.9%) were equal to or above 60 years old (26 missing values). The percentage of people over 65 years old in this sample is 29.9%, compared to 14.4% state-wide in Nebraska (U.S. Census Bureau, 2014), indicating some overrepresentation in the sample. There were 218 (22.2%) respondents with up to a high school education, 307 (31.3%) with some college or an associate degree, 250 (25.5%) with a bachelor's degree, and the remaining 147 (15.0%) with a master's or higher degree (46 missing values and 12 having other forms of education). Respondents showed a somewhat even distribution across different occupations. Households with lower than a $30,000 annual income accounted for 18.4% of the sample. There were 256 (26.1%), 217 (22.1%), and 203 (20.7%) households with annual incomes falling into the categories of $30,000-$60,000; $60,000-$100,000; and greater than $100,000 (124 were missing for the income question); respectively.

3.2 Analytical Methods

3.2.1 Random Parameters Binary Logit Model

Data analysis utilized the random parameters binary logit regression to investigate probabilities of injuries and no injuries in crashes. Compared to the traditional binary logit model, the random parameters binary logit model deals with the unobserved heterogeneity issue. Not accounting for unobserved heterogeneity in the analysis has implications for inferences drawn from modeling results, therefore, incorporating unobserved heterogeneity in traffic crash studies has been of significant interest in recent years (Mannering and Bhat, 2014). By allowing at least some of the parameters to vary across observations, random parameter models can potentially capture individual heterogeneity. Mathematically, the random parameters binary logit model is:

$$\pi_i = \Pr(Y_i = 1 \mid X_i = x_i) = \frac{e^{(\boldsymbol{\beta}_i \, \mathbf{x}_i + \varepsilon)}}{1+e^{(\boldsymbol{\beta}_i \, \mathbf{x}_i + \varepsilon)}} \quad (1)$$

Where,

π_i = probability of injury,

Y_i = binary response variable; Y_i=1 if driver is injured, and Y_i=0 if not injured;

$\boldsymbol{\beta}_i$ = a vector of estimated parameters and are randomly distributed following certain

probability distributions; and

$\mathbf{X}_i$ = a vector of the explanatory variables (e.g., driver behavior such as inattention, etc.).

The link function of the binary logit model indicates the cumulative standard logistic probability distribution function. To simplify the model, logit transformation (i.e., logit(π_i)) is employed, and eq. (1) can be expressed as:

$$\text{logit}\ (\pi_i) = \log\left(\frac{\pi_i}{1-\pi_i}\right) = \boldsymbol{\beta}_i\mathbf{X}_i + \varepsilon \quad (2)$$

The advantage of the logit transformation is allowing the right side of the equation to be a linear function of explanatory variables.

3.2.2 Confirmatory Factor Analysis

Factor analysis is a family of statistical methods that account for the covariance among a large set of observed variables (also called manifest variables) by identifying a set of unobserved variables (also called latent variables or factors). The latent variables are assumed to be underlying factors that influence the corresponding observed variables. Confirmatory factor analysis (CFA) is a restricted factor analysis, which can be used in an inductive way to test the hypotheses regarding unmeasured sources of variability responsible for the commonality among a set of observed variables (Hoyle, 2000; Albright and Park, 2009). CFA is usually understood as an instance or the measurement part of the more general structural equation model (SEM).

Latent variables in the CFA are not directly measured, but they account for the commonality among a set of observed variables (Hoyle, 2000). In **Figure 3.1**, the Venn diagram shows three observed variables (or say, measures), x1, x2 and x3, and their shared variance, or covariance, V. The three circles represent the three measures and the overlap shadow represents the underlying factor.

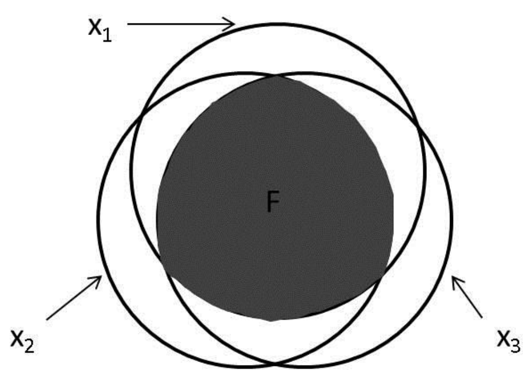


Figure 3.1 Venn diagram of three measures of a single construct and their shared commonality

(Recreated from Figure 16.1, Hoyle, 2000. “Confirmatory Factor Analysis.” Handbook of Applied Multivariate Statistics and Mathematical Modeling: 465-497)

The Venn diagram, however, is not a statistical means of modeling the factor. A path diagram, as presented in **Figure 3.2**, illustrates the same association between these variables.

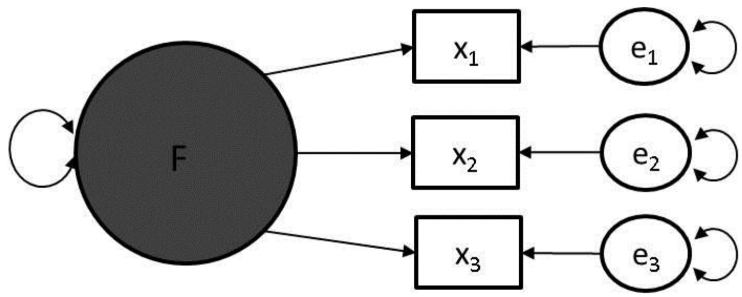


Figure 3.2 Path diagram of three measures of a single construct and their shared commonality

(Recreated from Figure 16.1, Hoyle, 2000. "Confirmatory Factor Analysis." Handbook of Applied Multivariate Statistics and Mathematical Modeling: 465-497)

In the above path diagram the x_1, x_2, and x_3 in the rectangles are measured variables, which are also referred to as indicators; ellipses in the diagram represent unmeasured variables; the F in the large ellipse is a factor (i.e., commonality); the e_i in the small ellipses are errors of the measures (i.e., uniqueness), which represent the unobserved sources of influence unique to the indicators; the single-headed straight arrows indicate the causal influence by showing that each indicator is caused by two unmeasured influences – the common factor and the additional unique errors; the double-headed curved arrows indicate variances without a causal interpretation. The path diagram can be translated into statistical form through measured equations. For example, x_1 in the above diagram can be translated into eq. (3).

$$x_1 = l_1 * F + e_1 \tag{3}$$

In which, l_1 is the factor loading.

When there is more than one factor influencing the same indicator, eq. (3) can be expanded to the format of eq. (4).

$$x_i = l_{i1} * F_1 + l_{i1} * F_1 + \cdots + l_{ik} * F_k + e_i \tag{4}$$

3.2.3 Robust Linear Regression

In general, robust regression is a form of regression analysis that is designed to circumvent some limitations of traditional regression methods. For example, ordinary least square regression is sensitive to outliers. If the outliers do not follow the patterns of other observations and are violating the normality assumption of the ordinary least squares, the validity of the non-robust regression results will be compromised. Robust regression provides an alternative to least squares by requiring less restrictive assumptions and decreasing the influence of outlying observations to provide a better fit to the majority of the data.

In ordinary least square regression, outliers receive more weightage (because of squared error terms in solving the least square equations), which can lead to distorted estimates of the regression coefficients and make it difficult to identify the outliers since the residuals are smaller than they would be if the estimates were not distorted. Robust regression down-weights the influence of outliers and makes the residuals larger and easier to identify.

M-estimator is a class of estimators commonly used in robust regressions. The M-estimator was introduced by Huber (1964). Consider the linear model:

$$y_i = \boldsymbol{x}_i^T \boldsymbol{\beta} + \varepsilon_i \tag{5}$$

Then,

$$\varepsilon_i = y_i - \boldsymbol{x}_i^T \boldsymbol{\beta} \tag{6}$$

For the i^{th} observation, the residual is

$$e_i = y_i - \boldsymbol{x}_i^T \boldsymbol{b} \tag{7}$$

M-estimators minimize the objective function, which is a sum of a chosen function $\rho(\cdot)$:

$$\sum_{i=1}^{n} \rho(e_i) = \sum_{i=1}^{n} \rho(y_i - \boldsymbol{x}_i^T \boldsymbol{b}) \tag{8}$$

In which, the function $\rho(\cdot)$ gives the contribution of each residual to the objective function. The "M" in the M-estimator stands for "maximum likelihood" since $\rho(\cdot)$ is related to the likelihood function for a suitably assumed residual distribution.

By differentiating the objective function with respect to the coefficients, b, and setting the partial derivatives to 0, a set of k+1 (k is the number of parameter estimates) estimating equations for the coefficients are obtained (Fox, 2012):

$$\sum_{i=1}^{n} \psi(y_i - \boldsymbol{x}_i^T \boldsymbol{b}) \boldsymbol{x}_i^T = \boldsymbol{0} \tag{9}$$

In which, $\psi = \rho'$ is the derivative of the function $\rho(\cdot)$. Then eq. (9) can be written as

$$\sum_{i=1}^{n} \omega_i (y_i - \boldsymbol{x}_i^T \boldsymbol{b}) \boldsymbol{x}_i^T = \boldsymbol{0} \tag{10}$$

In which, $\omega_i = \omega_i(e_i) = \psi(e_i)/e_i$ is defined as the weight function.

To solve the estimating equations in eq. (10), minimizing $\sum_{i=1}^{n} \omega_i^2 e_i^2$, an iterative solution that is called iteratively reweighted least-squares (IRLS), is required. This is because the weight depends on the residuals, the residuals depend upon the estimated coefficients, and the estimated coefficients depend upon the weights. The IRLS is used to iteratively estimate the weighted least squares estimates until the coefficients converge. That is, to start with an initial estimate $\boldsymbol{b}^{(0)}$, such as the least-square estimates. Then, at each iteration t, calculate residuals $e_i^{(t-1)}$ and weights $\omega_i^{(t-1)} = \omega[e_i^{(t-1)}]$ from the previous iteration. After that, solve for the new weighted-least-squares estimates

$$\boldsymbol{b}^{(t)} = [\boldsymbol{X}'\boldsymbol{W}^{(t-1)}\boldsymbol{X}]^{-1}\boldsymbol{X}'\boldsymbol{W}^{(t-1)}\boldsymbol{y} \tag{11}$$

In which, $\boldsymbol{W}^{(t-1)} = diag\{\omega_i^{(t-1)}\}$ is the current weight matrix.

The steps get repeated until the coefficients converge. The asymptotic covariance matrix of b is

$$V(\boldsymbol{b}) = \frac{E(\psi^2)}{[E(\psi')]^2}(\boldsymbol{X}'\boldsymbol{X})^{-1} \tag{12}$$

The estimated asymptotic covariance matrix, $\hat{V}(\boldsymbol{b})$, is produced when using $\sum[\psi(e_i)]^2$ to estimate $E(\psi^2)$ and $\sum[\psi'(e_i)/n]^2$ to estimate $[E(\psi')]^2$.

The objective function in eq. (9) could have several choices. Two common choices are Huber's method and Turkey's bisquare (or biweight) method. The objective functions and weight functions of Huber's and the bisquare methods are as below.

Huber objective function:

$$\rho_H(e) = \begin{cases} \frac{1}{2}e^2 \;\; for\ |e| \le k \\ k|e| - \frac{1}{2}k^2 \;\; for\ |e| > k \end{cases} \tag{13}$$

Huber weight function:

$$\omega_H(e) = \begin{cases} 1 \;\; for\ |e| \le k \\ k/|e| \;\; for\ |e| > k \end{cases} \tag{14}$$

Bisquare objective function:

$$\rho_B(e) = \begin{cases} \frac{k^2}{6}\{1 - \left[1 - \left(\frac{e}{k}\right)^2\right]^3\} \; for\ |e| \le k \\ k^2/6 \;\; for\ |e| > k \end{cases} \tag{15}$$

Bisquare weight function:

$$\omega_B(e) = \begin{cases} [1 - \left(\frac{e}{k}\right)^2]^2 \;\; for\ |e| \le k \\ 0 \;\; for\ |e| > k \end{cases} \tag{16}$$

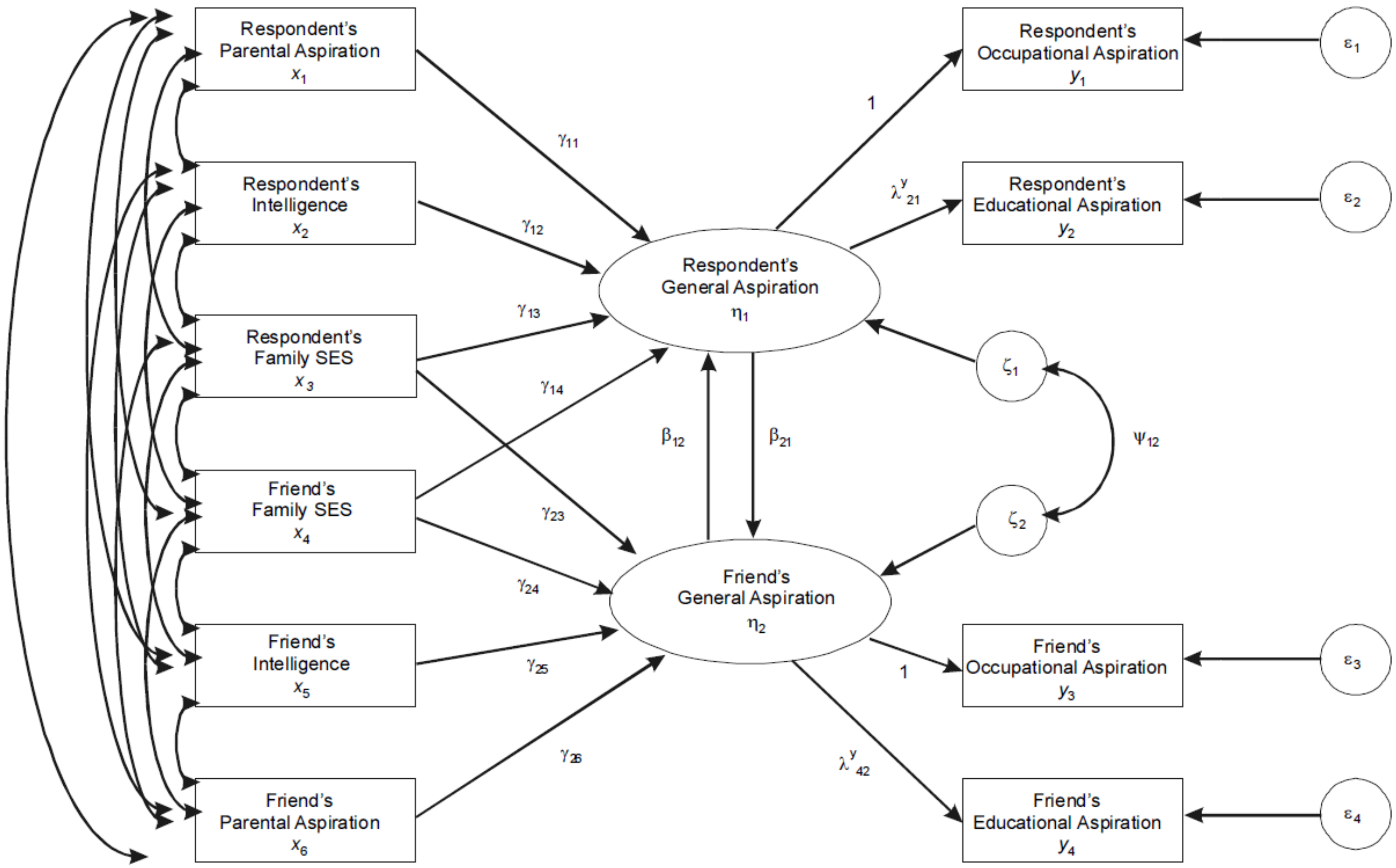
In eq. (13)-(16), the k values are called the turning constant. Smaller values of k produce more resistance to outliers, but at the expense of low efficiency if the errors are actually normally distributed. In Huber, $k = 1.345\sigma$ and in the bisquare method $k = 4.685\sigma$, where σ is the standard deviation of the errors. In applications, σ is approached by using the standard deviation of the residuals, $\hat{\sigma} = \frac{MAR}{0.6745}$, where MAR stands for the median absolute residual.

3.2.4 Structural Equation Model

Structural equation models (SEMs) are commonly described as a hybrid between some form of analysis of variance (ANOVA)/regression and some form of factor analysis. In the SEMs, the response variable in one equation may appear as a predictor in another equation; one variable could influence another variable reciprocally directly or indirectly through intermediaries. The SEM takes in two inputs – the qualitative causal assumptions from the researcher and the empirical data used for the research. The SEM then results in two consequences of the two inputs – the quantitate causal relationships and statistical measures of fit for the assumptions (Bollen et al., 2013).

The SEM usually has two parts: the measurement model and the structural model (Muthén and Muthén, 1998). The measurement model is analogous to the factor analysis introduced in section 3.2.2. It builds the relationships between latent variables (factors) and their manifest indicators. The structural model relates all variables, both latent and manifest. Specifically, the structural model describes three types of relationships- the relationships among latent variables, the relationships among observed variables, and the relationships between latent variables and observed variables that are not factor indicators. These relationships are described by a set of regression equations – linear regression equations for continuous latent variables that are dependent variables, linear regression equations for continuous observed dependent variables, censored normal or censored-inflated normal regression equations for censored observed dependent variables, Poisson or negative binomial regression equations for count observed dependent variables, logistic or probit regression equations for categorical observed dependent variables, etc. (Muthén and Muthén, 1998).

Besides the manifest variables that are directly observed and measured and the latent variables that are not directly measured, in an SEM, variables that are not influenced by other variables in the model are called exogenous variables (represented by x's); variables that are influenced by other variables in the model are called endogenous variables (represented by y's). In an SEM, γ's are representing the structural parameters relating an endogenous to an exogenous variable, and β's are for structural parameters relating one endogenous variable to another. Disturbances terms are represented by ζ's. An example from Fox (2002) is shown in **Figure 3.3**.



*SES stands for socioeconomic status.

Figure 3.3 Duncan, Haller, and Portes's general structural equation model for peer influences on aspirations

(Figure source: Fox. 2002. Structural Equation Models: Appendix to an R and S-PLUS Companion to Applied Regression.)

CHAPTER 4 DRIVER INATTENTION AND INJURY SEVERITY

The two major aspects of highway safety are crash avoidance and reduction of crash severity. Motor vehicle crashes at highway-rail grade crossings (HRGCs) are relatively uncommon, but highly injurious. Motor vehicle driver inattention is a major factor in the occurrence of crashes (Fell and Freedman, 2001; Klauer et al., 2006); it is attributed to about 41% of all US crashes reported in 2005 (Federal Railroad Administration, 2006; Searle et al., 2012). However, the role of motor vehicle drivers' inattention in HRGC crash injury severity requires investigation. This chapter focuses on the first objective of the dissertation - to investigate the association between motor vehicle inattentive driving and the severity of drivers' injuries sustained in crashes reported at or near HRGCs.

This chapter presents an investigation of crashes reported at or near HRGCs in Nebraska to assess the role of drivers' inattention in current injury severity. The study distinguished between single-vehicle crashes and multi-vehicle crashes. Moreover, it accounted for a number of other factors including seatbelt usage, presence of passengers in motor vehicles, driver age, gender, weather, highway speed, road surface condition and light condition, etc.

4.1 Single-Vehicle-Single-Driver (1V1D) Crashes

Excluding crashes involving pedestrians and pedal cyclists, there were 1,133 single-vehicle-single-driver (1V1D) crashes in the dataset. Aggregation of drivers' injury levels into two categories gave 833 no-injury crashes and 300 injury crashes. Based on available data fields in the dataset, driver-related crash factors were identified as driving under influence (DUI), inattentive driving, other improper driving, and no reported improper driving. Each of these four factors were used to create a dummy (indicator) variable as follows:

1) DUI if the driver's blood alcohol content was greater than 0.08 grams/deciliter (g/dl);

2) Inattentive driving if the contributing circumstance to the crash was reported as "inattention," "mobile phone distraction," "fatigued/asleep," "operating vehicle in erratic manner," "distracted – other," or the crash was reported as "alcohol related," but the driver's blood alcohol content was less than 0.08g/dl. The inclusion of BAC level lower than 0.08 as inattentive driving is based on the assumption that even a small amount of alcohol/drugs in the blood may impair driving capabilities and lead to some degree of inattention.

3) Other improper driving if the contributing circumstance to the crash was reported as "disregarded traffic signs, signals, road markings," "driving too fast for conditions," "exceeded authorized speed limit," "failed to yield right of way," "failure to keep in lane or running off road," "followed too closely," "made an improper turn," "operating defective equipment," "other improper action," "over-correcting/over-steering," "swerving or avoiding due to vehicle, wind, etc.," "visibility obstructed," or "wrong side or wrong way etc.;" and

4) No improper driving if the contributing circumstance to the crash was reported as "no improper driving," "not stated," or "unknown." This indicator was not included in the model when the other three indicators (above) were included.

Note that the classification of the above four driver factors utilizes the variable "driver contributing circumstances" in the data. The term "driver inattention" is not readily defined by the police-reported data. The determination of a driver's involvement in inattentive behavior has some ambiguity. Due to self-reporting, this factor may not always reflect the actual situation. For example, drivers involved in a crash may become reluctant to report using cellphones or other improper behavior to avoid legal penalty. In a crash where none of the drivers reported any improper driving, in reality there might be some unreported human mistakes. Additionally, a driver who reported "other improper driving" could be attributed in some way to "inattentive driving." Therefore, the inattentive driving behavior in general might be under-reported in police-reported crash data. However, under-reporting is a well-known problem for any police-reported crash data (Mannering and Bhat, 2014). Numerous studies have used police-reported data to analyze driver behavior. In addition, because pre-crash conditions are difficult to collect (naturalistic studies could help, but it is difficult to use naturalistic research to collect a large sample of crashes), police-report becomes a good choice for investigating crash injuries and pre-crash impacting factors such as inattentive driving. Because the dataset contains a relatively wide time span, from 2002 to 2013, the percentages of crashes associated with different driver factors for each year were calculated and compared, as shown in **Figure 4.1**, to justify there were no significant differences across the years. The percentage, which changes for each type of driver factor across the time span (especially the comparison between earlier years and the more recent years), did not vary beyond a reasonable range - the average percentages for each type of driver factor in the last six years changed within 5% compared with the average percentages in the first six years.

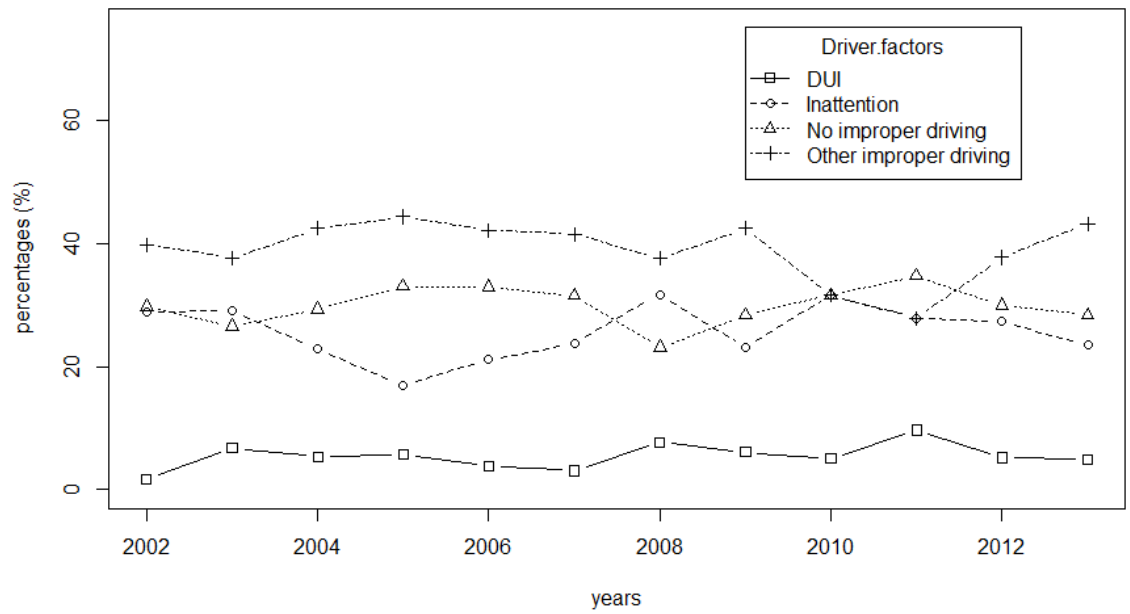


Figure 4.1 Percentages of crashes associated with different driver factors from 2002 to 2013

Other variables such as seatbelt use, driver gender, etc., were available from the police-reported data. **Figure 4.2** describes some features of the 1133 1V1D crashes. The estimated statistical model was a random parameters binary logistic model utilizing multiple explanatory variables in its specification. **Table 4.1** presents potential explanatory (independent) variables for model estimation.

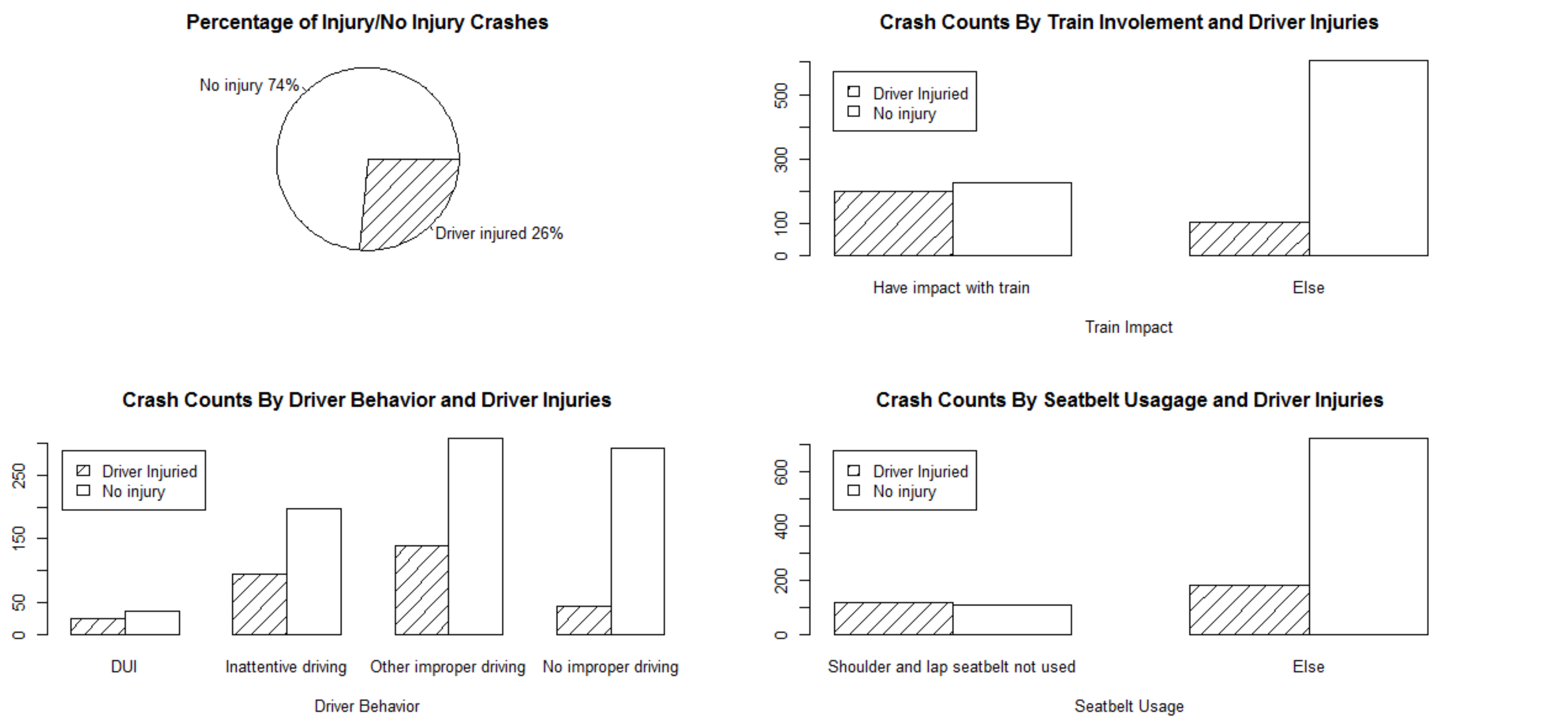


Figure 4.2 Number of crashes by situations and driver injuries for 1V1D crashes

Table 4.1 Description of independent variables for single vehicle data

Variable Names	Variable Categories and Percentages
DUI	1 = yes (5.3%); 0 = else (94.7%)
Inattentive.driving	1 = yes (25.8%); 0 = else (74.2%)
Other.improper.driving	1 = yes (39.3%); 0 = else (60.7%)
No.improper.driving	1 = yes (29.7%); 0 = else (70.3%); base level
No.seat.belt	1 = lap & shoulder belt not used (20.2%); 0 = else (79.8%)
Impact.with.train	1 = train hit vehicle or vehicle hit train (37.5%); 0 = else (62.5%)
Dark.no.light	1 = dark roadway not lighted (16.8%); 0 = else (83.2%)
Dark.light	1 = dark roadway lighted, dawn or dusk (17.0%); 0 = else (83.0%)
Day.light	1 = daylight (61.5%); 0 = else (38.5%); base level
Cloudy.weather	1 = cloudy (15.4%); 0 = else (84.6%)
Adverse.weather	1 = blowing sand, soil, dirt, snow, fog, smog, smoke, sleet, hail, freezing rain/drizzle, rain, snow, severe crosswinds (10.0%); 0 = else (90.0%)
Clear.weather	1 = clear (71.0%); 0 = else (29.0%); base level
Female.driver	1 = female (25.2%); 0 = else (74.8%)
Driver.age	Numeric
Hwy.speed.limit≥50	1 = highway speed limit ≥ 50mph (43.8%); 0 = else (56.2%)
Wet.road.surface	1 = ice, sand, mud, slush, snow or wet (21.9%); 0 = else (78.2%)
Passenger	1 = passenger(s) presence (26.5%); 0 = else (73.5%)
Asphalt	1 = asphalt (38.6%); 0 = else (61.4%)
Concrete	1 = concrete (28.4%); 0 = else (71.6%)
Gravel	1 = gravel (25.2%); 0 = else (74.8%)
Rural.area	1 = rural area (56.8%); 0 = else (43.2%)
No.environment.contributor	1 = no known environment contributor (75.6%); else (24.3%)
No.road.surface.contributor	1 = no known road surface contributor (72.6%); else (27.4%)
Non-NE.driver.license	1 = non-Nebraska driver license (11.5%); 0 = Nebraska driver license (88.5%)
Non-NE.plate.license	1 = non-Nebraska plate license (18.5%); 0 = Nebraska plate license (81.5%)
Home.in.city.of.crash	1 = home is in the city of crash (33.6%); 0 = else (66.4%); base level
Home.in.NE.city.beyond.25miles	1 = home is in a NE city beyond 25 miles away (24.9%); 0 = else (75.1%)
Home.in.NE.city.within.25.miles	1 = home is in a NE city within 25 miles (25.7%); 0 = else (74.3%)
Home.in.city.out.of.NE	1 = home is in a city of NE (10.0%); 0 = else (90.0%)

In the random parameters binary logit model, all parameters were assumed random at first and following a normal distribution. Then parameters that were tested to be fixed across observations were retained as fixed. **Table 4.2** presents the estimated model with driver behavior and other statistically significant variables. This table contains the estimated coefficients, standard errors of those coefficients, and statistical significance information for the 1V1D data. **Table 4.3** presents the marginal effects associated with the estimated parameters. For dummy variables, the marginal effects represent the changes in the estimated probabilities of the dependent variable with the dummy variable changed from 0 to 1 and other variables held at their means. For example, on average, the probability of getting injured increased by 6.8% when the driver was involved in inattentive driving compared to no inattentive driving. The probability of injury increased by 20.7% when the driver did not wear a seatbelt compared to wearing a seatbelt.

Table 4.2 Estimated random parameters binary logit model for 1V1D data

Variables	Estimate	Std. Error	z value	Pr(>|z|)
(Intercept)	-2.08	0.17	-12.62	0.00
Random parameters*				
Inattentive.driving (location)	0.36	0.18	1.97	0.05
Inattentive.driving (scale)	1.77	0.22	8.07	0.00
DUI (location)	0.73	0.29	2.52	0.01
DUI (scale)	1.62	0.44	3.70	0.00
Adverse.weather (location)	-0.55	0.25	-2.17	0.03
Adverse.weather (scale)	1.63	0.37	4.42	0.00
Concrete.pavement (location)	-0.48	0.15	-3.16	0.00
Concrete.pavement (scale)	0.90	0.19	4.73	0.00
Nonrandom parameters				
Other.improper.driving	0.51	0.16	3.22	0.00
Speed.limit≥50mph	0.42	0.17	2.49	0.01
No.seatbelt	1.10	0.14	8.02	0.00
Impact.with.train	1.23	0.13	9.76	0.00
Female	0.44	0.13	3.26	0.00
AIC=1092.0, AICc= 1092.4, BIC=1162.5				
Sample size = 1133				

*"Location" represents the location (i.e., mean) of the normal distribution for the random parameter to be estimated; the "scale" represents the scale (i.e., standard deviation) of the normal distribution for the random parameter to be estimated.

Table 4.3 Partial effects and elasticities of the estimated parameters for 1V1D data

	Partial Effect	z	Prob. |z|>Z*	95% Confidence Interval	
DUI	0.138	2.52	0.012	0.031	0.246
Inattentive.driving	0.068	1.96	0.050	0.000	0.135
Other.improper.driving	0.096	3.2	0.001	0.037	0.154
Adverse.weather	-0.103	-2.17	0.030	-0.197	-0.010
Concrete.pavement	-0.091	-3.39	0.001	-0.144	-0.038
Speed.limit≥50mph	0.079	2.49	0.013	0.017	0.141
No.seatbelt	0.207	7.96	0.000	0.156	0.258
Impact.with.train	0.232	9.38	0.000	0.184	0.281
Female	0.083	3.25	0.001	0.033	0.133

The model revealed that the impact of inattentive driving, DUI, adverse weather, as well as concrete pavement on driver injuries varies across the population. The estimated random parameters model suggests that the coefficient on inattentive driving for an individual i is 0.36+1.77 vi (where vi ~ N[0,1]). This is a normal distribution with a mean of 0.36 and a standard deviation of 1.77. Because zero is within 1.0 standard deviation from the estimated mean, the model suggests the effect of inattentive driving on driver injury severity could be opposite for different observations. This information cannot be identified using a traditional binary logit model. The effects of DUI, adverse weather, and concrete pavement can be interpreted in a similar way. **Figure 4.3** presents the distributions of the four random parameter estimates. As shown in the figure, inattentive driving and DUI are most associated with higher injury severity in drivers while adverse weather and concrete road pavement are associated with lower injury severity.

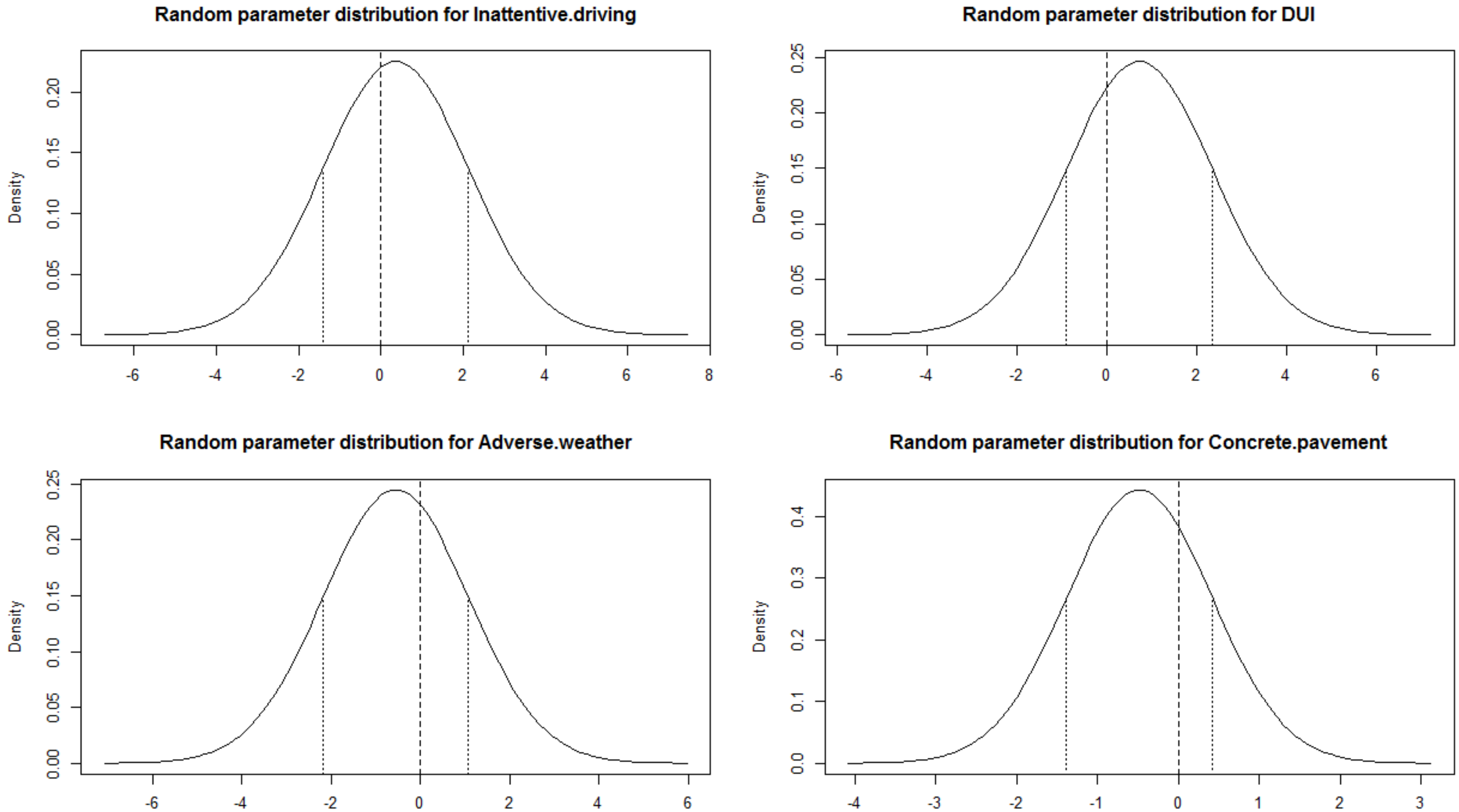


Figure 4.3 Normal distributions for the estimated random parameters

All the other variables estimates, including estimates for other improper driving, speed limit greater than or equal to 50 mph, not wearing shoulder and lap seatbelt, impacting a train, and female drivers were not found to vary across the population and thus retained as fixed parameter estimates. Being involved in other improper driving, a highway speed limit greater than or equal to 50mph, a driver not wearing a shoulder and lap seatbelt, the vehicle impacting a train, and female drivers have a higher probability of injuries.

4.2 Two-Vehicle-Two-Driver (2V2D) Crashes

The 2V2D category comprised 890 crashes with 1,780 drivers and 1,780 vehicles. Of the 1,780 drivers, 220 (12.4%) were injured (includes one single fatality) while the rest were not injured. For 2V2D crashes, a driver's injury outcome was not necessarily associated with his/her own driving actions. For example, a vehicle safely stopped for a train at a rail crossing may get involved in a rear-end accident because the driver in the following vehicle was distracted by a cellphone. In this case, the first driver might still be injured without having made any driving mistakes. Considering the contributory factors from the two drivers, there were 17 (1.9%) crashes wherein both drivers were inattentive. In aggregate there were 383 (43.0%) crashes that involved at least one inattentive driver. At least one driver was driving under influence (DUI) in 18 (2.0%) two-vehicle crashes, while 363 (40.8%) crashes reported at least one driver involved in improper driving. In the remaining 146 (16.4%) two-vehicle crashes, neither driver was reported to have improper driving actions. An examination of the 146 "no improper driving" crashes revealed that 12 of them occurred under adverse weather or road surface condition (wet, icy, snow, slush, etc.). Three of the 146 crashes were reported at a location where the traffic control device was inoperative, missing, etc. Another two crashes resulted from animals in the roadway and vision obstruction, respectively. The reasons behind the remaining 129 crashes were unknown based on information from the crash data. The percentages of crashes associated with different driver factors for each year were calculated and compared, as shown in **Figure 4.4**, to justify the lack of significant changes in the general trending across the years. The percentage changes for each type of driver factor across the time span (especially the comparison between earlier years and the more recent years) did not seem to vary beyond a reasonable range.

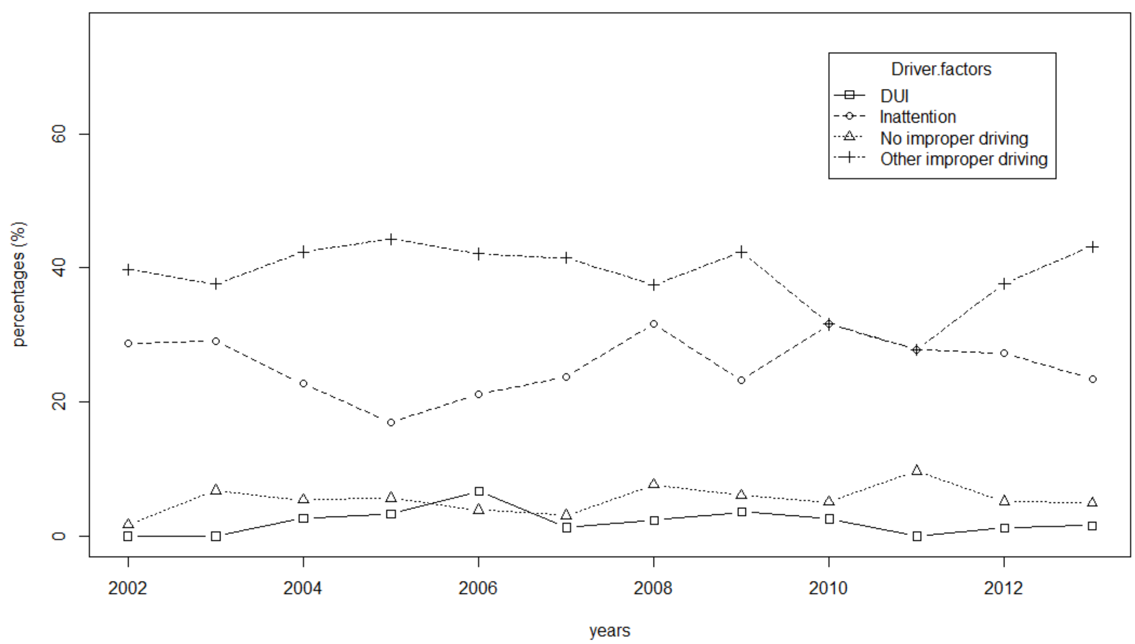


Figure 4.4 Percentages of crashes associated with different driver factors from 2002 to 2012

Figure 4.5 describes some features of the 890 2V2D crashes. The categorization of driver factors contributing to the crashes was as follows:

1) DUI if at least one of the involved driver's blood alcohol content was greater than 0.08 g/d;

2) Inattentive, among crashes that did not involve any DUI and at least one of the drivers was inattentive;

3) Other improper driving if among crashes that did not involve DUI or inattentive driving at least one of the drivers had other improper driving behavior; and

4) No improper driving if neither driver had any improper driving actions.

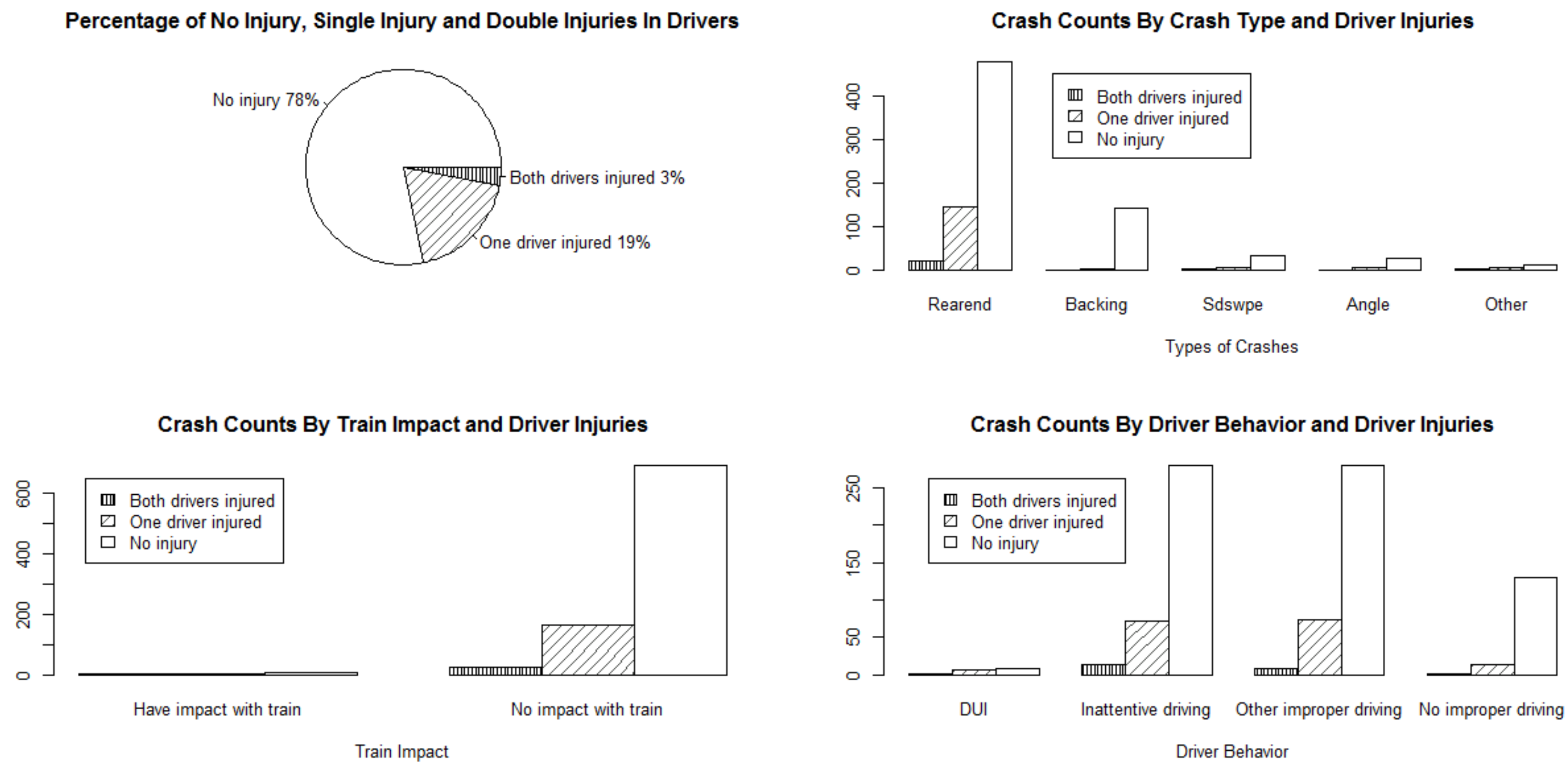


Figure 4.5 Number of crashes by situations and driver injuries

Figure 4.5 showed that 22% of the 2V2D crashes resulted in at least one injured driver (top-left). Rear-end collisions accounted for a large portion of these crashes and many involved injuries (top-right). Collisions with trains were a small portion of the 2V2D crashes (bottom-left). Crashes involving inattentive driving had higher probabilities of injuries than crashes that did not involve any improper driving (bottom-right).

A random parameters binary logit regression model was estimated to investigate the effects of driving factors on drivers' injury severity outcomes (1 = injury; 0 = no injury) along with other relevant factors. Potential relevant variables tried in the model are listed in **Table 4.4**, all of which were assumed to follow normal distributions. Model results are shown in **Table 4.5** and **Table 4.6** presents the marginal effects and elasticities of the estimated parameters.

Table 4.4 Description of independent variables for 2V2D crash data

Variable Names	Variable Categories and Percentages
DUI	1 = yes (2.0%); 0 = else (98.0%)
Inattentive.driving	1 = yes (41.0%); 0 = else (59.0%)
Other.improper.driving	1 = yes (40.6%); 0 = else (59.4%)
No.improper.driving	1 = yes (16.4%); 0 = else (83.6%); base level
No.seat.belt	1 = at least one of the two drivers did not use lap & shoulder belt (12.8%); 0 = else (87.2%)
Impact.with.train	1 = at least one the two vehicles hit a train or were hit by a train (1.6%); 0 = else (98.4%)
Dark.no.light	1 = dark roadway not lighted (3.3%); 0 = else (96.7%)
Dark.light	1 = dark roadway lighted, dawn or dusk (12.6%); 0 = else (87.4%)
Day.light	1 = daylight (79.2%); 0 = else (20.8%); base level
Cloudy.weather	1 = cloudy (20.7%); 0 = else (79.3%)
Adverse.weather	1 = blowing sand, soil, dirt, snow, fog, smog, smoke, sleet, hail, freezing rain/drizzle, rain, snow, severe crosswinds (7.4%); 0 = else (92.6%)
Clear.weather	1 = clear (67.0%); 0 = else (33.0%); base level
Female.driver	1 = at least one of the two drivers were female (67.3%); 0 = else (32.7%)
Driver.age	Numeric, the younger driver's age
Hwy.speed.limit≥50	1 = highway speed limit ≥ 50mph (16.3%); 0 = else (83.7%)
Wet.road.surface	1 = ice, sand, mud, slush, snow or wet (18.5%); 0 = else (81.5%)
Asphalt	1 = asphalt (49.8%); 0 = else (50.2%)
Concrete	1 = concrete (42.2%); 0 = else (57.8%)
Gravel	1 = gravel (2.5%); 0 = else (97.5%)
Rural.area	1 = rural area (28.3%); 0 = else (71.7%)
No.environment.contributor	1 = no known environment contributor (84.9%); else (15.1%)
No.road.surface.contributor	1 = no known road surface contributor (81.0%); else (19.0%)
Non-NE.driver.license	1 = non-Nebraska driver license (11.5%); 0 = Nebraska driver license (88.5%)
Non-NE.plate.license	1 = non-Nebraska plate license (18.5%); 0 = Nebraska plate license (81.5%)
Home.in.city.of.crash	1 = at least one of the drivers' home was in the city of crash (70.8%); 0 = else (29.2%); base level
Home.in.NE.city.beyond.25miles	1 = at least one of the drivers' home was in a NE city beyond 25 miles away (26.9%); 0 = else (73.1%)
Home.in.NE.city.within.25.miles	1 = at least one of the drivers' home was in a NE city within 25 miles (26.3%); 0 = else (73.7%)
Home.in.city.out.of.NE	1 = at least one of the drivers' home was in a city of NE (10.4%); 0 = else (89.6%)

Table 4.5 Estimated random parameters binary logit model for 2V2D data

Variables	Estimate	Std. Error	z value	Pr(>|z|)
(Intercept)	-3.01	0.32	-9.47	0.00
Random parameters*				
Other.improper.driving (location)	0.66	0.26	2.58	0.01
Other.improper.driving (scale)	1.28	0.19	6.76	0.00
Rearend.crash (location)	0.47	0.19	2.44	0.01
Rearend.crash (scale)	1.90	0.17	11.16	0.00
Nonrandom parameters				
DUI	1.99	0.45	4.38	0.00
Inattentive.driving	0.77	0.25	3.07	0.00
Impact.with.train	1.34	0.46	2.93	0.00
At.least.one.no.seatbelt	0.50	0.20	2.45	0.01
At.least.one.female	0.42	0.16	2.53	0.01
Rural.area	0.83	0.16	5.24	0.00
AIC=8758.4, AICc= 878.7, BIC=910.89				
Sample size = 890				

*"Location" represents the location (i.e., mean) of the normal distribution for the random parameter to be estimated; the "scale" represents the scale (i.e., standard deviation) of the normal distribution for the random parameter to be estimated.

Table 4.6 Partial effects and elasticities of the estimated parameters for 2V2D data

	Partial Effect	z	Prob. |z|>Z*	95% Confidence Interval	
DUI	0.307	4.10	0.000	0.160	0.454
Inattentive.driving	0.120	3.03	0.002	0.042	0.197
Other.improper.driving	0.103	2.52	0.012	0.023	0.182
Rearend.crash	0.072	2.02	0.044	0.002	0.142
Impact.with.train	0.207	2.71	0.007	0.058	0.356
At.least.one.no.seatbelt	0.077	2.37	0.018	0.013	0.140
At.least.one.female	0.064	2.48	0.013	0.014	0.115
Rural.area	0.128	4.74	0.000	0.075	0.181

The model results indicated that in 2V2D crashes, the effects of factors such as DUI, inattentive driving, impacting trains, at least one of the two drivers not wearing a seatbelt, at least one of the two drivers being female, and crashes reported at rural areas were not found to randomly vary across the population. The impacts of another two factors – being involved in other improper driving action and rear-end crashes – were found to vary across the population following normal distributions. The distributions of the two random parameter estimates are presented in **Figure 4.6**.

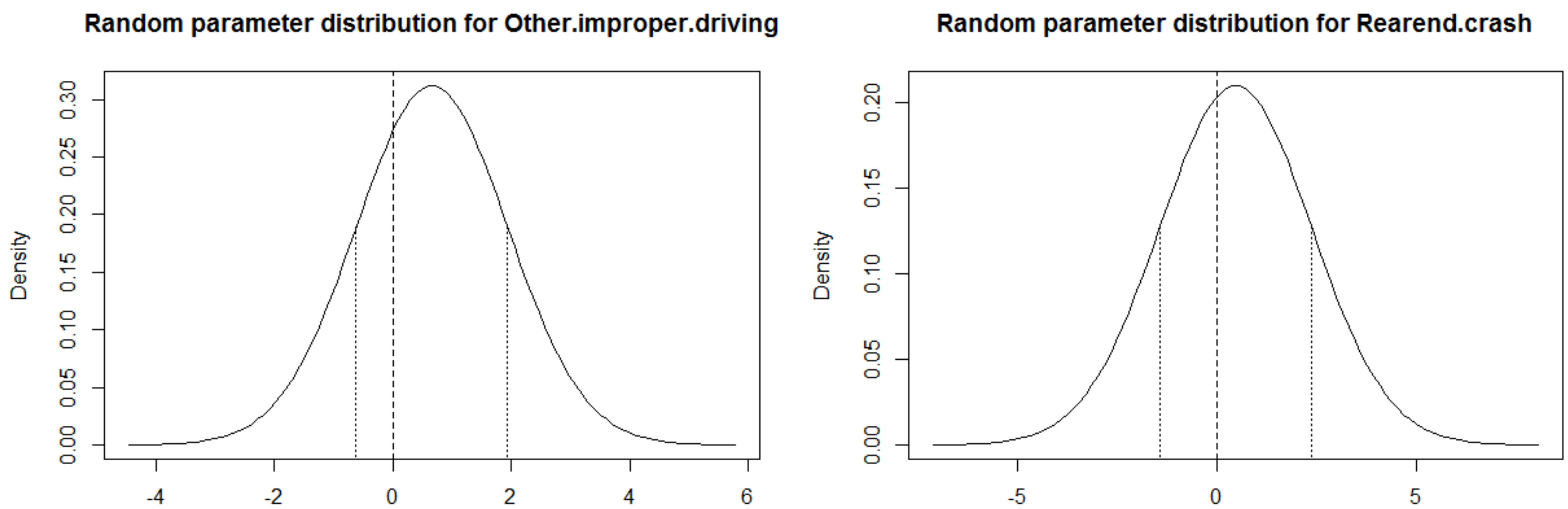


Figure 4.6 Normal distributions for the estimated random parameters

As shown in the figure, other improper driving and rear-end crashes were most associated with a higher probability of driver injury than crashes in which drivers were not involved in other improper driving or were not rear-end crashes. The model results also revealed that being involved in a DUI, inattentive driving, impacting trains, at least one of the two drivers not wearing a seatbelt, at least one of the two drivers being female, and crashes reported at rural areas were associated with a higher probability of resulting in driver injuries.

4.3 More-than-Two-Vehicle Crashes

The three-vehicle-three-driver (3V3D) category consisted of 90 crashes. These crashes did not contain any DUIs, 21 crashes involved at least one of the three drivers driving inattentively, in 20 crashes at least one of the drivers had other improper driving behavior, and four crashes did not involve any improper driving. The relatively small sample size for this category of crashes restricted model estimation. Instead, comparative histograms (**Figure 4.5**) show drivers' injury distribution by different driving behavior. About 60% of the 3V3D crashes resulted in injuries to drivers. Crashes involving inattentive driving appeared to have higher injury probability than other improper driving.

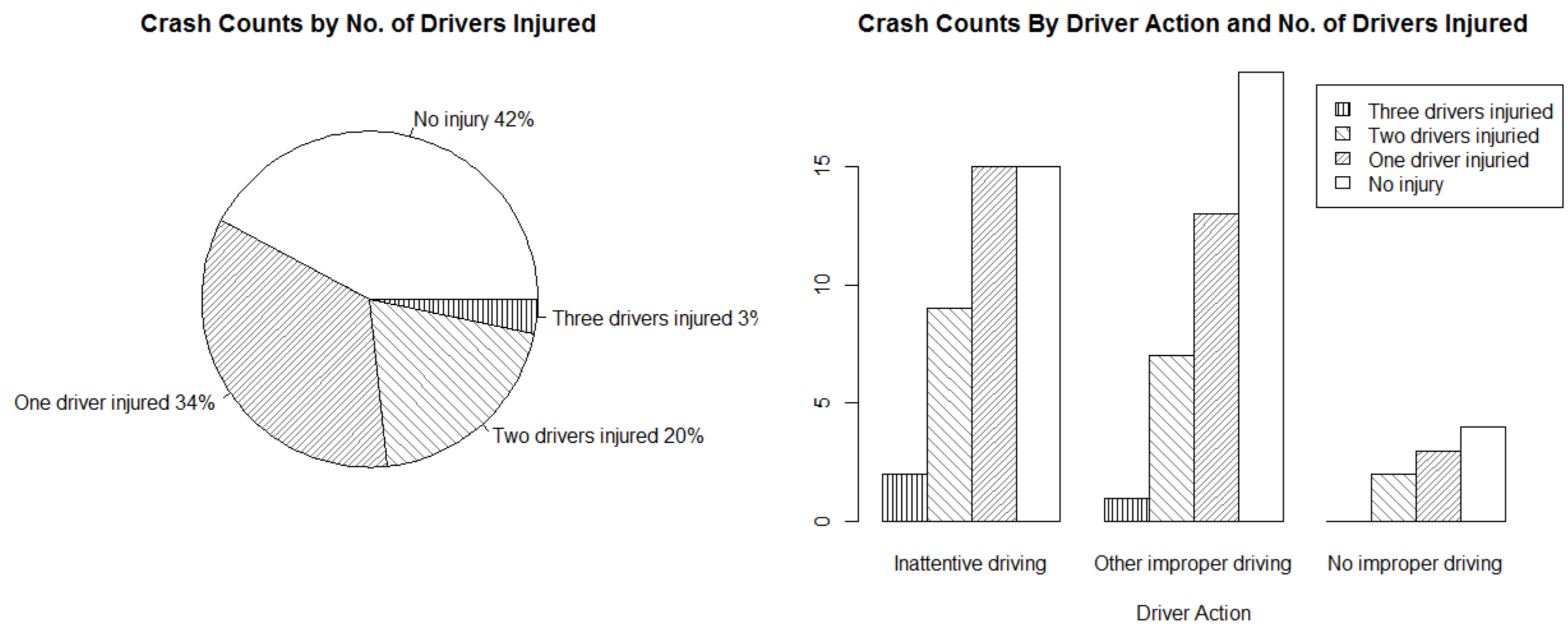


Figure 4.7 Three-vehicle-three-driver crash counts by driver actions and driver injury

Of the 10 crashes involving four vehicles and four drivers (4V4D), 7 (70%) included inattentive driving, two crashes (20%) had some drivers involved in other improper driving behavior, and one 4V4D crash (10%) did not report any improper driving. The one five-vehicle-five-driver crash and six-vehicle-six-driver crash reported one of the drivers followed too closely while the other was driving too fast for the situation, but no inattentive driving.

4.4 Chapter Summary

This chapter addressed the first objective of the dissertation, which is to investigate the impact of motor vehicle driver inattention on the severity of drivers' injuries sustained in crashes reported at or near highway-rail crossings. Results showed that driver inattention led to more severe injuries compared to attentive driving and that it could be as dangerous as driving under the influence of alcohol or drugs. Modeling results revealed that besides drivers' hazardous behavior, other factors such as not using a seatbelt, female drivers, rural areas, rear-end crashes, and high speeds on highways were associated with a higher probability of injury. Adverse weather and concrete pavement were found to be associated with a lower probability of injury. Train-involved crashes invariably resulted in more severe outcomes.

In terms of driver injury severity, driver inattention should be regarded as hazardous as DUI. While motor vehicle drivers should be attentive to the driving task at all times, as the findings from this study show, their attention is critical at HRGCs. In this context, texting, headphone usage, or other diversions that could potentially distract drivers should not be allowed at HRGCs. Drivers' education and awareness programs and radio and video public service announcements should emphasize the need for drivers to pay attention to the task of driving. For public safety improvement at HRGCs, the enforcement of existing laws against inattentive driving (e.g., mobile phone usage), strengthening of existing laws, formulation of new laws, improving visibility of rail crossings and warnings for approaching trains, and designing crossing features that are less distracting are some of the options.

CHAPTER 5 DRIVER INATTENTION AND HUMAN FACTORS

A review of published literature did not uncover research on potential factors that contribute to motor vehicle driver inattention at HRGCs. Previous research on HRGCs mostly focuses on the occurrences and consequences of drivers' inattentive behavior. In general highway settings, efforts have been made to explain the reasons behind risky driving behavior. Personality traits such as sensation-seeking and aggressiveness, attitude and perception towards safety and risk, gender and age, etc., play roles in explaining variances in drivers' risky behavior (Constantinou et al., 2011; Iversen, 2004; Oltedal and Rundmo, 2006; Rhodes and Pivik, 2011; Ulleberg and Rundmo, 2003). Considering the potential harm from crashes at HRGCs, it is important to identify the factors associated with motor vehicle inattentive driving behavior. Therefore, this chapter focuses on the second objective of the dissertation - to investigate the association between drivers' self-reported inattentive driving experience and a series of factors such as drivers' usage of rail crossings, knowledge of safe driving, attitudes towards safe driving, expectations of encountering trains at rail crossings, previous noncompliance behavior, etc. This chapter first presents summary statistics for Dataset 2 (collected through the statewide mail self-report survey), shows patterns in the surveyed motor vehicle driver behavior at local HRGCs, explores drivers' attitudes towards safety issues at HRGCs, and then explores variables that may influence drivers' risks of being involved in inattentive driving at HRGCs.

5.1 Summary Statistics

Tables 5.1-5.7 provide summary statistics for questions included in the survey questionnaire. **Table 5.1** shows driver perception of safety, delays, reliability, etc., at local HRGCs. **Tables 5.2-5.4** summarize drivers' vehicle types, usage frequencies of HRGCs, and estimated daily train passages at their local HRGCs. **Table 5.5** presents a summary of the answers for the questions testing drivers' knowledge on safely driving at HRGCs. **Table 5.6** shows the distribution of drivers' involvement with inattentive driving at HRGCs. **Table 5.7** summarizes drivers' attitudes towards safety and regulations at HRGCs. **Table 5.8** presents a few traffic accidents or near accidents reported by the participants. Demographic information for the participants is summarized and presented in **Table 5.9**.

Table 5.1 presents a summary of the responses of the first five single choice questions. Respondents generally believed that the traffic signs and pavement markings at their local rail crossings were clear and not confusing (80.5% = 55.9% + 24.6%), that the rail crossings were safe (74.0% = 47.0% + 27.0%), and that the train warning devices such as flashing lights, bells, gates, etc., were reliable (73.5% = 49.6% + 23.9%). Most of the complaints came from excessive delays at rail crossings (16.0% = 4.9% + 11.1% agree or strongly agree the delays at their local rail crossings are excessive with 24.2% of the respondents reporting neutral) and no safety information was received on local rail crossings (42.1% = 13.8% + 28.3% with 17.7% of the respondents feeling natural to this question). These collected responses were a good indicator of the respondents' attitudes towards their local rail crossings.

Table 5.1 Driver perceptions of local rail crossings (in percentage %)

Aspects of perceptions	Strongly agree	Agree	Neutral	Disagree	Strongly disagree	Not answered
Excessive delays	4.9	11.1	24.2	35.3	18.2	6.3
Unsafe	1.3	5.2	12.9	47.0	27.0	6.5
Confusing signs and markings	0.6	2.1	10.1	55.9	24.6	6.6
Unreliable warning devices	1.8	5.8	12.0	49.6	23.9	6.8
No safety info received	13.8	28.3	17.7	22.6	10.6	7.1

Sample size: 980

Table 5.2 presents the percentages of different types of motor vehicles used by the respondents. The majority of the respondents (67.2%) drove passenger cars (including SUVs) for personal use followed by pickup trucks (16.3%). Among respondents who drove a work or company motor vehicle, the first two categories were also passenger cars (14.2) and pickup trucks (11.3%).

Table 5.2 Types of vehicles (in percentage %)

Vehicle type	Passenger car	Pickup truck	Minivan	Motorcycle	Other	Not drive	Not answered
Personal motor vehicle	67.2	16.3	6.5	0.3	0.6	1.7	7.2
Work motor vehicle	14.2	11.3	2.2	-	4.4	64.7	4.5

Sample size: 980

Respondents were asked to indicate how often they used a rail crossing during the past 14 days (i.e., times/2 weeks). The responses were then grouped into six categories, as shown in **Table 5.3**. About 17.1% of respondents did not use a rail crossing in the past

14 days. The majority of the respondents (75.8% = 34.3% + 15.7% + 13.9% + 11.9%) used a HRGC at least once during the past two weeks. The research assumed that people who did not use HRGCs in the past 14 days or who did not answer this question had valid responses to other questions in the survey.

Table 5.3 Frequency of HRGC usages (in percentage %)

Use frequency of rail crossings (times/day)	None	0<freq.< =7	7<freq.< =14	14<freq.< =28	freq.>28	Not answered
Percentage %	17.1	34.3	15.7	13.9	11.9	7.0

Sample size: 980

Participants were asked how many trains pass (per day) at the HRGC they use most frequently. The responses were then grouped into four categories, as shown in **Table 5.4**. There were 9.6% of the respondents who believed there was less than one train per day at the crossing. Another 20.6% of the participants reported more than 10 trains per day, and the final 38.0% thought there were less than 10 trains per day, but greater than 0. A large portion (31.8%) of the participants did not answer this question or reported they had no idea how many trains were passing every day.

Table 5.4 Estimated daily train passages at local HRGCs

Expected train passages per day	None	0<freq.<=10	freq.>10	Unknown or not answered
Percentage %	9.6	38.0	20.6	31.8

Sample size: 980

Questions 8-16 of the questionnaire tested drivers' knowledge about safety at HRGCs, which included questions asking about basic understanding of signs at HRGCs (e.g., crossbuck, no train horn), correct maneuvers when facing flashing lights and activated gates, proper actions when an emergency occurs (e.g., stalled on the tracks), and other knowledge about HRGCs (e.g., 1-800 number, vehicles that must stop at crossings). **Table 5.5** shows the results of the participants' knowledge. Each cell represents the percent of participants choosing that particular answer, and the correct answers for each question are highlighted in grey.

The table indicates that respondents generally take correct actions at rail crossings with active traffic control devices, but many respondents do not fully understand the signs at rail crossings, the risks of certain violations, and the necessary actions to take when an emergency occurs.

Table 5.5 Questions testing drivers' knowledge of driving at rail crossings (in percentage %)

Questions	Choices (cells highlighted in green indicate the correct answers)				
	A	B	C	D	Not answered
Meaning of crossbuck signs	23.8	45.2	23.2	1.3	6.5
Use of railroad 1-800 number	73.5	30.7	58.3	18.5	3.9
Actions when lights flashing	0.2	5.1	90.7	0.1	3.9
Actions when lights start flashing while crossing	0.5	92.1	2.3	1.0	4.0
Meaning of Quiet Zone	9.3	3.6	66.7	15.5	4.9
Actions when stalled on tracks	0.2	7.9	84.3	1.2	6.4
Considered of violations	77.6	91.8	65.0	1.7	3.8
Actions when gates did not ascend immediately after train passed	1.0	91.2	0.2	3.3	4.3
Vehicles must stop at rail crossings	95.3	79.1	81.4	1.3	3.4

* Correct answers were highlighted in grey.
Sample size: 980

Table 5.6 lists the most common attentive or inattentive driving behaviors and the frequencies of these behaviors. Each cell in the table represents the percent of drivers that selected that particular frequency. Cells highlighted in grey are considered as safe behaviors. As seen from **Table 5.6**, the majority of people (over 82%) did not cross rail crossings when warning devices or gates were activated. Texting or using apps were considered dangerous by most people and they never conducted such behaviors when cross a rail crossing (82.4%). These behaviors required drivers' eyes to be diverted from the road and focused on their hand-held devices instead and thus poses the highest risks to drivers. Most people always stopped at STOP signs (77.9%) and always looked left and right to check for trains (70.9%). Some activities were not considered dangerous and only around half of the drivers always kept from becoming involved in such activities, including reaching for objects in the vehicle (66.2%), talking on a phone (53.7%), mental distraction (53.0%), and adjusting in-vehicle objects (51.3%). These activities involve some degrees of visional, manual, or mental distraction and can be very dangerous in critical locations, such as a rail crossing. Fewer drivers consider the following behaviors as risky: distraction by outside objects, eating or drinking, or talking to passengers. These behaviors were therefore conducted by the respondents from time to time. As to smoking, because some participants may not smoke at all, the high percentage of people choosing "Never" (84.5%) cannot be evaluated properly.

Table 5.6 Participation of attentive and inattentive driving activities (in percentage %)

Activities	Participation frequency (cells highlighted in green indicate choices that are considered safe driving)					
	Always	Often	Sometimes	Rarely	Never	Not answered
a. Look left and right to check for trains	70.9	13.4	5.8	3.1	3.2	3.7
b. Cross when warning devices activated	0.6	0.1	1.7	11.1	82.4	4.0
c. Cross when gates descending, ascending or leveled	0.5	0.3	1.2	7.0	86.0	4.9
d. Stop at STOP signs	77.9	8.3	2.1	1.0	5.4	5.3
e. Talk to passengers	2.3	11.2	36.6	19.4	26.0	4.4
f. Eat or drink	1.0	5.4	24.4	23.4	41.5	4.2
g. Talk on a phone	0.6	4.1	19.6	18.1	53.7	4.0
h. Text or use apps	0.2	0.7	3.8	8.9	82.6	3.9
i. Reach for objects	0.3	1.3	8.7	19.7	66.2	3.8
j. Adjust in-vehicle equipment	0.5	2.9	13.9	27.6	51.3	3.9
k. Distracted by outside object	0.1	1.5	13.1	36.1	44.9	4.3
l. Mental distraction	1.0	1.4	9.4	30.9	53.0	4.4
m. Smoke cigarettes	0.7	2.9	5.2	2.7	84.5	4.1
n. Other form of inattention	0.1	0.1	3.4	14.8	77.2	4.4

* Safe behavior was highlighted in grey.
Sample size: 980

Questions 18 (a to m) of the questionnaire asked for drivers' attitudes towards safety and safety improvement strategies at HRGCs, as well as drivers' intent to violate rules at HRGCs. **Table 5.7** presents a summary for this section. Questions a, i, j, k, and l were about attitudes toward rail crossing safety and strategies to improve safety. The majority of the respondents agreed that safety is a significant issue at rail crossings (83.2% = 54.7%+28.5%). Over 54% supported technologies that can block cellphone signals at rail crossings (except for emergency calls) to reduce distracted driving. About 58.3% of the drivers supported stronger law enforcement towards rule violations at HRGCs. On the other side, although the respondents seemed to know little about public information programs dedicated to reducing collisions, injuries, and fatalities at HRGCs (only 21.9% acknowledged they knew), such as Operation Lifesaver, only 23.6% respondents indicated a desire to receive information on rail crossing safety. The survey found that although the respondents generally did not like to wait for trains to pass, most of them did not accelerate to cross when warning devices are activated. They routinely stopped when warning devices were activated, they did not regret stopping for trains even if there was a chance to cross, they did not cross under activated warning devices even if a train had passed, they ensured all warning devices were off before crossing, they did not like to drive around fully lowered gates, and they did not find it fun to play "chicken" with an approaching train.

Table 5.7 Attitudes and intentions of safe driving at rail crossings (in percentage %)

Questions	Agreement or disagreement					
	Strongly agree	Agree	Neutral	Disagree	Strongly disagree	Not answered
a. Safety at rail crossings is important	54.7	28.5	9.5	4.7	1.0	1.6
b. Do not like to wait for trains to pass	10.8	32.4	28.9	13.0	12.7	2.2
c. Like to accelerate to cross through when warning devices are activated	1.8	2.4	6.1	33.9	53.9	1.8
d. Routinely stop when warning devices are activated even there is a chance to cross	48.9	34.1	5.6	3.5	6.0	1.9
e. Regret for stopping for trains when there is a chance to cross	2.6	5.9	13.5	34.7	41.5	1.8
f. Like to cross after train passage but warning devices still active	1.0	1.2	3.4	35.0	57.6	1.8
g. Ensure warning devices off before crossing	57.2	34.3	3.0	1.7	2.0	1.7
h. Like to drive around fully lowered gates	0.9	0.1	0.3	16.1	80.7	1.8
i. Support technology that blocks cell phone signals at rail crossings	33.5	21.1	20.5	11.2	11.6	2.0
j. Support stronger law enforcement	29.2	29.1	27.9	7.2	4.4	2.2
k. Familiar with Operation Lifesaver	10.6	11.3	21.3	26.5	26.0	4.2
l. Would like to receive info on rail crossing safety	8.9	14.7	34.2	21.4	17.7	3.1
m. Feel it is fun to play "chicken" at rail crossings	1.2	0.0	0.3	3.7	93.2	1.6

Sample size: 980

Eight out of the 980 participants reported that they had been involved in an accident or near-accident at or near rail crossings in the past three years. Except for one participant who did not specify what type of accident s/he had, the other seven participants reported in total two single-vehicle accidents, two multi-vehicle accidents, one single vehicle near-accident, and one multi-vehicle near-accident.

Table 5.8 Reported number of accidents/near-accidents at HRGCs

Crash type	Yes	No
Single-vehicle crash	2	6
Multi-vehicle crash	2	6
Single-vehicle near crash	1	7
Multi-vehicle near crash	2	6
vehicle-train crash	0	0
vehicle-train near crash	0	0

Sample size: 980

Five of the seven drivers who reported having accident experiences at rail crossings believed that there were some forms of inattentive driving involved in the accidents: talking to passengers (mentioned twice), texting or using apps (mentioned twice), distracted by persons or objects outside of the vehicle (mentioned twice), eating or drinking (mentioned once), talking on cellphones (mentioned once), adjusting in-vehicle equipment, and mentally distracted (mentioned once).

Table 5.9 General information on survey respondents (in percentage %)

Variable	Distribution
Years of residence in his/her current city	<1 yr (2.6%), >=1 and <3 yrs (8.0%), >=3 and <10 yrs (13.9%), >=10 and <20 yrs (15.3%), >=20 and <30 yrs (16.2%), >=30 and <40 yrs (10.7%), >=40 and <50 yrs (11.1%), >=50 and <60 yrs (9.1%), >=60 yrs (9.7%), not answered (3.5%)
Number of adults in household	0 (3.7%), 1 (27.1%), 2 (55.0%), >2 (10.5), not answered (3.7%)
Years as a licensed driver	<1 (0.2%), 1-2 yrs (0.7%), 3-5 yrs (1.0%), 6-10 yrs (4.9%), >10 yrs (90.7), not answered (2.6%)
Gender	Female (55.5%), male (41.4%), not answered (3.1%)
Age	<20 yrs (0.4%), 20-24 yrs (3.1%), 25-29 yrs (6.3%), 30-34 yrs (5.7%), 35-39 yrs (6.0%), 40-44 yrs (6.7%), 45-49 yrs (5.1%), 50-54 yrs (9.2%), 55-59 yrs (11.9%), 60-64 yrs (13.0%), 65-69 yrs (10.2%), >=70 yrs (19.7%), not answered (2.7%)
Highest level of education	Less than High School (2.1%), high school diploma or equivalent (20.1%), some college (no degree) (21.5%), associate's degree (9.8%), bachelor's degree (25.5%), master's degree (11.6%), doctorate degree (3.4%), other (1.2%), not answered (4.7%)
Primary occupation	Management/financial (6.7%), government/military (2.4%), student (2.6%), leisure/hospitality/sales/art (3.3%), construction/farming/technical (9.2), healthcare/legal/protective services (10.1%), transportation/production (5.8%), office/administration (6.7%), community/social/family (3.4%), computers/architecture/engineering/ science (4.2%), other (10.4%), unemployed/laid off (1.4%), retired (27.8%), not answered (6.0%)
Annual household income	Less than \$20k (9.2%), \$20k – 30k (9.2%), \$30k – 40k (8.1%), \$40k – 50k (10.4%), \$50k – 60k (7.7%), \$60k – 70k (6.6%), \$70k – 80k (6.1%), \$80k – 90k (5.2%), \$90k – 100k (4.2%), \$100k – 110k (5.5%), \$110k – 120k (2.7%), \$120k or higher (12.6%), not answered (12.7%)

Sample size: 980

5.2 Patterns in Responses

This section presents patterns in the participants' inattentive driving, perception of local HRGCs, knowledge of safely driving at HRGCs, and their attitudes towards safety issues at HRGCs. Participants were asked to report their involvement with varied inattentive driving behavior at HRGCs in Section 4 of the questionnaire. As mentioned in Section 3.1.2, those measurements were assessed via a 5-point Likert scale from "Always" to "Never." Results were presented in **Figure 5.1** (missing values were not displayed). Talking to passengers, eating or drinking, distraction by outside people or objects, and talking on a phone are some of the most frequently conducted inattentive activities.

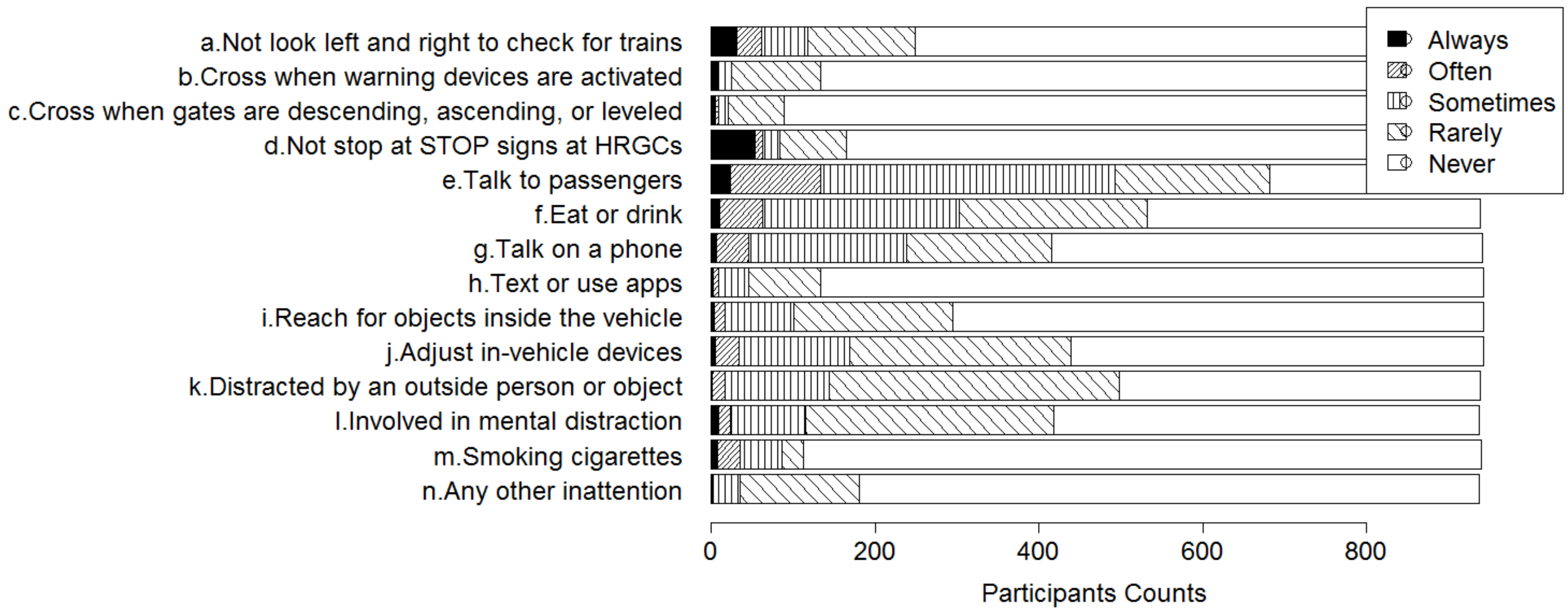


Figure 5.1 Involvement of inattentive driving

To evaluate a participant's overall risk level with regard to driving inattention, items in this section were integrated into one variable. Notably, questions 17a -17d were not directly asking drivers' inattentive behavior and thus were not integrated, although they may reflect some inattentive behavior. Literature has shown that Likert scales can be analyzed effectively as interval scales (Brown, 2011) and in this case the full scale was treated as a total of answers to the 10 items (questions 17e-17n). A participant was given a score of risk from 1 to 5 for each of the above 10 items. For example, if a respondent chose "always" for "talking on a phone," the respondent was given a score of 5, meaning that the respondent had a very high risk of being involved in this particular class of inattentive behavior; if the respondent selected "never" to the same question, the respondent was then given a score of 1, meaning that the respondent had a very low risk for that aspect. A participant's risk scores on all 10 items were aggregated into one overall risk score that theoretically ranges from 10 to 50.

Figure 5.2 presents a kernel density plot of the total scores. Kernel density estimation (KDE) is a non-parameter method to estimate the probability density function of a random variable. The KDE is a smoothing technique of histograms. It overcomes the disadvantages of simple histograms, which require defining the width of the bins and the end points of the bins, and presents an overall risk distribution of the sampled population. The majority of the sampled drivers had a low risk of inattentive driving, with the overall risk score falling between 10 and 20. Very few participants reported a risk score of more than 30. The Cronbach's alpha value (eq.(17)) was 0.86, suggesting that the 10 items have relatively high internal consistency and it is reasonable to combine them into one variable.

The formula for the standardized Cronbach's alpha is:

$$\alpha = \frac{N \cdot \bar{c}}{\bar{v} + (N-1) \cdot \bar{c}} \qquad \text{eq. (17)}$$

In the above equation N is the number of items, $\bar{c}$ is the average inter-item covariance among the items, and $\bar{v}$ is the average variance.

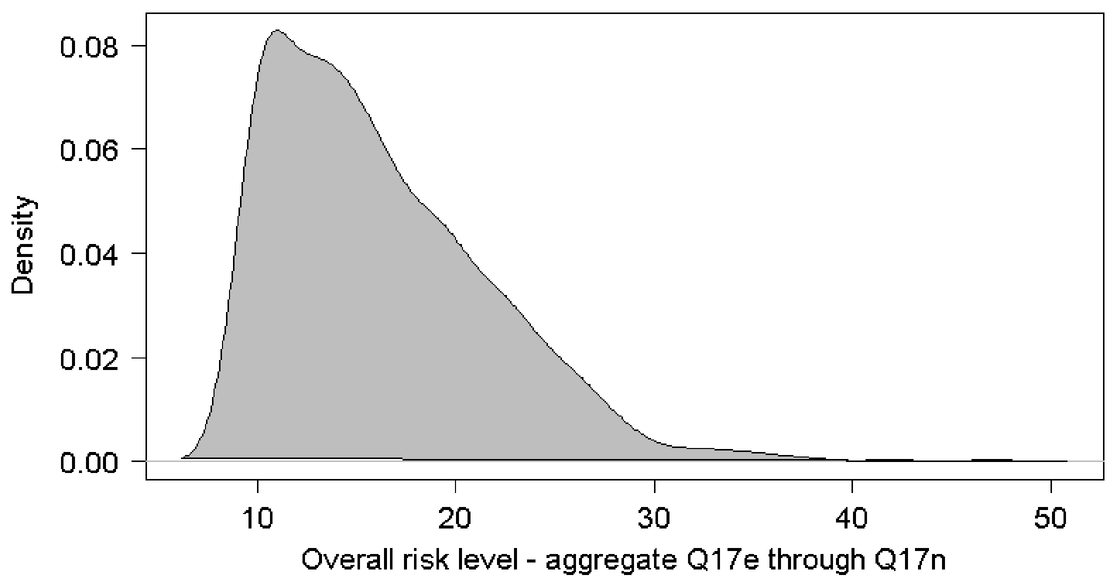


Figure 5.2 KDE of individual overall risks of being involved in inattentive driving

Participants were asked about their perceptions of safety, reliability, etc., of local HRGCs in Section 1 of the questionnaire. All five questions were measured via a 5-point Likert scale from "strongly disagree" to "strongly agree." **Figure 5.3** presents a summary of the responses. The collected responses are indicators of people's attitudes towards their local rail crossings and could be used as factors that affect their behavior at HRGCs. The Cronbach's alpha value for those five items was lower than 0.7, indicating that the five items did not have enough internal consistency. As the five items inquire about quite different aspects of the participants' perceptions of local HRGCs, it is reasonable to recognize that they are not in the same scale and thus should not be integrated.

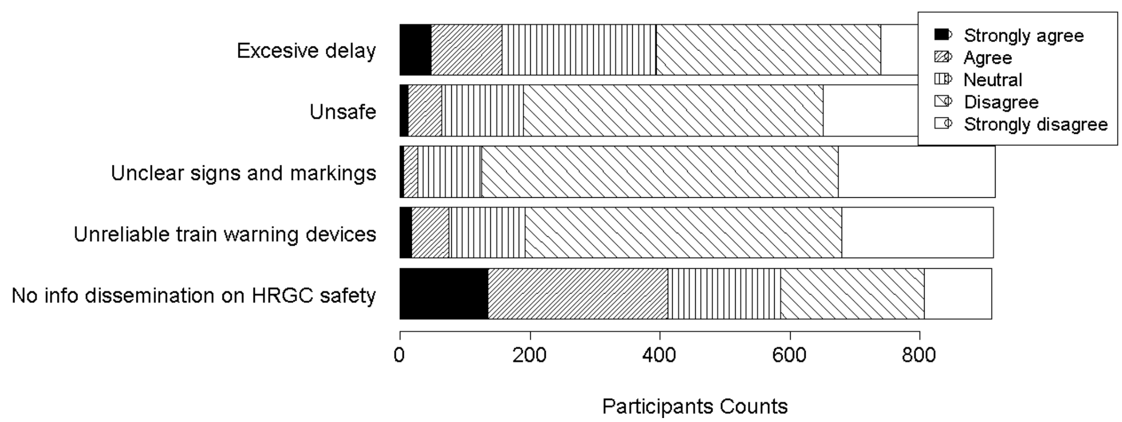


Figure 5.3 Perceptions of delay, safety, clarity of signs and markings, reliability of warning devices, and safety information dissemination at local HRGCs

Participants were asked nine questions that tested their knowledge of safely driving at HRGCs in Section 3 of the questionnaire, including six single choice questions and three multiple choice questions. For each question a participant received a score based on his/her responses. For single choice questions, a correct answer was given 3 points; an incorrect answer received zero points. For multiple choice questions, people received full credit (i.e., 3 points) if all correct choices were marked; got partial credit if the answers were partially correct; and got zero credit if "I don't know" was selected (missing values were not displayed). The nine items were integrated into one variable that theoretically ranges from 0 to 27 to evaluate a participant's overall knowledge of safely driving at HRGCs. The Cronbach's alpha value for those five items was 0.45, indicating that the nine items are not measuring the same underlying construct. This is expected because the nine items were originally designed to test different aspects of knowledge, and a summary of the items was assumed to reflect a participant's overall knowledge level. The integrated variable has a mean of 21.7 and a standard deviation of 3.8, indicating that the participants generally have good knowledge of safely driving at HRGCs. **Figure 5.4** presents a KDE for the overall knowledge of safely driving at HRGCs. The majority of the participants had knowledge scores falling between 18 and 25.

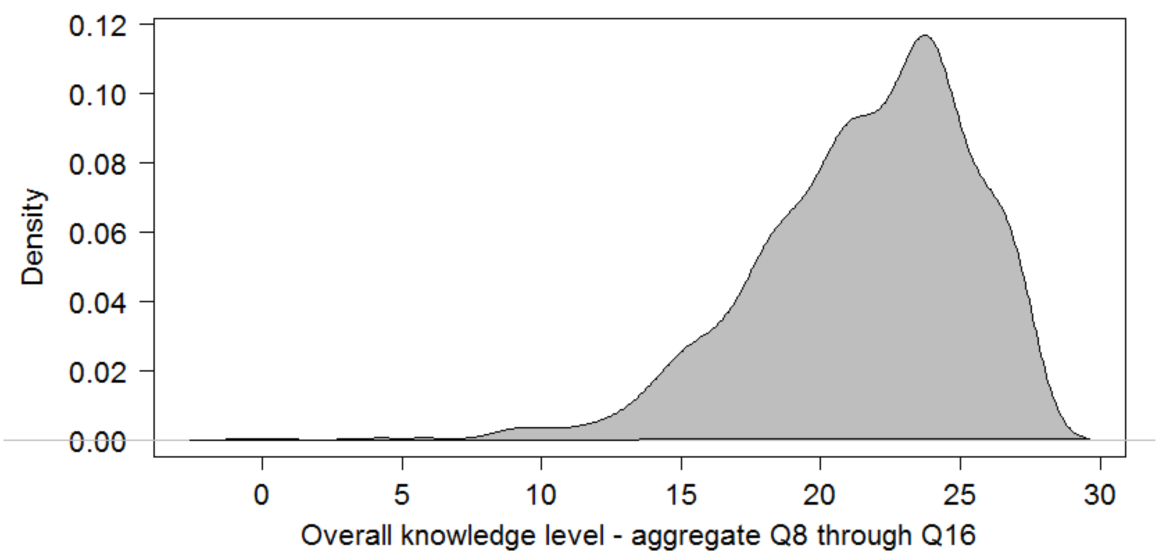


Figure 5.4 KDE of individual overall knowledge of safely driving at HRGCs

Section 5 of the questionnaire included 13 questions asking about drivers' attitudes towards safety issues, safety strategies, and their intent to violate rules at HRGCs. The measurements were assessed via a 5-point Likert scale from "Strongly agree" to "Strongly disagree." Results are presented in **Figure 5.5** (missing values are not displayed). A lack of educational training (e.g., Operation Lifesaver), lack of enthusiasm for rail crossing safety information, lack of support for stronger law enforcement, and lack of patience for waiting for trains are some of the issues with the surveyed participants.

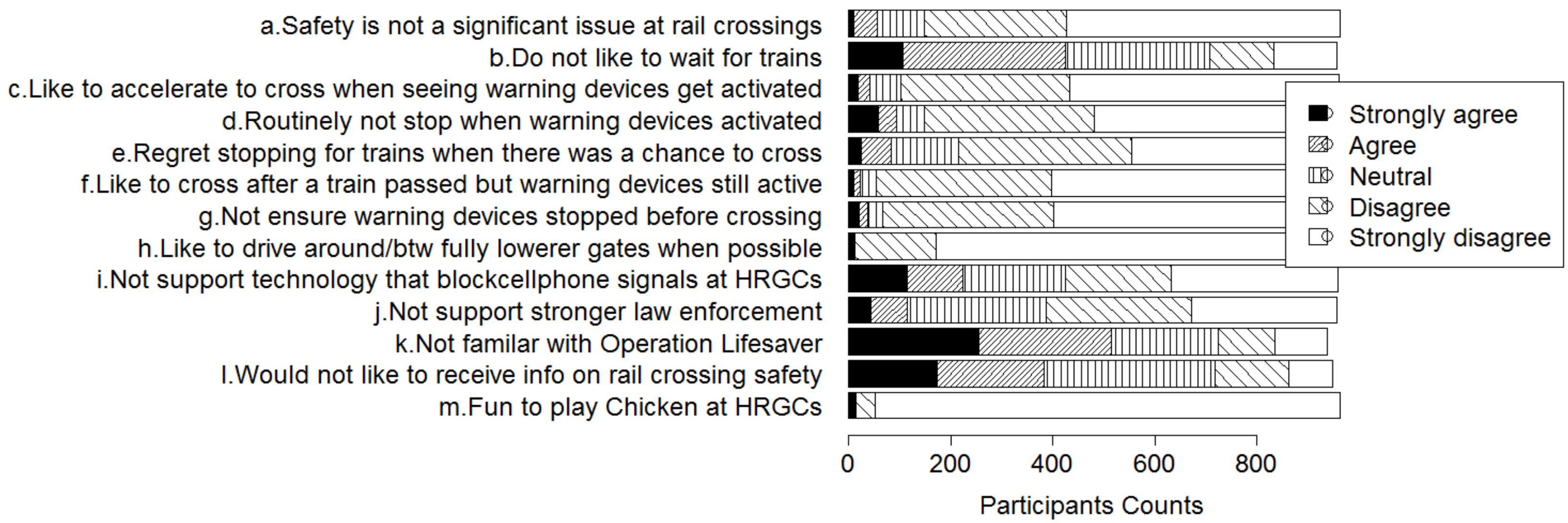


Figure 5.5 Attitudes towards safety issues and intention to violate at HRGCs

5.3 Handling Missing Data

Missing data is a common issue in survey research. In this research, there were missing data resulting from survey respondents not providing responses to some of the questions. In survey research, this is called item nonresponse. In data analysis, dropping entire records that are missing a data item may result in a significant reduction in sample size. Another form of compensation for this type of missing data is imputation, which means assigning a value (e.g., mean) for the missing data (Brick and Kalton, 1996). But because the same value is used for each missing data, the method artificially reduces variance of the variable that has missing data and also reduces relationships with other variables.

Therefore, in this dissertation, a compromise between the two methods – the case-wise deletion that drops the entire record and the imputation method that imputes with an average value – was adopted: the pairwise deletion. The pairwise deletion of missing data makes maximum use of the available survey data. For example, when using pairwise deletion, each correlation between each pair of variables is calculated from all cases that have valid data on those two variables, even though there might be missing data for other variables of the same cases. Missing values were assumed to be missing completely at random (MCAR), which means the propensity for a missing data point is completely random and there is no relationship between whether a data point is missing and any values in the data set.

5.4 Factor Analysis of Attitude

This section explores drivers' attitudes towards safety issues at HRGCs and their intent to commit rule violations using Section 5 of the questionnaire. This section included 13 questions that were initially designed to reflect several aspects of participants' personalities, such as their patience for waiting for trains at rail crossings, their routine behavior, and their attitudes towards safety. Two or more items were designed to measure each aspect. Some items of this section were expected to be closely correlated because they shared the same underlying causal mechanism (e.g., intent to violate rules either due to an impatient personality or sensation-seeking personality). Three latent variables were assumed to explain the relationships between the 13 manifest questions. Questions 18a and 18i to 18l (five questions) were assumed to reflect participants' attitudes towards safety and safety enhancing strategies at HRGCs, namely Att_safety; Questions 18b, 18c, 18e, 18f, 18h, and 18m (six questions) were to test participants' patience and sensation-seeking personalities, meaning their intent to violate rules at HRGCs, namely Att_violate; Questions 18d and 18g (two questions) were to evaluate participants' safe driving habits/routine behavior, meaning their intent to obey the rules at HRGCs, namely Att_obey.

The confirmatory factor analysis (CFA), which is a statistical technique to verify the factor structure of a set of observed variables, was used in the analysis to confirm the underlying latent factors. The underlying measurement structure of the latent variables is presented in **Figure 5.6**. In the CFA analysis, those endogenous ordinal Likert scale variables were treated as ordinal, as suggested by Rosseel (2015). Notice the five levels for each measurement item (from Q18a to Q18m) are reordered to indicate the most unsafe intent using “1” and the safest intent using “5.” For example, if a respondent chose “Strongly agree” to Question 18b, which stated “I do not like to wait for passing trains at rail crossings,” then the respondent was given a score of “1” to indicate the most unsafe intent.

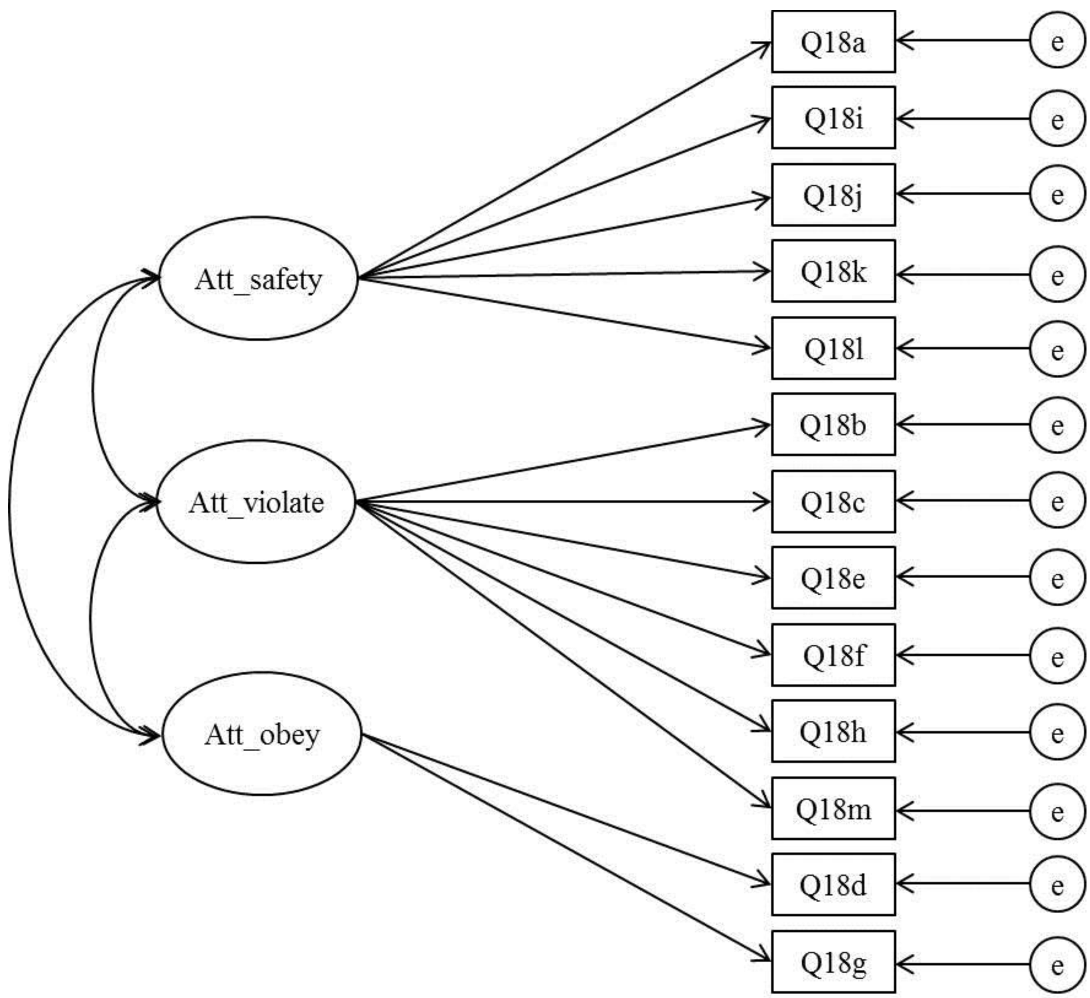


Figure 5.6 Proposed measurement structures of the latent variables

The lavaan package (version 0.5.20) in R (Rosseel, 2015; Rosseel et al., 2015) was used to conduct the CFA. The Robust weighted least squares (WLS) estimator, which uses diagonally weighted least squares to estimate model parameters and full weight matrix to compute robust standard errors, and a mean- and variance-adjusted test statistic, was utilized considering the categorical nature of the Likert scale items. A robust WLS estimator is recommended for ordinal indicator variables (such as Likert-type items) instead of ML (maximum likelihood) estimator (Flora and Curran, 2004; Brown, 2006; Barendse et al., 2014). The CFA model yielded a CFI (Comparative Fit Index) of 0.976 and a SRMR (Standardized Root Mean Squared Residual) of 0.062, which met the combinational rule for acceptable model fit of CFI>=0.95 and SRMR<=0.06 to 0.08 (Hooper et al., 2008; Hu and Bentler, 1999), indicating the model fit was good. **Figure 5.7** presents the final CFA model results.

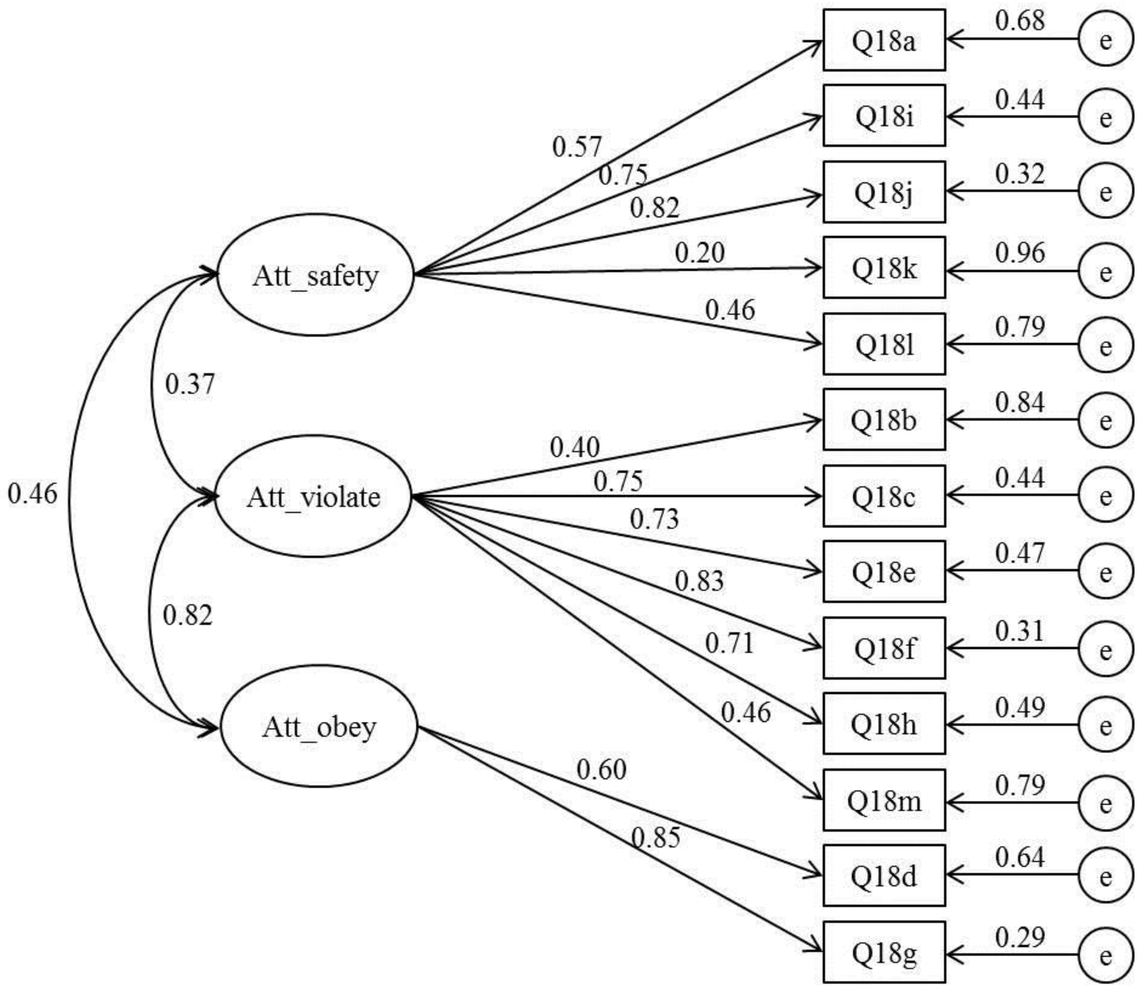


Figure 5.7 Result of the confirmatory factor analysis for questions 18a-18m

In **Figure 5.7**, variables in oval-shaped boxes are latent variables and those in square boxes are observed variables. A lower case "e" in circular boxes is an error term. The straight arrow from a latent variable to the observed variables indicates the causal effect of the latent variable on the observed variables. The curved arrows between two latent variables indicate they are correlated with each other. All estimates are from a standardized solution and all estimates are statistically significant at $\alpha = 0.05$. The model fit index CFI = 0.976, TLI = 0.970, RMSEA = 0.062 with C.I. of 0.055 to 0.070, and SRMR = 0.075.

For subsequent analyses, the factor scores were calculated for all cases on the three latent variables. Factor scores are composite numerical values that indicate an individual's relative spacing or standing on a latent factor (Distefano et al., 2009). The factor scores were calculated by the Empirical Bayes approach, which is available in the "lavaan" package for categorical indicators (Rosseel et al., 2015). Factors scores were stored in the dataset for later use in the analysis. **Figure 5.8** presents distributions of the three latent factor scores (which were centered at 0.0) in histograms and kernel density plots.

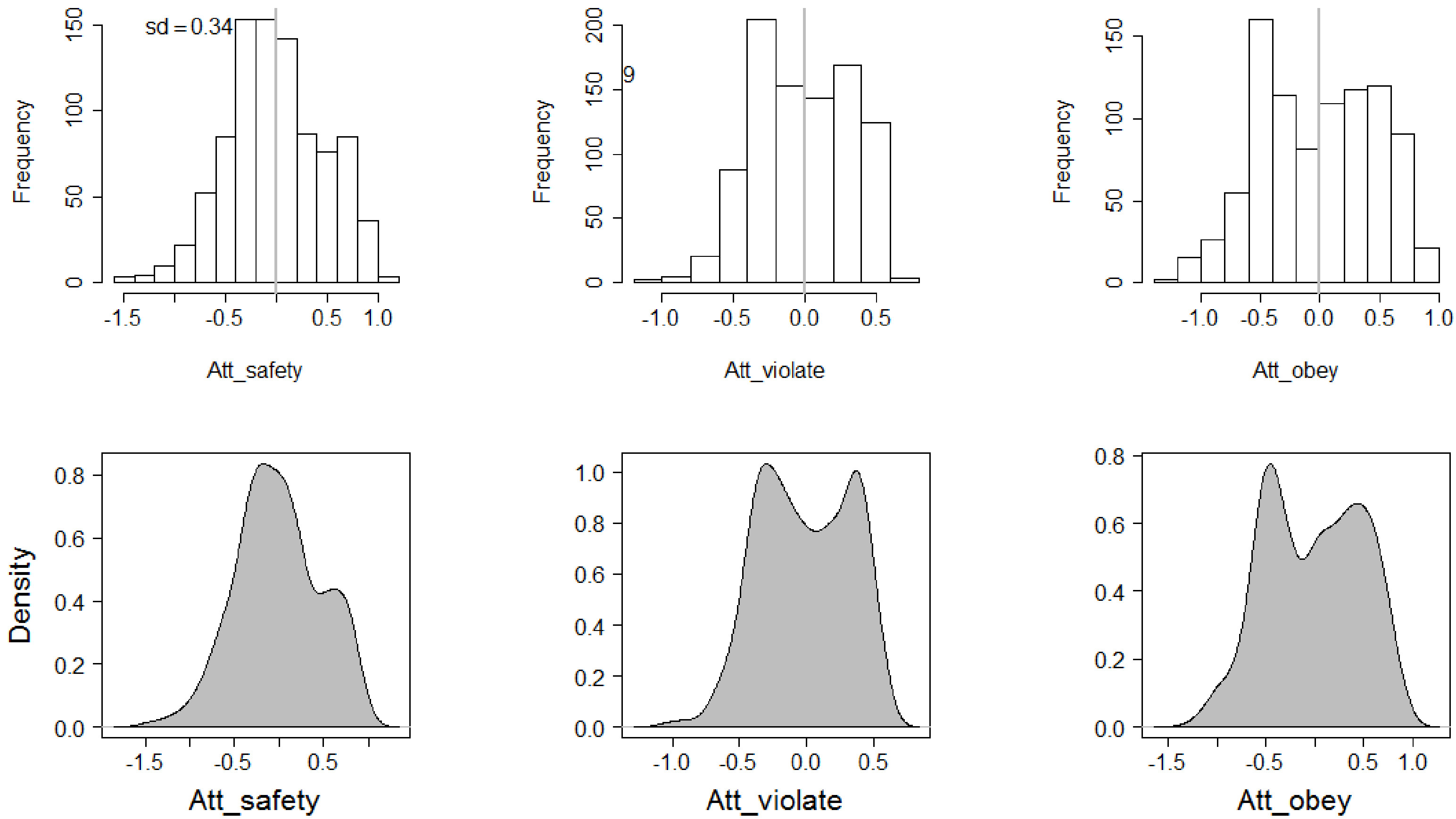


Figure 5.8 Histogram (above) and kernel density (below) distributions of the three latent factors scores

5.5 Multiple Regression on Inattentive Behavior

This section explores variables that may influence drivers' involvement in inattentive driving at HRGCs. Variables that were assumed to be associated with driver's inattentive behavior include:

Drivers' perceptions of safety, delay, clarity, reliability, safety program received;

Vehicle types;

Frequency of using HRGCs;

Expected train through movements;

Knowledge of safely driving at HRGCs;

Attitudes towards safety issues at HRGCs;

Attitudes towards violating rules at HRGCs;

Attitudes towards obeying rules at HRGCs; and

Drivers' residency years, license years, gender, age, education, and income.

Table 5.10 presents summary statistics for the potential variables. Least squares multiple linear regression using an all-subsets variable selection method was implemented. The reason for treating the overall risk of being involved in attentive driving as a continuous variable is that there is no evidence of distinct thresholds that could be used to categorize the risk and no previous experience that can be borrowed. A linear relationship is simple and easy to interpret as long as the assumptions hold. Among all the potential independent variables listed in the table, drivers' perceptions of safety, delay, clarity, reliability, and safety programs received (i.e., question 1a to 1e) were on an ordinal scale. There is debate whether a single Likert scaled item could be treated as a continuous variable. In this research the Likert scaled variables were treated as continuous and numeric (i.e., 1 to 5) because: (1) based on the essence of the questions, it is reasonable to assume the distances between adjacent choices of each item are more or less the same; (2) treating them as categorical and creating five dummy variables for each item would neglect the ordinal information contained in the answers.

Table 5.10 Summary of interested variables in the multiple linear regression

Variables	Range	Mean	SD
Dependent Variable			
Overall risk of being involved in inattentive driving (Q17e-n)	10-50: low risk to high risk	16.31	5.50
Independent Variables			
Perception of delay (Q1a)	1-5: low to high delay	3.55	1.10
Perception of safety (Q1b)	1-5: unsafe to safe	4.01	0.88
Perception of safety (Q1c)	1-5: confusing to clear signs and markings	4.10	0.71
Perception of reliability (Q1d)	1-5: unreliable to reliable train warning signals	3.95	0.90
Perception of safety info outreach (Q1e)	1-5: low to high information	2.89	1.26
Vehicle type: passenger car or SUV (Q3)	1= yes (63.78%), 0= no (23.27%)		
Use of HRGCs <1 in the past two weeks (Q5)	1= yes (15.82%), 0= no (78.98%)		
Use of HRGCs >=1 and <=7 in the past two weeks (Q5)	1= yes (32.55%), 0= no (62.24%)		
Use of HRGCs >7 and <=14 in the past two weeks (Q5)	1= yes (14.80%), 0= no (80.00%)		
Use of HRGCs >14 and <=28 in the past two weeks (Q5)	1= yes (13.57%), 0= no (81.22%)		
Use of HRGCs >28 in the past two weeks (Q5)	1= yes (11.02%), 0= no (83.78%)		
Expected daily train passages <1 (Q7)	1= yes (8.78%), 0= no (62.76%)		
Expected daily train passages >=1 and <=10 (Q7)	1= yes (35.92%), 0= no (35.61%)		
Expected daily train passages >10	1= yes (19.80%), 0= no		

(Q7)	(51.73%)		
Knowledge of safely driving at HRGCs (Q8-16)	0-27: low to high knowledge	21.67	3.76
Attitude towards safety and safety enhancing strategies at HRGCs (Att_safety, Q18 partial)	-2-2: negative to positive attitude (scaled)	-0.01 (scaled)	0.48
Intent to violate rules at HRGCs (Att_violate, Q18 partial)	-2-2: high to low violating intent (scaled)	-0.01 (scaled)	0.34
Intent to obey rules at HRGCs (Att_obey, Q18 partial)	-2-2: low to high obeying intent (scaled)	-0.02 (scaled)	0.49
Residency in current city (Q23)	0-99 years	27.61	20.95
Licensed driver for more than 10 years (Q25)	1= yes (84.80%), 0= no (6.43%)		
Female driver (Q26)	1= yes (51.63%), 0= no (39.29%)		
Driver age <30 (Q27)	1= yes (9.39%), 0= no (88.88%)		
Driver age >=30 and <60 (Q27)	1= yes (42.96%), 0= no (55.31%)		
Driver age >=60 (Q27)	1= yes (38.88%), 0= no (59.39%)		
Up to high school education (Q28)	1= yes (19.80%), 0= no (76.63%)		
Up to associate degree education (Q28)	1= yes (29.59%), 0= no (66.84%)		
Up to bachelor's degree education (Q28)	1= yes (24.69%), 0= no (71.73%)		
Higher than bachelor's degree education (Q28)	1= yes (15.31%), 0= no (81.12%)		
Household annual income <30,000 (Q30)	1= yes (16.73%), 0= no (72.45%)		
Household annual income >=30,000 and <60,000 (Q30)	1= yes (24.29%), 0= no (64.90%)		
Household annual income >=60,000 and <100,000 (Q30)	1= yes (21.43%), 0= no (67.76%)		
Household annual income >=100,000 (Q30)	1= yes (19.69%), 0= no (69.49%)		

The all-subsets variable selection method revealed a best model that contained 18 variables, but not all of them are statistically significant at the 90% level. By keeping only variables that are at least statistically significant at a 90% level, the model was reduced to contain 12 parameter estimates that were statistically significant at the 95% level, and another two estimates that were marginally significant at a 90% level. The model had an adjusted R-squared value of 0.272. The results of the ordinary least-square (OLS) regression model are presented in **Table 5.11**.

Table 5.11 OLS regression model results

Variable	Estimates	Std.Error	Z-stat	P-value
(Intercept)	18.944	1.598	11.853	0.000***
Female driver (female)	1.366	0.383	3.565	0.000***
Perceived safety at local HRGCs (Q1b)	0.611	0.260	2.351	0.019*
Perceived reliability of warning devices at local HRGCs (Q1d)	-0.459	0.254	-1.803	0.072.
Use of HRGCs <1 in the past two weeks (useL)	-1.975	0.563	-3.510	0.000***
Use of HRGCs >=1 and <=7 in the past two weeks (useM)	-1.004	0.408	-2.464	0.014*
Knowledge of safely driving at HRGCs (Q8_16s)	-0.148	0.052	-2.864	0.004**
Attitude towards safety and safety enhancing strategies at HRGCs (Att_safety)	-1.087	0.505	-2.151	0.032*
Intent of violating rules at HRGCs (Att_violate)	-7.264	1.669	-4.351	0.000***
Habit of obeying rules at HRGCs (Att_obey)	1.987	1.219	1.630	0.104
Years living in current city (yearslive)	-0.026	0.011	-2.402	0.017*
Driver age <30 (ageY)	3.223	0.703	4.588	0.000***
Driver age >=30 and <60 (ageM)	1.763	0.451	3.906	0.000***
Associate's degree (asdegree)	-0.930	0.398	-2.339	0.020*
Household annual income <30,000 (incL)	-1.214	0.489	-2.481	0.013*

Significance codes: '***' 0.001, '**' 0.01, '*' 0.05. Insignificant main effects were kept in the model when an interaction was significant.
Residual standard error = 4.739 (*df* = 648). Adjusted R^2 = 0.272. $F_{14,648}$ = 18.63 ($p <$ 0.0005). Sample size =663.

To assess the linear model assumptions, the R package "gvlma" was used. It performed a single global test as well as several specific directional tests designed to diagnose skewness, kurtosis, a nonlinear link function, and heteroscedasticity (Pena and Slate, 2015). **Table 5.12** shows the results, which indicate that the fitted model did not meet the linear regression assumptions.

Table 5.12 Test of OLS regression assumptions

	Value	p-value	Decision
Global stat	69.162	0.000	Assumptions NOT satisfied!
Skewness	40.209	0.000	Assumptions NOT satisfied!
Kurtosis	22.068	0.000	Assumptions NOT satisfied!
Link Function	6.734	0.009	Assumptions NOT satisfied!
Heteroscedasticity	0.151	0.698	Assumptions acceptable

Residuals of the fitted model were also checked for outliers and any violations of the assumptions. **Figure 5.9** and **5.10** present the residual plots. As can be seen from the figure, the normality of the residuals was questionable. In fact, the distribution of the residuals was quite skewed. There were also a few outliers with relatively high leverage.

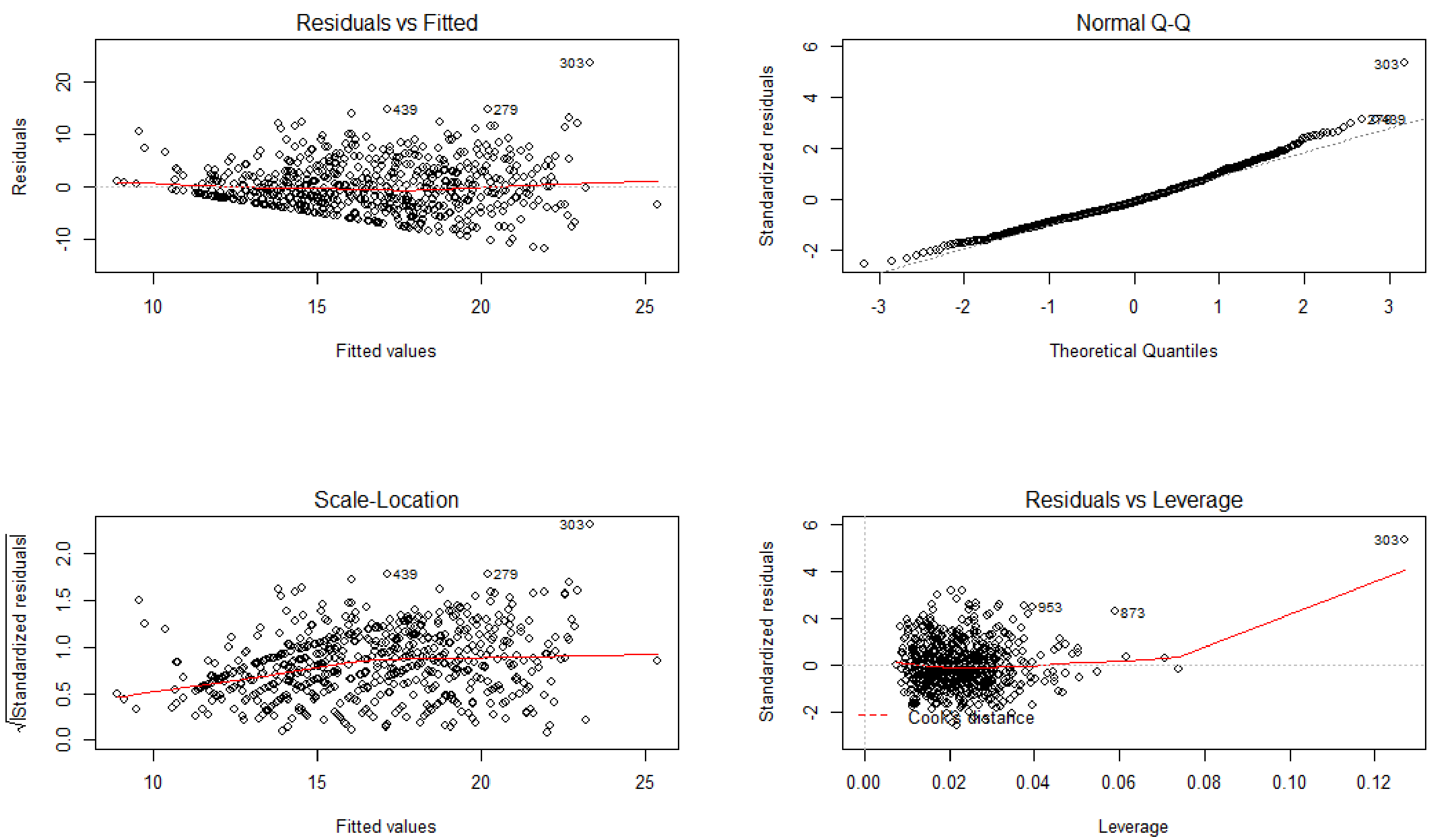


Figure 5.9 Residual plots for the OLS regression

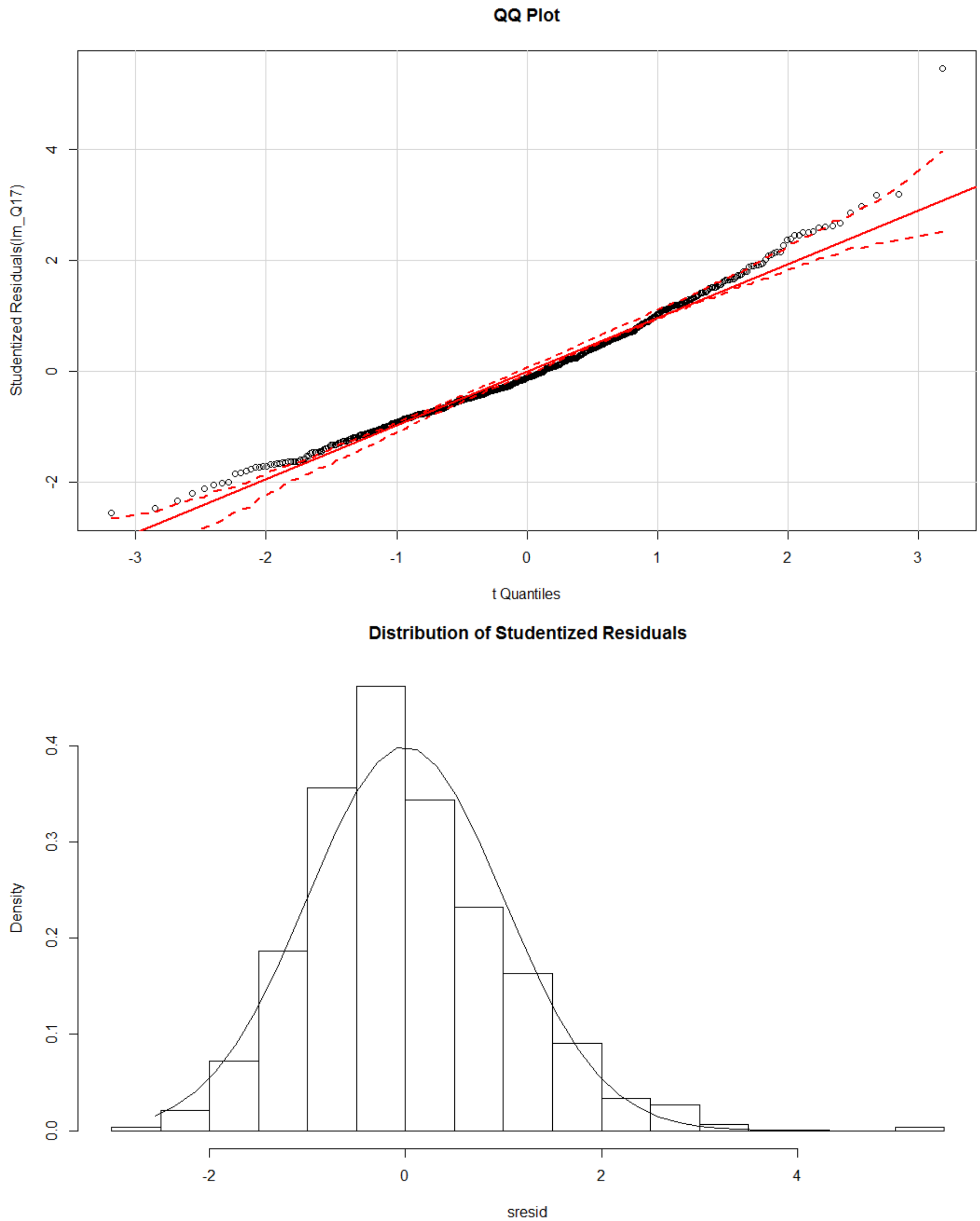


Figure 5.10 Normal probability plot of the residuals and residual histogram for the OLS regression

Transformation is one of the methods used to deal with skewness. Natural log-transformation of the dependent variable was attempted. The statistical significance of the independent variables remained almost unchanged, as presented in **Table 5.13**. **Table 5.14** shows the results of the model assumption tests, which indicated that the fitted model met the linear regression assumptions. The residual plots in **Figures 5.11** and **5.12** show significant improvement of the normality.

Table 5.13 Natural log-transformed OLS regression model results

Variable	Estimates	Std.Error	Z-stat	P-value
(Intercept)	2.956	0.074	39.791	0.000***
Female driver (female)	0.078	0.022	3.558	0.000***
Perception of safety info outreach (Q1e)	-0.016	0.009	-1.915	0.056.
Use of HRGCs <1 in the past two weeks (useL)	-0.156	0.032	-4.891	0.000***
Use of HRGCs >=1 and <=7 in the past two weeks (useM)	-0.075	0.023	-3.190	0.001**
Knowledge of safely driving at HRGCs (Q8_16s)	-0.007	0.003	-2.435	0.015*
Attitude towards safety and safety enhancing strategies at HRGCs (Att_safety)	-0.047	0.026	-1.800	0.072.
Intent of violating rules at HRGCs (Att_violate)	-0.256	0.037	-7.006	0.000***
Years living in current city (yearslive)	-0.001	0.001	-2.300	0.022*
Driver age <30 (ageY)	0.200	0.040	4.997	0.000***
Driver age >=30 and <60 (ageM)	0.113	0.026	4.387	0.000***
Associate's degree (asdegree)	-0.052	0.023	-2.267	0.024*
Household annual income <30,000 (incL)	-0.083	0.028	-2.984	0.003**

Significance codes: '***' 0.001, '**' 0.01, '*' 0.05. Insignificant main effects were kept in the model when an interaction was significant.
Residual standard error = 0.272 (*df* = 650). Adjusted R^2 = 0.278. $F_{12,650}$ = 22.4 (p < 0.0005). Sample size = 663.

Table 5.14 Test of natural log-transformed OLS regression assumptions

	Value	p-value	Decision
Global stat	2.591	0.628	Assumptions acceptable
Skewness	0.315	0.575	Assumptions acceptable
Kurtosis	1.921	0.166	Assumptions acceptable
Link Function	0.341	0.559	Assumptions acceptable
Heteroscedasticity	0.014	0.907	Assumptions acceptable

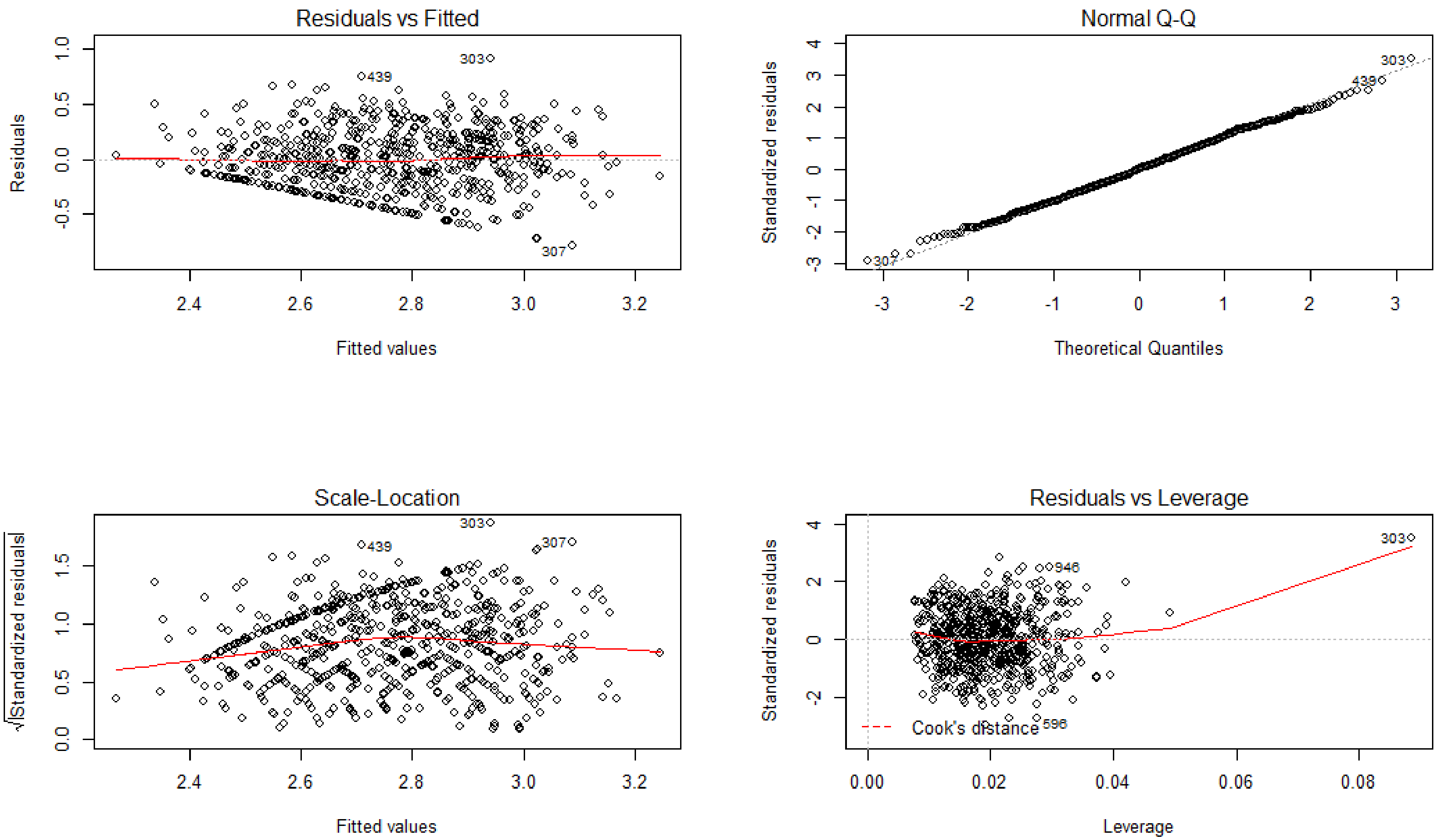
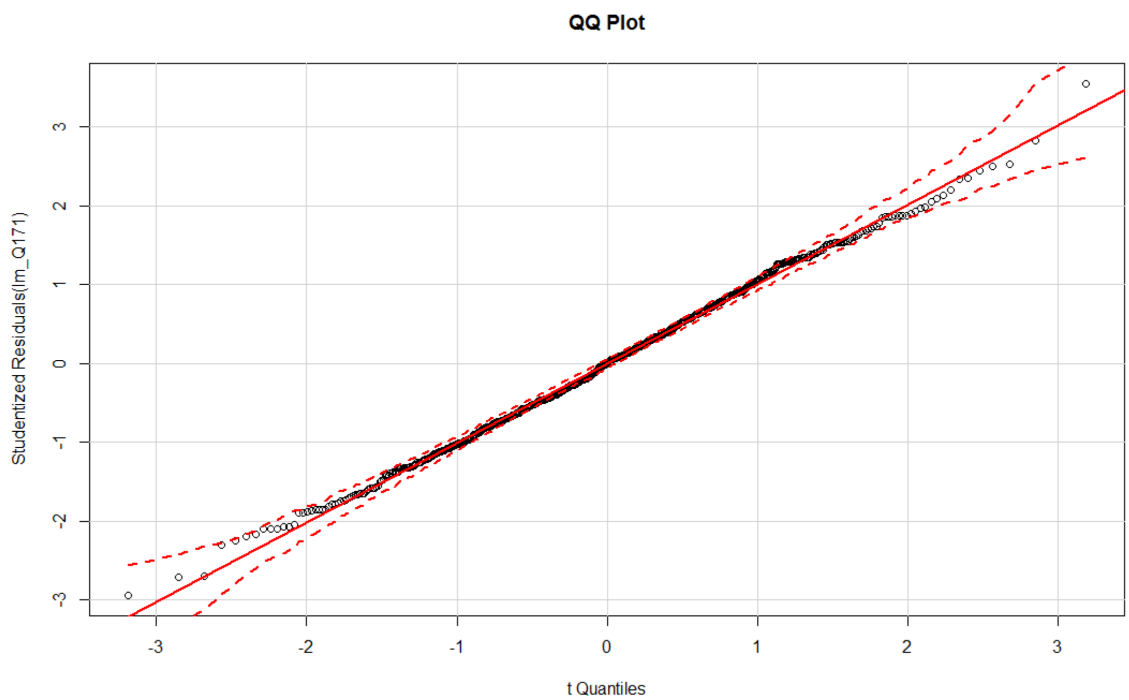


Figure 5.11 Residual plots for the log-transformed OLS regression



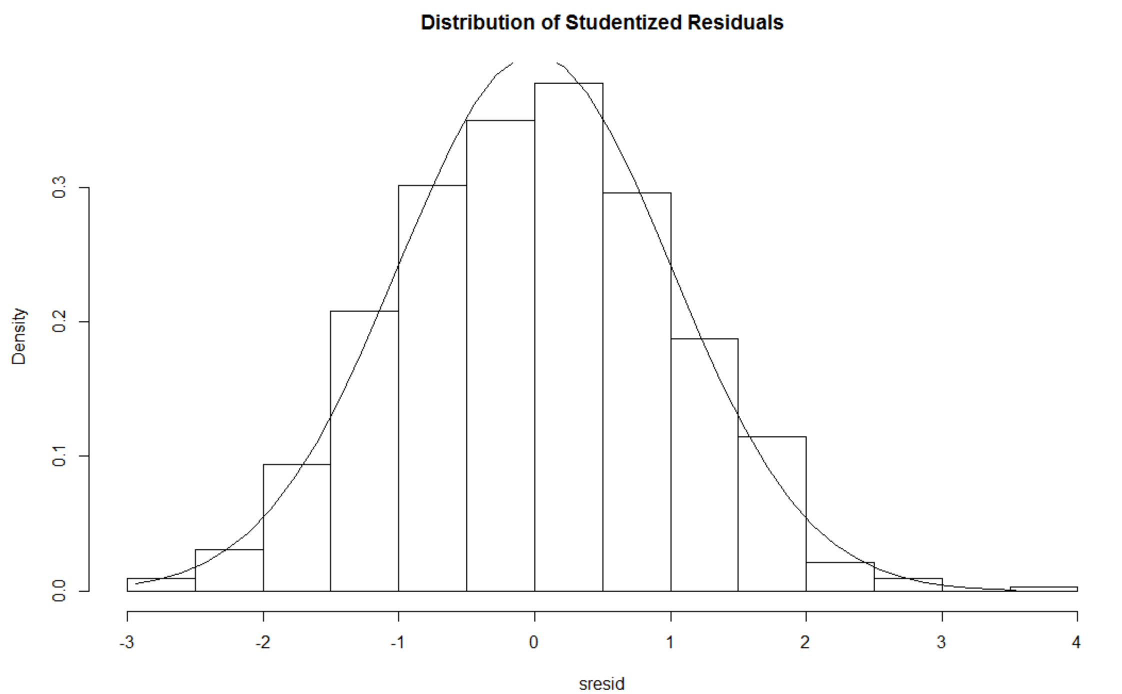


Figure 5.12 Normal probability plot of the residuals and residual histogram for the log-transformed OLS regression

Residuals of the fitted model showed acceptable conformation to the model assumptions, but the plots also found several observations that may be of concern (e.g., with large residuals or Cook's distance). However, the survey essence makes it very difficult to determine whether an "abnormal" observation should be treated as an outlier and excluded from the study. In this case, robust regression is a good alternative as it is not as vulnerable as least squares to unusual data and can be considered as a compromise between excluding the unusual observations from the analysis and treating them equally in the least square regression (UCLA: Statistical Consulting Group, 2014). Robust regression commonly uses M-estimator and the estimating equations are solved using Iteratively Reweighted Least Squares (IRLS). The "rlm" function in the "MASS" package was used to carry out robust regression. The robust regression results were compared with the log-transformed least square regression results. Although the signs and statistical significance remained mostly the same for the parameter estimates (except for the estimate for "habit of obeying rules at HRGCs" that lost its statistical significance), the estimates scales changed from an absolute change of 0.6% to 29%, indicating some model parameters were influenced by outliers and it was necessary to implement the robust regression model. As the robust regression did not address issues of potential heteroscedasticity of variance, robust standard errors of the coefficients were estimated using the "sandwich" package (Lumley and Zeileis, 2015). **Table 5.15** presented the robust regression model and robust standard error results and **Figure 5.13** showed the residual plots.

Table 5.15 Robust regression results

Variable	Estimates	Std.Error	Z-stat	P-value
(Intercept)	2.939	0.080	36.906	0.000***
Female driver (female)	0.084	0.022	3.830	0.000***
Perception of safety info outreach (Q1e)	-0.019	0.009	-2.060	0.039*
Use of HRGCs <1 in the past two weeks (useL)	-0.167	0.039	-4.283	0.000***
Use of HRGCs >=1 and <=7 in the past two weeks (useM)	-0.077	0.023	-3.360	0.001**
Knowledge of safely driving at HRGCs (Q8_16s)	-0.006	0.003	-2.037	0.042*
Attitude towards safety and safety enhancing strategies at HRGCs (Att_safety)	-0.060	0.029	-2.099	0.036*
Intent of violating rules at HRGCs (Att_violate)	-0.258	0.038	-6.732	0.000***
Years living in current city (yearslive)	-0.002	0.001	-2.551	0.011*
Driver age <30 (ageY)	0.205	0.046	4.479	0.000***
Driver age >=30 and <60 (ageM)	0.116	0.024	4.732	0.000***
Associate’s degree (asdegree)	-0.047	0.023	-1.981	0.048*
Household annual income <30,000 (incL)	-0.092	0.026	-3.553	0.000***

Significance codes: ‘***’ 0.001, ‘**’ 0.01, ‘*’ 0.05. Insignificant main effects were kept in the model when an interaction was significant.
Residual standard error = 0.273 (df = 650). Adjusted R^2 = 0.276. $F_{12,650}$ = 23.2 (p < 0.0005). Sample size =663.

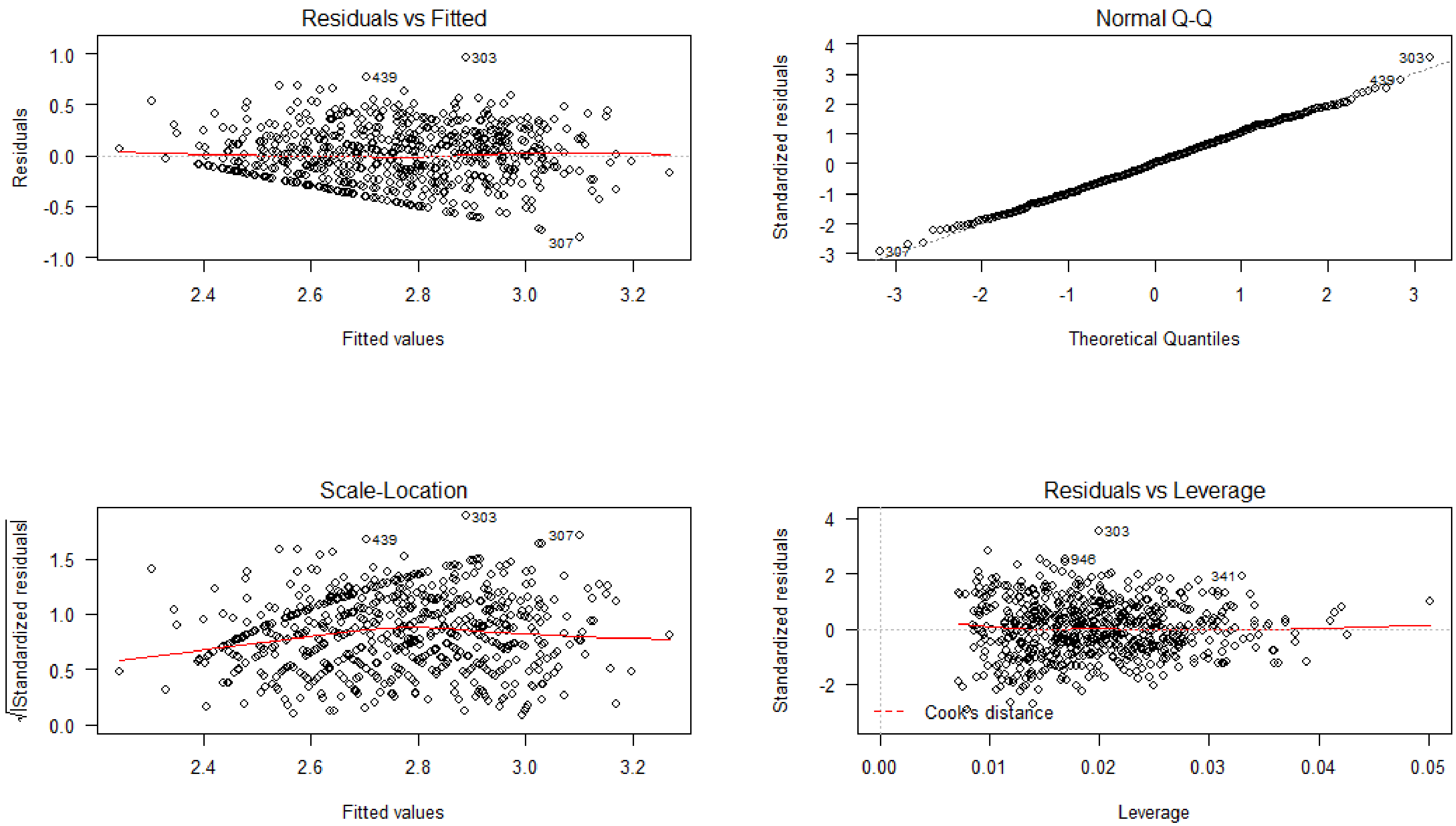


Figure 5.13 Residual plots for the log-transformed robust regression

5.6 Model Results Interpretation

The robust regression model fitted in Section 5.5 identified a few factors that were associated with drivers' inattentive behavior at HRGCs. Recall that the dependent variable – overall risk of being involved in inattentive driving – had a continuous score from 10 to 50, with a higher score indicating higher risk. Females and drivers younger than 60 years were found to be positively associated with the risk of inattentive driving. Compared with males, females had a 0.084 increase in natural log of the risk of inattentive driving, keeping other factors the same. This is an interesting finding because males were usually found to be the typical non-compliant crossing users at HRGCs (Edquist et al., 2011; Freeman and Rakotonirainy, 2015) and male drivers were found to be more aggressive in their driving styles (Yeh and Multer, 2008). An explanation for this finding could be that female drivers may take various responsibilities that could distract them during driving and thus indulge more often in such behavior. Younger drivers (especially those <30) have a higher risk of inattentive driving, compared with older drivers (age >=60). This could be a result of the cautious driving habits of older people or fewer distractions than young people.

Drivers living in a lower (< 30k per year) income household had about a 0.1 decrease in the risk of inattentive driving compared to drivers whose household income was higher (>= 30k), holding other factors constant. The reason could be that people with higher household incomes may also be the group of people that have more business to take care of during their drive, which may induce them to be involved in more non-driving tasks. For example, answering phone calls or talking of business when driving is not uncommon nowadays.

Drivers that used HRGCs less often (<10 per 14 days) had lower risk of being involved in inattentive driving, compared with drivers who used HRGCs more frequently (>=10 per 14 days). This could be an "exposure" aspect of reason – the less frequent a driver being exposed to an HRGC, the less likely the driver be involved in inattentive driving at HRGCs.

Drivers who received more information about safety at HRGCs had a lower risk of being involved in attentive driving. Also, a one unit increase in the overall knowledge of safely driving at HRGCs would decrease the natural log of the risk of inattentive driving by 0.006. Safety programs at HRGCs, therefore, could be of help in reducing dangerous driving behavior.

Drivers that had more positive attitude toward safety at HRGCs and lower intent to violate rules at HRGCs had a lower risk of inattentive driving. A one unit increase in drivers' attitudes towards safety issues could decrease the natural log of the risk of inattentive driving by 0.060; a one unit decrease in drivers' intent to violate rules could decrease the natural log of the risk by 0.258. Drivers' behavior was suitably explained by their safe driving attitude and habits.

Finally, the overall risk of inattentive driving decreased as the driver's residency years in their current city increased. Besides the effect of age, this could be explained by the fact that as people become more familiar with the city, they have a better understanding of the surroundings and are more focused on their driving tasks.

5.7 Chapter Summary

This chapter addressed the second objective of the dissertation, which is to identify some of the factors associated with driving inattention at HRGCs through a statewide mail self-report survey from the state of Nebraska, U.S. Confirmatory factor analysis and robust linear regression were used as analysis tools.

The confirmatory factor analysis successfully summarized the 13 items in question 18 of the questionnaire into three distinct latent variables, which were used as three new explanatory variables in the regression analysis of inattentive driving. After optimizing the least square regression models, a robust model that was not significantly affected by outliers and thus had robust coefficient estimates and standard errors was estimated. The linear model assumptions were checked through statistical parameters and residual plots, which both concluded the model result conformed to the linear regression assumptions and the model result was valid.

Factors that were found to be statistically associated with drivers' inattentive behavior at HRGCs included gender, age, education, income level, residency years, use frequency of HRGCs, safety information received, knowledge of safely driving at HRGCs, attitudes towards safety issues at HRGCs, and intent to violate rules at HRGCs. Drivers that seemed to have a higher risk of inattentive driving at HRGCs were female, younger drivers, higher household income drivers, drivers with fewer residency years in the current city, drivers that more frequently used HRGCs, drivers that received less information on safety at HRGCs, drivers that had less knowledge of safely driving at

HRGCs, drivers with negative attitudes towards safety issues at HRGCs, and drivers with a higher intent to violate rules at HRGCs.

These research findings provide useful information for future research, to policy makers, and educational program providers on what groups of drivers are more vulnerable to non-driving distractions and aspects of safety education that need attention. Information dissemination on safety at HRGCs seems to be positively associated with lower involvement with inattentive driving. Such programs, as well as stricter law enforcement, will hopefully enhance people's safe driving attitudes and habits and therefore reduce inattentive driving at HRGCs.

CHAPTER 6 DRIVER KNOWLEDGE AND IMPACTING FACTORS

Educational programs that aim to improve motor vehicle drivers' safety awareness at HRGCs, such as Operation Lifesaver, have been playing an important role in enhancing rail safety and reducing drivers' hazardous driving behavior at HRGCs. The previous programs, however, do not often have specific target audiences although some program do target certain groups of people (the e-learning for school bus drivers, rail safety lesson plans for all grade kids, photographer safety tips, etc.) . The lack of knowledge regarding which groups of drivers are in urgent need of such information and what aspects of safety knowledge those drivers are lacking could lead to inefficient or insufficient programs. This chapter focuses on the third and fourth objective of the dissertation - to identify driver groups that have lower or higher levels of knowledge of correct rail crossing negotiation and to investigate the direct and indirect effects between drivers' characteristics and their knowledge level as well as their involvement with inattentive driving behavior at HRGCs. The data used in this chapter is dataset 2 (collected through the statewide mail self-report survey).

6.1 Differences in Drivers' Overall Knowledge

Recall that the participants' overall knowledge scores vary between 0 and 27, with higher scores indicating higher overall knowledge of safely negotiating HRGCs. The sampled population has an average score of 21.7 and a standard deviation of 3.8. To visually show the relationships between driver knowledge scores and other driver-related factors, a series of box- whisker diagrams are plotted and presented in **Figures 6.1-6.7**.

Figure 6.1 shows that there are differences in knowledge about correct rail crossing negotiation amongst people who perceived different levels of delays, safety, reliability, etc., of local rail crossings. The groups of people who perceived less delay, more safety, less confusing signs and markings, more reliable warning devices, and more safety information outreach are generally also the groups of people who had higher knowledge of safely driving at rail crossings. **Figure 6.2** shows that the frequency of using HRGCs does not seem to be associated with drivers' knowledge. People who drive passenger cars seem to have slightly better knowledge than people driving other vehicles, but no significant difference can be found from the diagram. **Figure 6.3** shows that drivers' attitudes towards safety issues at HRGCs do not seem to be closely associated with higher or lower knowledge (Q18a, Q18i, and Q18j), although people who claimed to be familiar with Operation Lifesaver seem to have higher knowledge (Q18k) and those who would like to receive more information on safety at HRGCs are also the groups of people who had lower levels of knowledge (Q18l). It is evident from the figure that people who had lower intent to violate regulation rules at HRGCs are the groups of people that had better knowledge (Q18b, Q18c, Q18e, Q18f, Q18h, and Q18m). Meanwhile, those with good habits of obeying rules at HRGCs also have better knowledge of safely negotiating at HRGCs (Q18d and Q18g). **Figure 6.4** shows that drivers who have an accident history at HRGCs on average have a lower level of knowledge; residency in the current city and household size do not seem to be associated with knowledge level; drivers licensed longer have slightly higher knowledge; and gender does not seem to make a difference. As presented in **Figure 6.5**, younger drivers seem to have more knowledge than older drivers. A background of education makes some differences in levels of knowledge – drivers with less than a high school education seem to have lower knowledge while drivers with a bachelor's degree seem to have more knowledge. **Figure 6.6** shows that people with different occupations have different levels of knowledge. Those in the fields of leisure/hospital/sales/art and computers/architecture/engineering/science have higher levels of knowledge, while people in community/social/family and office/administration seem to have slightly lower levels of knowledge. **Figure 6.7** shows that household income is marginally associated with knowledge – respondents with higher household income on average have slightly better knowledge compared to respondents with lower household income.

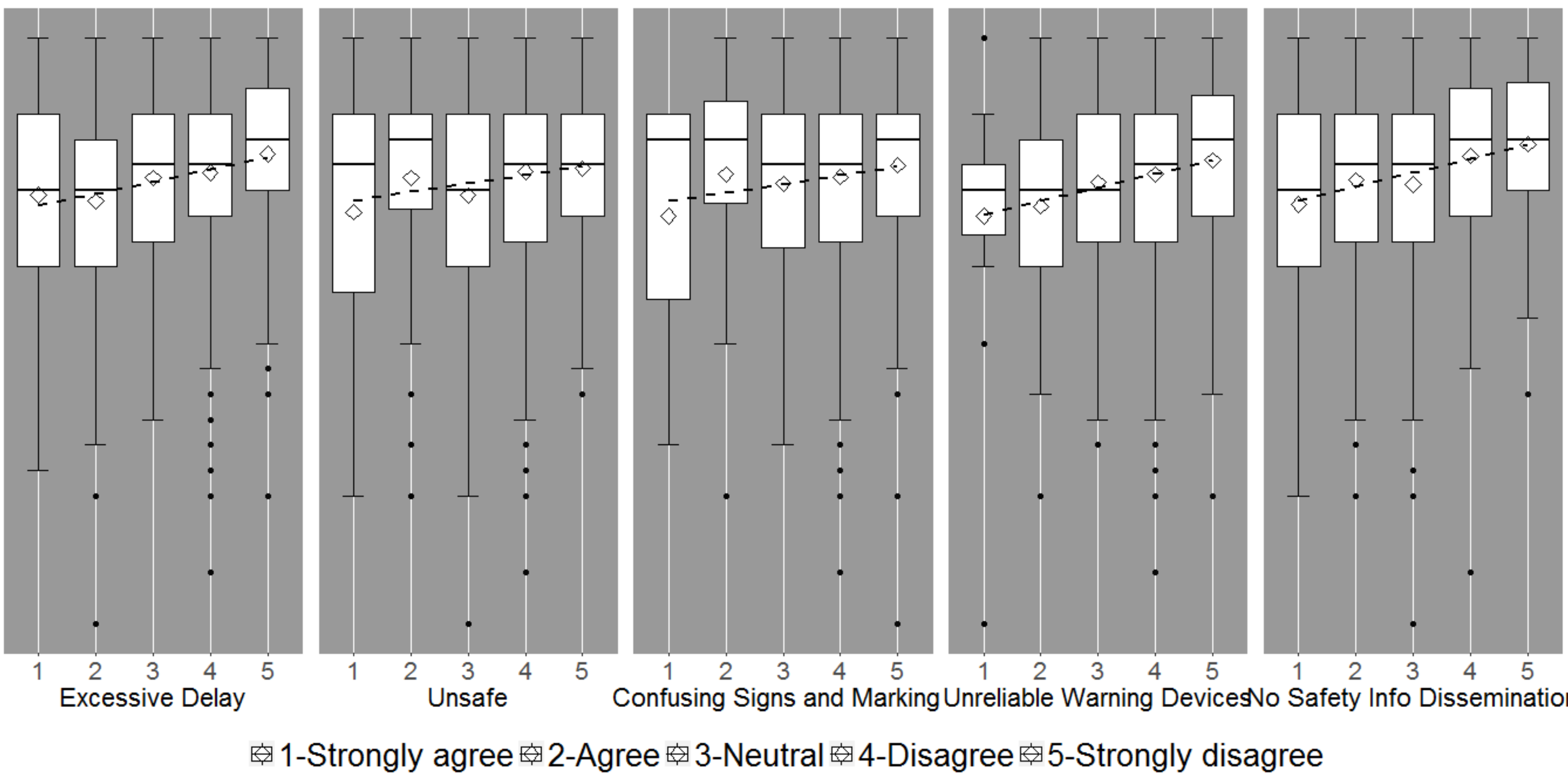


Figure 6.1 Differences in knowledge and perceptions of local HRGCs

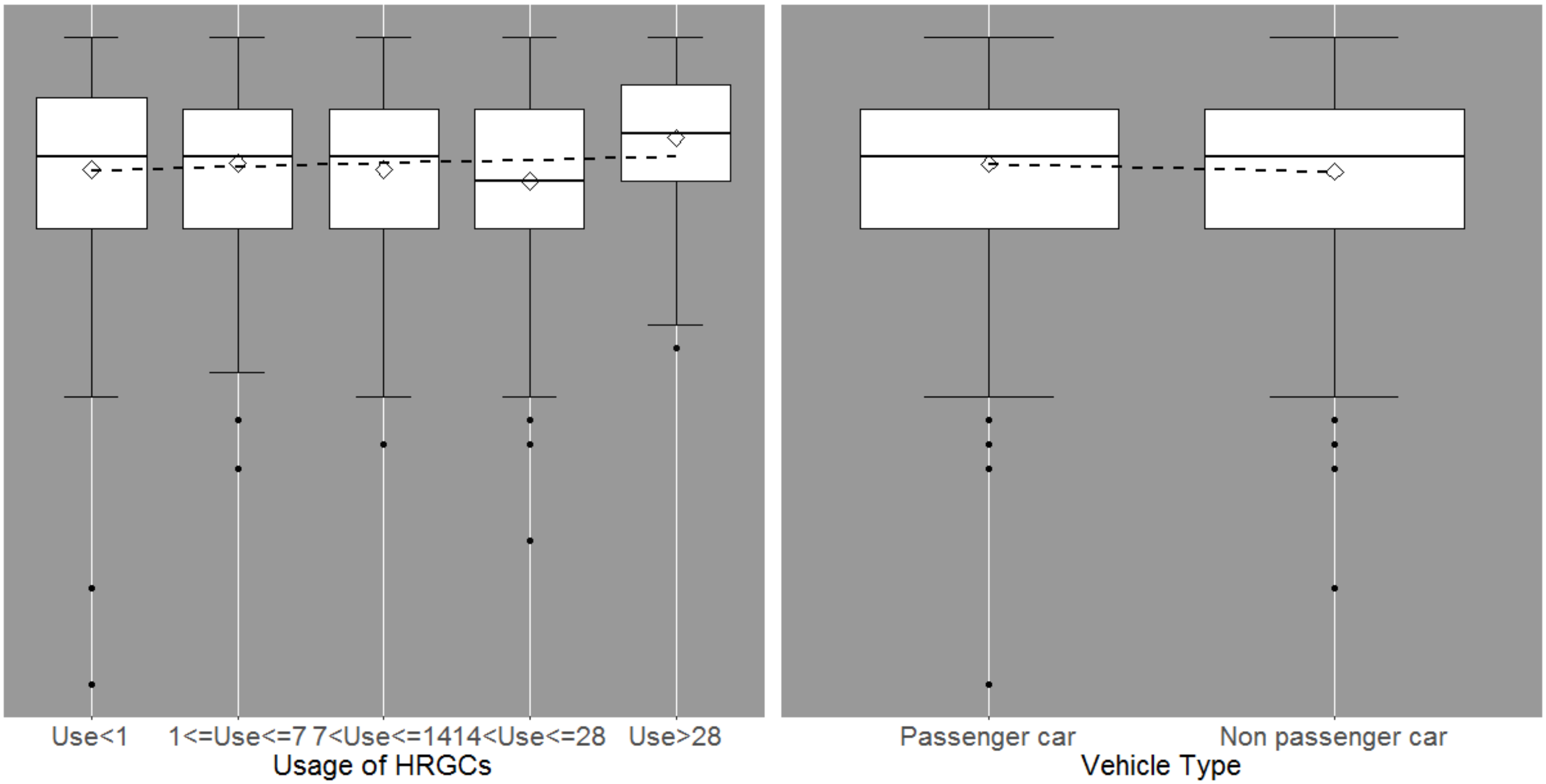


Figure 6.2 Differences in knowledge and use of HRGCs and vehicle types for commute

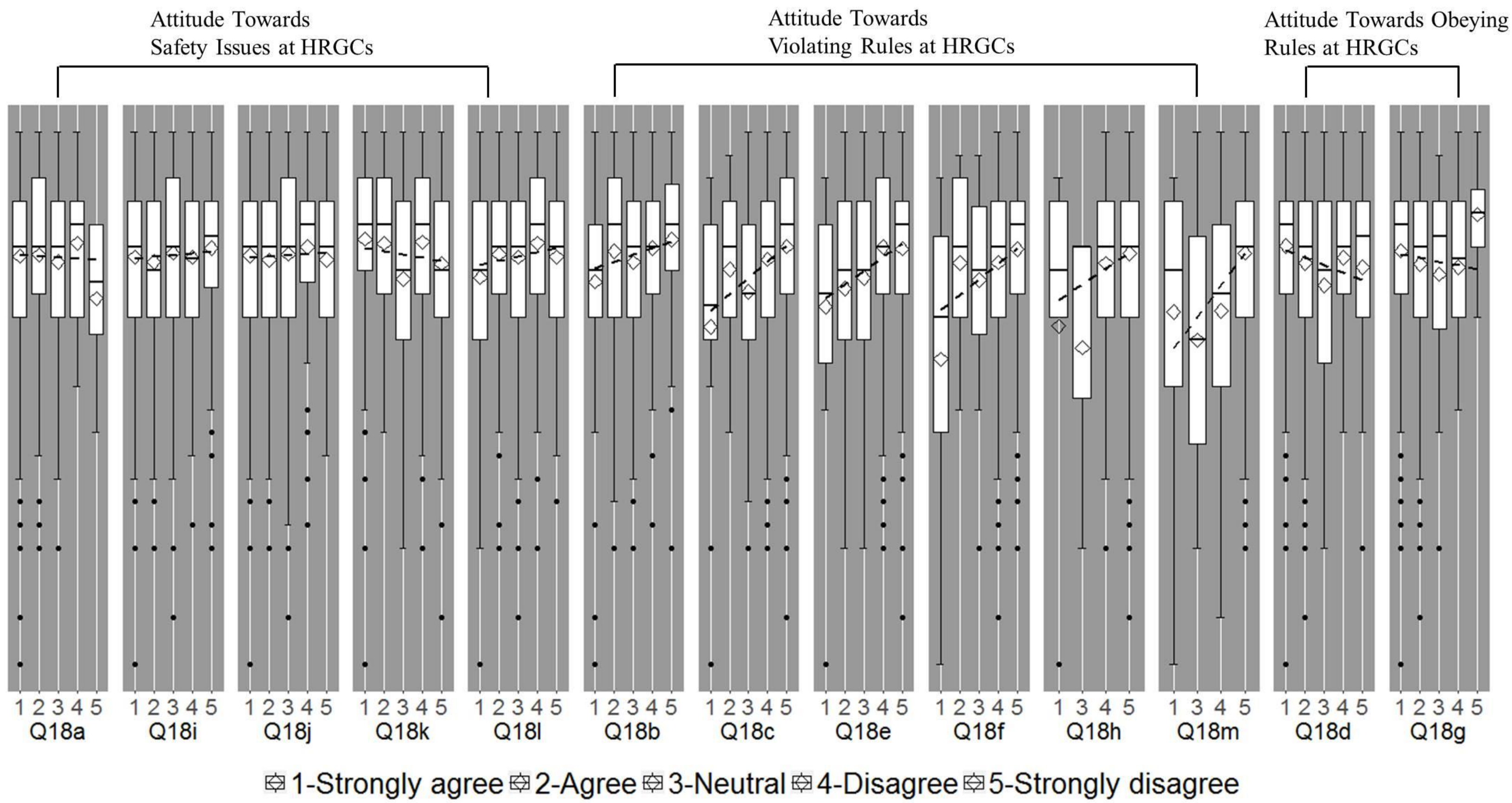


Figure 6.3 Differences in knowledge and attitude towards HRGCs

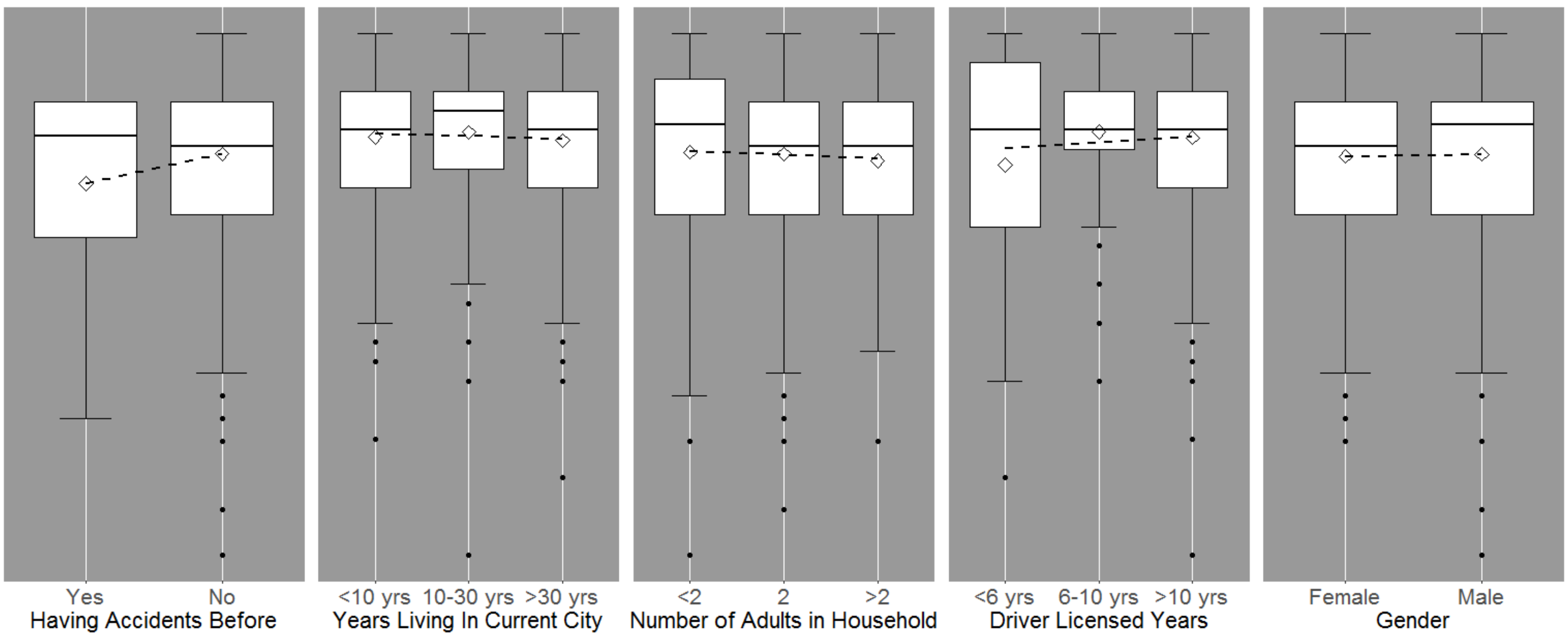


Figure 6.4 Differences in knowledge and demographic information-1

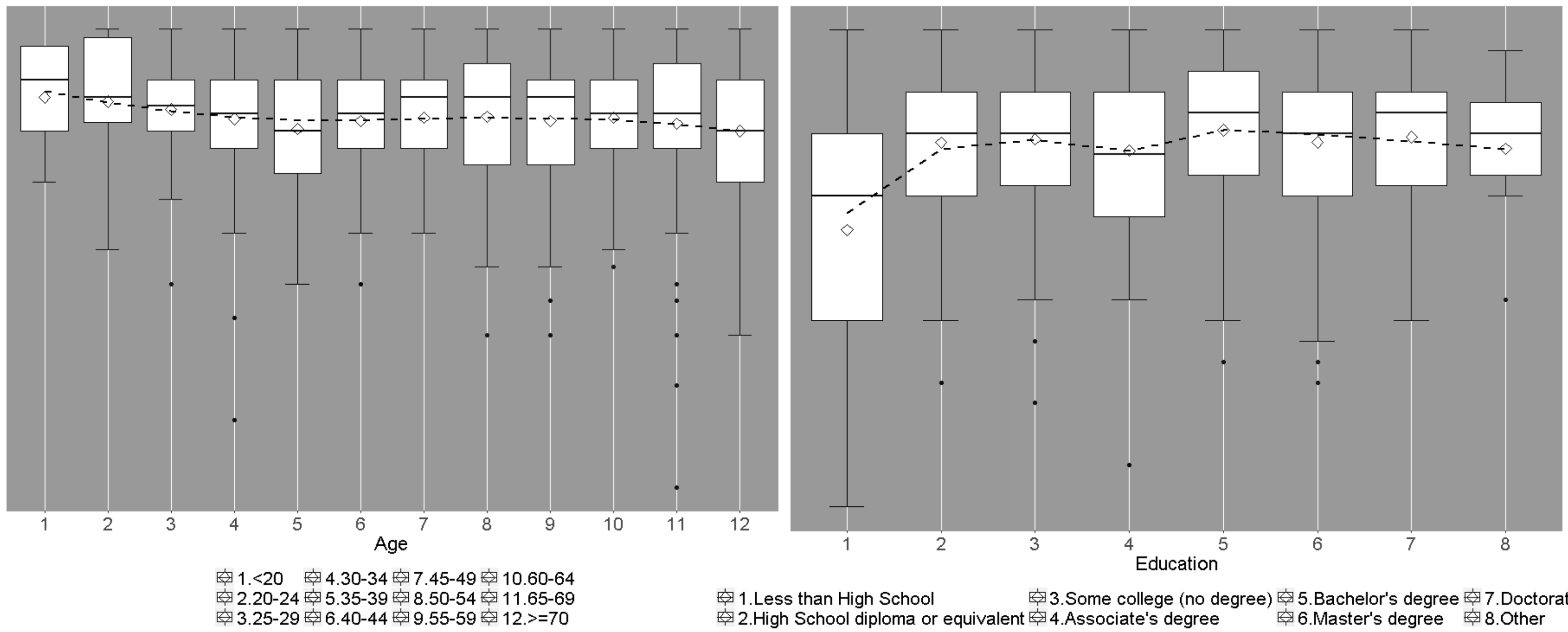


Figure 6.5 Differences in knowledge and demographic information-2

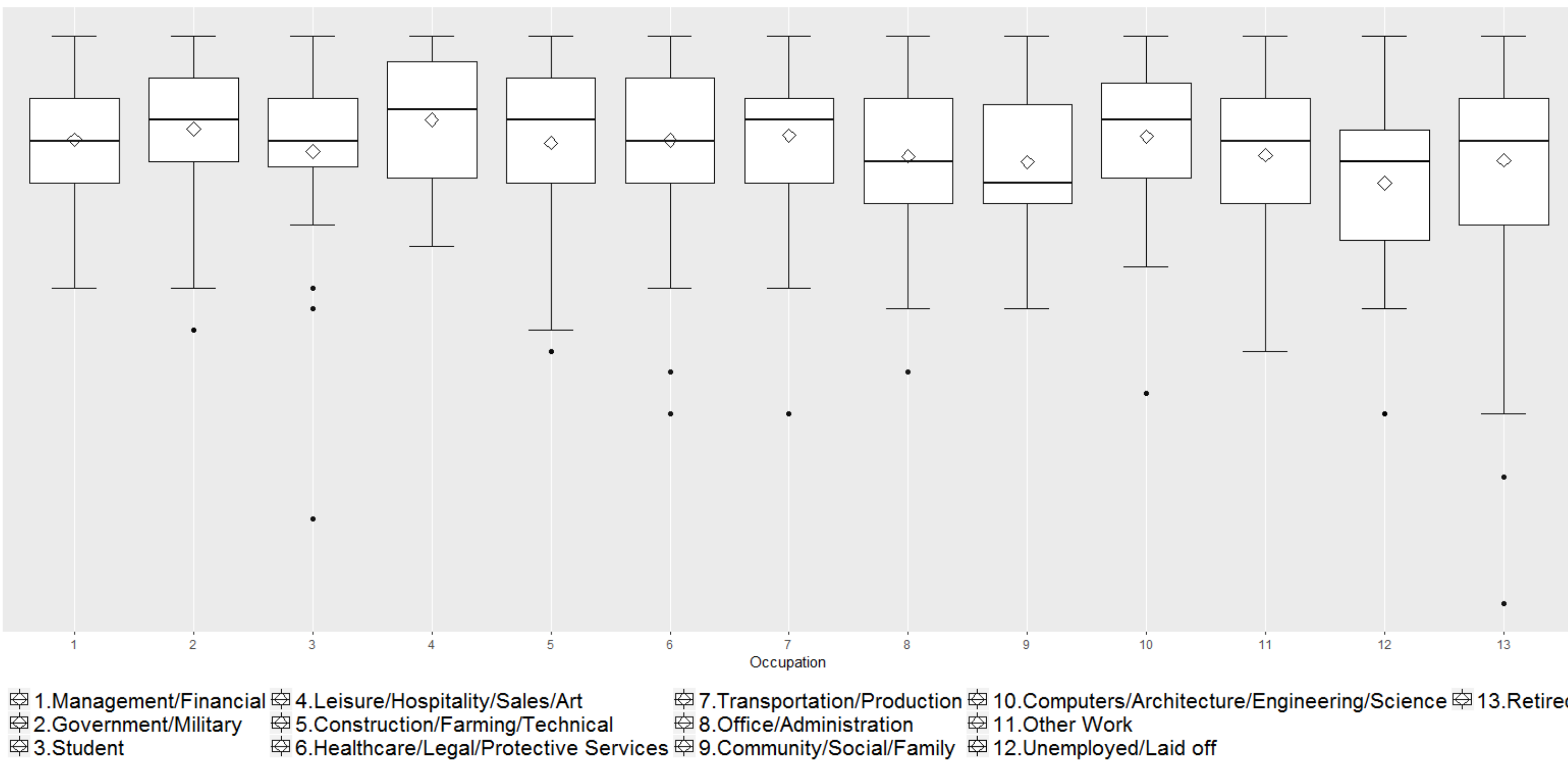


Figure 6.6 Differences in knowledge and demographic information-3

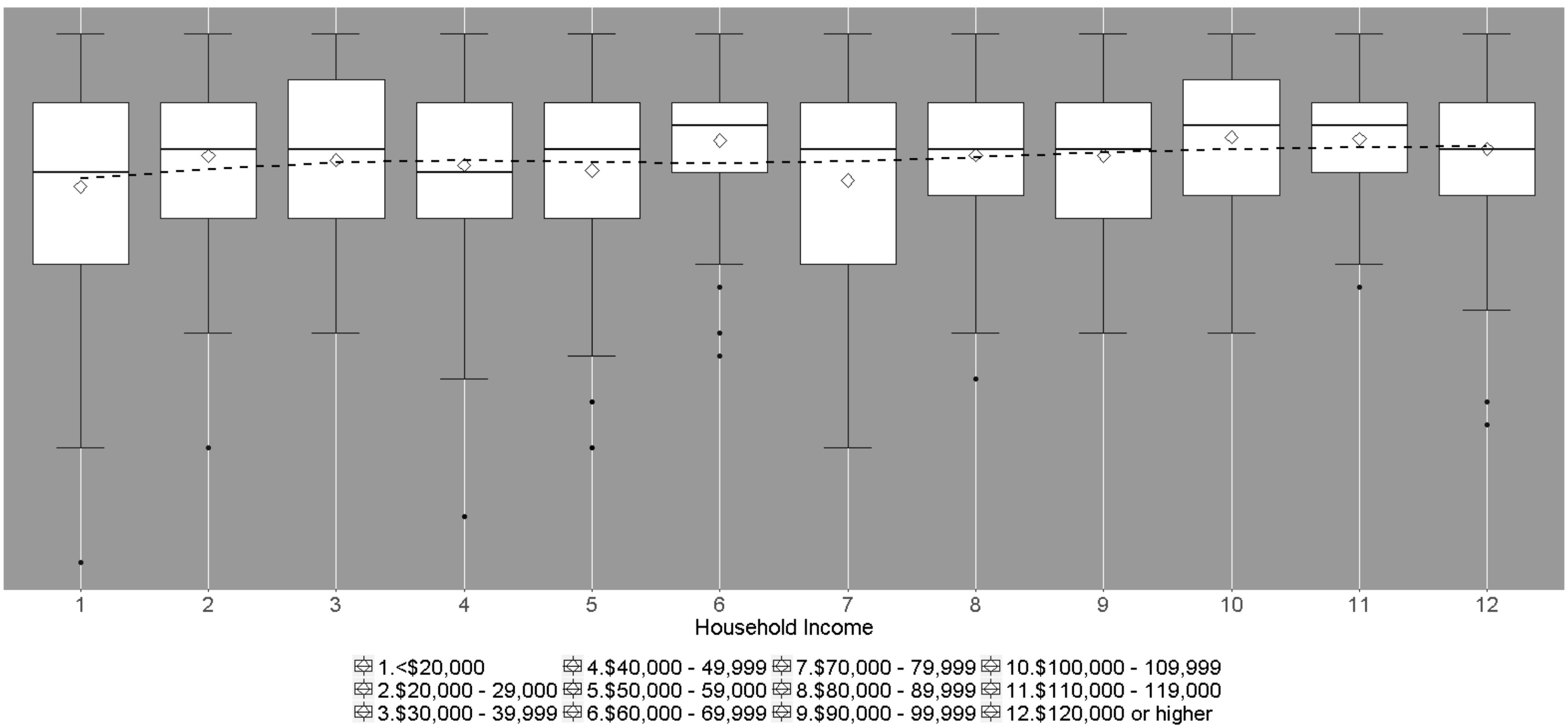


Figure 6.7 Difference in knowledge and demographic information - 4

6.2 Regression Analysis of Drivers' Overall Knowledge

To investigate factors associated with drivers' overall knowledge of safely driving at HRGCs, an ordinary least square regression model was first estimated with "overall knowledge" being a continuous dependent variable. The model was checked for any violations of the linear regression model assumptions. The result showed unacceptable skewness and kurtosis of the residuals and a violation of the identity linear link function ($\mu = E(\boldsymbol{Y}) = \boldsymbol{X\beta}$) between the response variable (i.e., overall knowledge score) and the explanatory variables. The dependent variable – the overall knowledge of a driver – was then categorized into four levels, described below.

Knowledge level 1 – overall knowledge score between 0 to 18 (>=0 and <18), 12.1% of the sample;

Knowledge level 2 – overall knowledge score between 18 to 21 (>=18 and <21), 17.9% of the sample;

Knowledge level 3 – overall knowledge score between 21 to 24 (>=21 and <24), 26.2% of the sample; and

Knowledge level 4 – overall knowledge score between 24 and 27 (>=24 and <27), 33.9% of the sample.

The thresholds between levels were determined by the fact that the sampled population had scores mostly clustered between 18 and 27. The thresholds are the scores that are on average getting six questions answered correctly (score of 18), seven questions correct (score of 21), eight questions correct (score of 24) and all nine questions correct (score of 27).

Multinomial logistic (MNL) regression was then used to build relationships between knowledge levels and other explanatory variables. **Table 6.1** presents summary statistics for the interested variables considered in the MNL model. The ordered logistic models, which take into account the ordinal nature of the overall knowledge levels, were also tried but did not reveal more statistically significant explanatory variables.

Table 6.1 Summary of interested variables in the MNL model

Variables	Range	Mean	SD
Dependent Variable			
Knowledge of safely driving at HRGCs (Q8-16)	Level 1 (12.07%), Level 2 (17.89%), Level 3 (26.23%), Level 4 (33.92%)		
Independent Variables			
Perception of delay (Q1a)	1-5: low to high delay	3.55	1.10
Perception of safety (Q1b)	1-5: unsafe to safe	4.01	0.88
Perception of safety (Q1c)	1-5: confusing to clear signs and markings	4.10	0.71
Perception of reliability (Q1d)	1-5: unreliable to reliable train warning signals	3.95	0.90
Perception of safety info outreach (Q1e)	1-5: low to high information	2.89	1.26
Vehicle type: passenger car or SUV (Q3)	1= yes (63.78%), 0= no (23.27%)		
Use of HRGCs <1 in the past two weeks (Q5)	1= yes (15.82%), 0= no (78.98%)		
Use of HRGCs >=1 and <=7 in the past two weeks (Q5)	1= yes (32.55%), 0= no (62.24%)		
Use of HRGCs >7 and <=14 in the past two weeks (Q5)	1= yes (14.80%), 0= no (80.00%)		
Use of HRGCs >14 and <=28 in the past two weeks (Q5)	1= yes (13.57%), 0= no (81.22%)		
Use of HRGCs >28 in the past two weeks (Q5)	1= yes (11.02%), 0= no (83.78%)		
Attitude towards safety and safety enhancing strategies at HRGCs (Att_safety, Q18 partial)	5-25: negative to positive attitude	-0.01 (scaled)	0.48
Intent to violate rules at HRGCs	6-30: low to high violating	-0.01	0.34

(Att_violate, Q18 partial)	intent	(scaled)	
Intent to obey rules at HRGCs (Att_obey, Q18 partial)	2-10: low to high obeying intent	-0.02 (scaled)	0.49
Residency in current city (Q23)	0-99 years	27.61	20.95
Licensed driver for more than 10 years (Q25)	1= yes (84.80%), 0= no (6.43%)		
Female driver (Q26)	1= yes (51.63%), 0= no (39.29%)		
Driver age <30 (Q27)	1= yes (9.39%), 0= no (88.88%)		
Driver age >=30 and <60 (Q27)	1= yes (42.96%), 0= no (55.31%)		
Driver age >=60 (Q27)	1= yes (38.88%), 0= no (59.39%)		
Up to high school education (Q28)	1= yes (19.80%), 0= no (76.63%)		
Up to associate degree education (Q28)	1= yes (29.59%), 0= no (66.84%)		
Up to bachelor's degree education (Q28)	1= yes (24.69%), 0= no (71.73%)		
Higher than bachelor's degree education (Q28)	1= yes (15.31%), 0= no (81.12%)		
Household annual income <30,000 (Q30)	1= yes (16.73%), 0= no (72.45%)		
Household annual income >=30,000 and <60,000 (Q30)	1= yes (24.29%), 0= no (64.90%)		
Household annual income >=60,000 and <100,000 (Q30)	1= yes (21.43%), 0= no (67.76%)		
Household annual income >=100,000 (Q30)	1= yes (19.69%), 0= no (69.49%)		

Table 6.2 presents the final estimated model. The model contains seven variables that are statistically significant at the 90% level. Knowledge level 1 is set as the baseline and the other three levels are compared with this baseline. Responding drivers who received prior information about rail crossing safety had a higher probability of possessing more knowledge about safely negotiating HRGCs. Vehicle types played a

marginal role in differentiating people with higher knowledge from people with lower knowledge – those who drove passenger cars, including SUVs, had a higher knowledge level. Responding drivers with a longer driving history (i.e., licensed for more than 10 years) had higher knowledge than those who had a shorter driving history. Older drivers (i.e., >=30 years old) had lower levels of knowledge than younger drivers (<30 years old). Respondents with higher household income had higher levels of knowledge. Finally, drivers that reported a lower intent to violate rules at HRGCs displayed higher levels of knowledge of safely negotiating at HRGCs.

Table 6.2 The MNL model results for knowledge levels

Variables	Knowledge Level 2		Knowledge Level 3		Knowledge Level 4	
	Estimate (Std.err)	Z-stat (P-value)	Estimate (Std.err)	Z-stat (P-value)	Estimate (Std.err)	Z-stat (P-value)
(Intercept)	-2.136 (0.904)	-2.364 (0.018)	0.073 (0.584)	0.124 (0.901)	0.282 (0.569)	0.496 (0.620)
Perception of safety info outreach (Q1e)	0.228 (0.115)	1.979 (0.048)	0.299 (0.108)	2.777 (0.005)	0.422 (0.105)	4.014 (0.000)
Vehicle type: passenger car or SUV (Q3)	0.567 (0.307)	1.845 (0.065)	0.472 (0.283)	1.666 (0.096)	- -	- -
Licensed driver for more than 10 years (Q25)	3.767 (1.043)	3.613 (0.000)	1.534 (0.756)	2.031 (0.042)	1.852 (0.753)	2.458 (0.014)
Driver age >=30 and <60 (Q27)	-2.232 (0.832)	-2.681 (0.007)	-2.094 (0.785)	-2.668 (0.008)	-2.495 (0.780)	-3.201 (0.001)
Driver age >=60 (Q27)	-2.407 (0.855)	-2.814 (0.005)	-2.254 (0.813)	-2.772 (0.006)	-2.680 (0.806)	-3.324 (0.001)
Household annual income >=100,000 (Q30)	- -	- -	0.841 (0.338)	2.484 (0.013)	0.720 (0.335)	2.149 (0.032)
Intent to violate rules at HRGCs (Att_violate, Q18 partial)	- -	- -	1.060 (0.396)	2.674 (0.008)	1.466 (0.389)	3.767 (0.000)

Log likelihood function = -883.3. $X^2_{(1, 21)} = 78.3$ ($p < 0.0005$).
Residual Deviance: 1766.53, AIC: 1814.53.
Sample size = 698.

To directly interpret the relationships between the explanatory variables and the response variable (drivers' overall knowledge of safely negotiating at HRGCs), **Table 6.3** presents the odds ratios, which are helpful because the log-odds are being modeled in the MNL regression. Recall the MNL model is:

$$\log(\pi_j/\pi_1) = \beta_{0j} + \beta_{1j}X_1 + \beta_{2j}X_2 \ldots \text{ for j = 2, 3, 4}$$

In which, π_j is the probability/odds of one individual falling into the category of knowledge level j and π_1 is the probability/odds of knowledge level 1. Then the odds of falling into knowledge level j vs. falling into knowledge level 1 are $\exp(\beta_{0j} + \beta_{1j}X_1 + \beta_{2j}X_2 \ldots)$. The odds of knowledge level j vs. the odds of knowledge level 1 increase by $\exp(c\beta_{1j})$ for every c units increase in X_1, keeping other variables constant in the model. The merit of using odds ratios is that the change in the odds ratio remains constant for each explanatory variable X and does not change with different values of X.

Table 6.3 Odds ratio in the knowledge level for every unit increase in Xs

Variables	Knowledge Level 2	Knowledge Level 3	Knowledge Level 4
Perception of safety info outreach (Q1e)	1.26	1.35	1.53
Vehicle type: passenger car or SUV (Q3)	1.76	1.6	-
Licensed driver for more than 10 years (Q25)	43.27	4.64	6.37
Driver age >=30 and <60 (Q27)	0.11	0.12	0.08
Driver age >=60 (Q27)	0.09	0.11	0.07
Household annual income >=100,000 (Q30)	-	2.32	2.05
Intent to violate rules at HRGCs (Att_violate, Q18 partial)	-	2.89	4.33

Sample size = 698

As shown in **Table 6.3**, the estimated odds of knowledge level 2 vs. the knowledge level 1 response changes by 1.26 times for one unit increase in the perception of safety information outreach, keeping other variables constant. The estimated odds of knowledge level 2 vs. level 1 for drivers who drive passenger cars are 1.76 times higher than for drivers that drive vehicles other than passenger cars. Being a licensed driver for more than 10 years significantly increases the odds of knowledge level 2 vs. level 1. Older age categories decrease the odds of the driver falling into knowledge 2 vs. level 1. Odds ratios between the other two levels of knowledge vs. level 1 can be interpreted in a similar way. The odds ratio table provides a quantitative method of evaluating the relationships between overall knowledge level and factors, including safety information outreach, vehicle type, licensed years, driver age, income, and intent to violate rules at HRGCs.

6.3 Direct and Indirect Effects Analysis Using SEM

A structural equation model (SEM) is used to investigate the direct and indirect effects between motor vehicle drivers' characteristics and their knowledge level as well as their involvement with inattentive driving behavior at HRGCs. Notably, SEM does not establish causal relations from associations alone. Instead, it is an inference tool that has to take in causal assumptions from the researcher and fit it with empirical data. If the model fits the data, the causal assumptions are not "proved," but are tentatively made more plausible; if the model fails to fit the data, then it casts doubt on the model specifications (Bollen et al., 2013).

A theoretical SEM model including the assumed direct and indirect effects was built based on the previous regression models. The proposed SEM was separated into the "measurement model" and the "structural model" and is presented in **Figure 6.8** and **Figure 6.9**.

The measurement model illustrates the mapping of measures onto the theoretical latent variable constructs: (1) drivers' perceptions of local HRGCs, i.e., factor 4; (2) drivers' attitude toward safety at HRGCs, i.e., factor 1; (3) drivers' intent to violate rules at HRGCs, i.e., factor 2; and (4) drivers' habit of obeying rules at HRGCs, i.e., factor 3. Factors 1-3 are the same as assumed in Section 5.4 Factor Analysis of Attitude. Questions 18a and i-l measured factor 1. Questions 18b-f, e-f, and h measured factor 2. Questions 18 d and g measured factor 3. Additionally, questions in the beginning of the survey, 1a-1d, were assumed to measure a latent factor 4. No correlations were assumed between the measurement variables.

The structural model shows the direct and indirect causal and correlational links between the latent variables as well as other observed variables that are not part of the measurement model. The uni-directional arrows indicate direct effects assumptions and the bi-directional arrows reflect correlation assumptions between two variables. The lack of an arrow from one variable to another indicates an assumption that no direct or indirect causal relationship or correlation exists between the two. Drivers' overall knowledge level of safely negotiating at HRGCs (Q8-16 → Q17e-n), attitude towards safety issues at HRGCs (F1 → Q17e-n), intent to violate rules at HRGCs (F2 → Q17e-n), habit of obeying rules at HRGCs (F3 → Q17e-n), and perceptions of delay, safety, clarity, and reliability of local HRGCs (F4 → Q17e-n) were all assumed to have direct effects on inattentive driving behavior at HRGCs. Drivers' perceptions of local crossing conditions was assumed to affect drivers' attitudes towards safety issues (F4 → F1) and affect drivers' rule violating (F4 → F2) or obeying intent (F4 → F3). Drivers' attitudes towards safety also affects their rule violating (F1 → F2) and obeying intent (F1 → F3). The latter two were assumed to share some underlying common reasons that are not revealed by factors considered here (F2 ~~ F3). Drivers' perceptions of local crossing conditions were assumed to have a direct effect on their higher or lower attitudes towards safety (F4 → F1) and intent to violate (F4 → F2) and obey rules (F4 → F3). Question 1e asked for drivers' exposure to information on rail crossing safety and was assumed to affect their knowledge at HRGCs (Q1e → Q8-16). The overall knowledge level, on the other hand, affects drivers' intent to violate rules (Q8-16 → F2) or obey rules (Q8-16 → F2) at HRGCs. Finally, driver related characteristics including gender, age groups, household income groups, education level, licensed years being a driver, residency years in the current city, and frequency of using HRGCs were all tentatively assumed to have some direct effects on higher or lower levels of all the other factors (Driver info → F1, F2, F3, F4, Q8-16 and Q17e-n). The last point is more with an explorative nature.

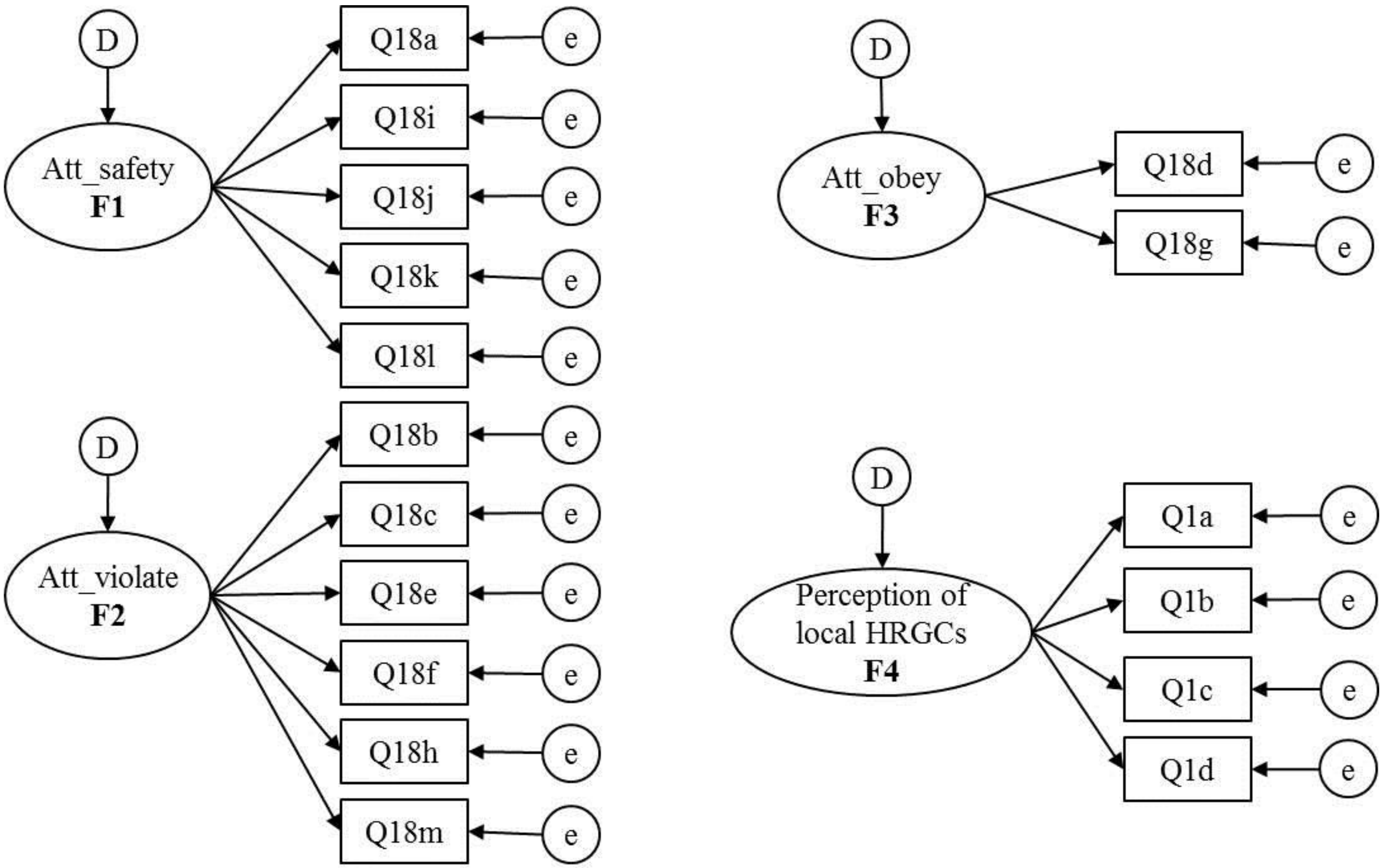


Figure 6.8 Measurement model

*Q18a – m are questions 18a to 18m in the survey; Q1a – d are questions 1a to 1d in the survey

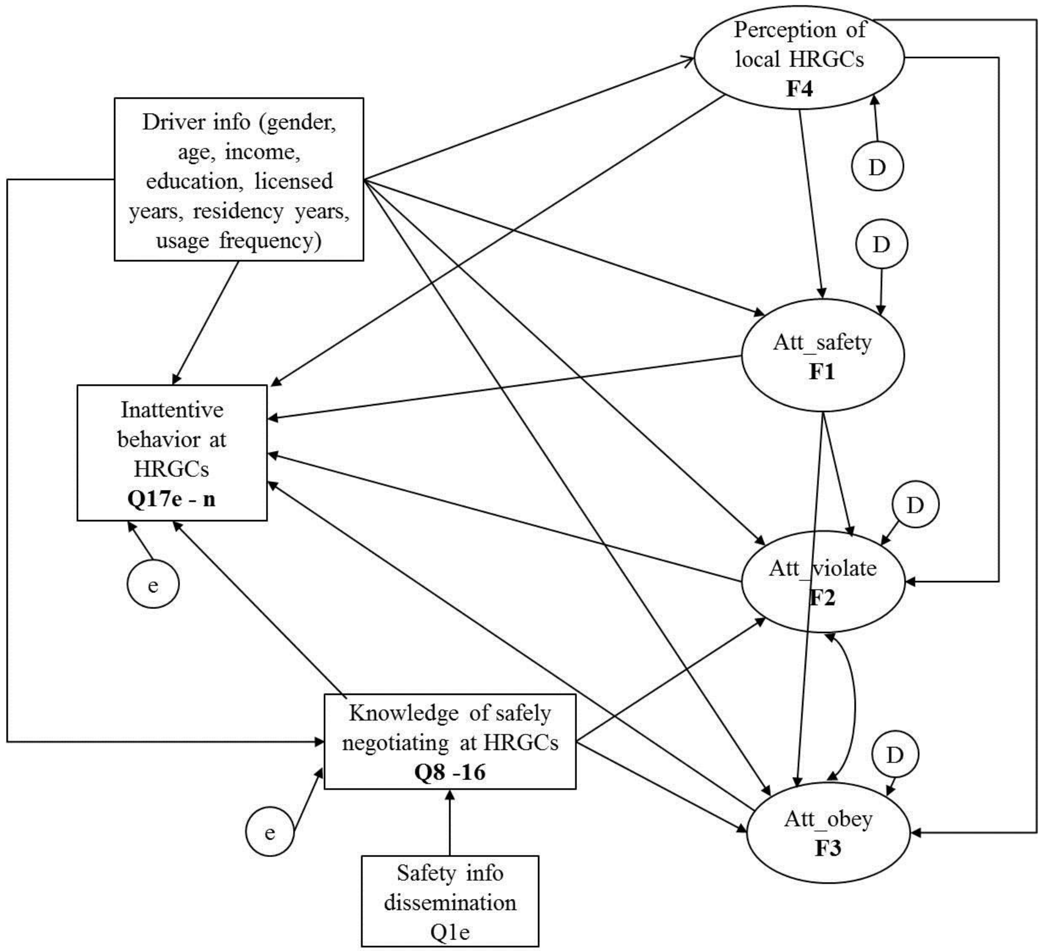


Figure 6.9 Structural model

*Knowledge of safely negotiating at HRGCs was categorized into four levels, as described in Section 6.2.

By linking one variable to another using an arrow, an assumption of a direct effect is made between the two variables; the absence of a link indicates that no causal relationship or correlation exists. The above SEM model was established in R using the “lavaan” package and the model fit criteria including CFI, RMSEA, and SRMR were used to evaluate the model result. As suggested by previous research on SEM, CFI > 0.95, RMSEA < 0.05, and SRMR $< 0.06 \sim 0.08$ indicate good model fit. The result of the proposed SEM structure (above) showed poor model fit (CFI < 0.90) and suggested re-specifying the model. The model re-specifying process combined adding parameters (e.g., adding correlations, repressors) that improved the model fit and deleting parameters that were not statistically significant at the 90% level. The modification index (MI) was computed for each fixed (at zero) parameter. The value of a given MI reflects the minimum amount that the chi-square statistic is expected to decrease if the parameter is set free (Hox and Bechger, 1998). Thus a large MI may indicate significant improvement in the model fit if that particular parameter is freed for estimation instead of fixed at zero. Notably, any modification in the structured model requires theoretical justification. After several modifications to the originally assumed model, a model with good fit was reached. **Figure 6.10** presents the final model; this model achieves a CFI = 0.969, RMSEA = 0.029, and SRMR = 0.074, which indicate the good fit of the model.

By comparing the final model in **Figure 6.10** with the original proposed model in **Figures 6.8** and **6.9**, it can be seen that key relations between the latent variables (F1-F4) and their relations to the inattentive behavior variable remain unchanged. An arrow missing from the overall knowledge level variable to the inattentive behavior variable indicated that the former does not have a direct effect on the latter, which is also true for the missing arrow from F4 to inattentive driving behavior. Driver related characteristics, including gender, age, income, education, licensed years, residency years, and HRGC usage frequency were found significant in some of the relations, but not all. Removing the insignificant arrows from these variables to the key variables (such as the latent variables and the response variables including inattentive behavior and knowledge level) were not considered a violation of the theoretical assumptions because they were tentatively included in the first place. For the measurement models of the latent factors, a couple of the measures were removed (Q18k and Q18m) and three extra correlations between the measures were added (Q18i~~Q18j, Q18j~~Q18l, and Q18f~~Q18h).

Table 6.4 presents the parameter estimation results, including the unstandardized estimates (the “estimate” column), standard error of the estimates, z-value of the estimates, p-value, and standardized estimates (the “std.lv” column for standardized solutions when only latent variables are standardized and the “std.all” column for standardized solutions when both latent and observed variables are standardized). The unstandardized estimates kept the scaling information of the variables and can only be interpreted with reference to the scales of the variables. The standardized estimates are non-scaling and comparable, which may help pick up more important factors and relationships. Standardized estimates with absolute values greater than 0.50 indicate a “large” direct effect, values around 0.30 indicate a “medium” direct effect, and values a less than 0.10 may indicate a “small” effect (Suhr, 2006). However, as many of the variables contained in the model are binary variables and standardization of binary variables is usually not very informative, it was decided not to interpret only the standardized estimates.

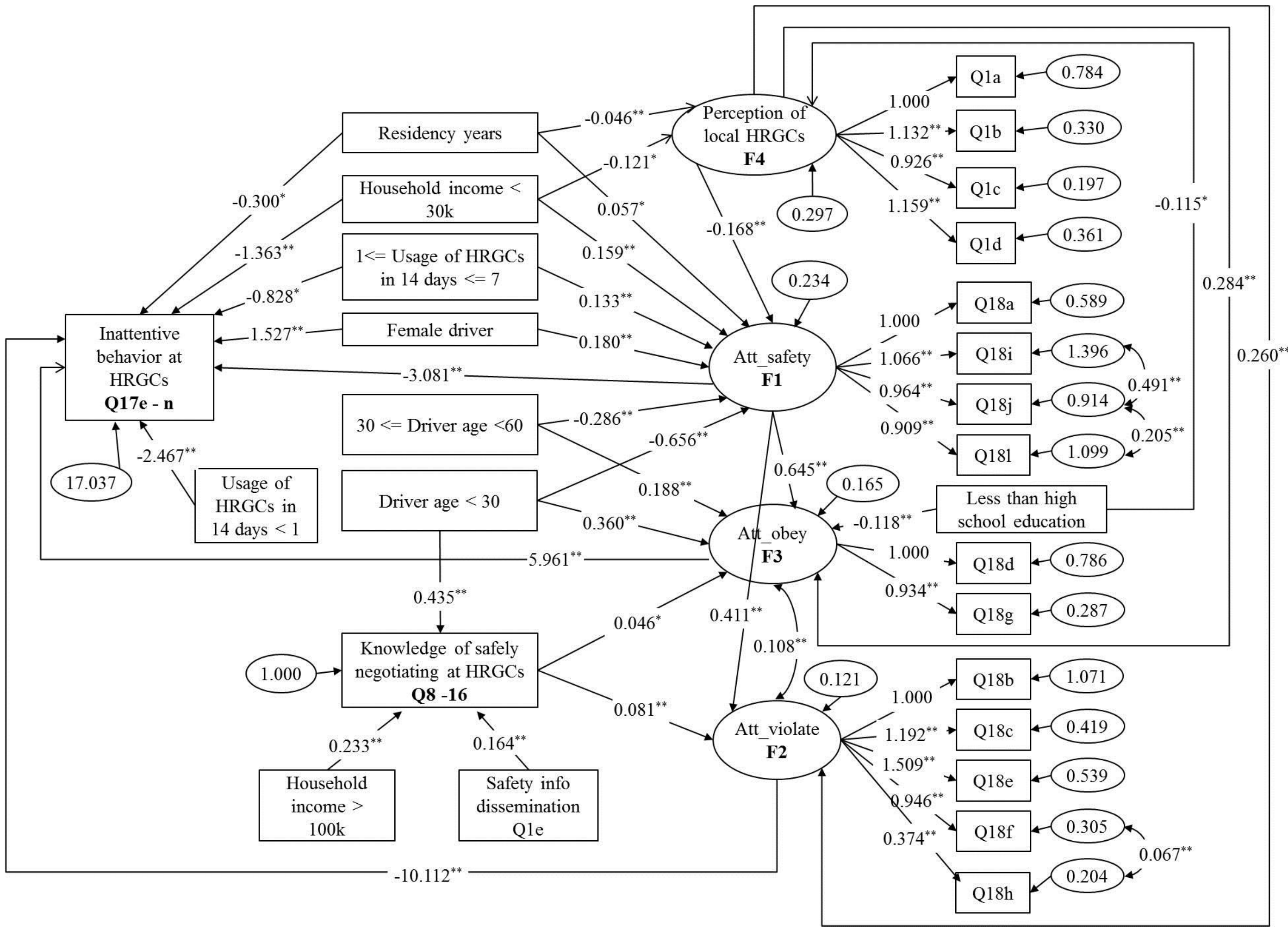


Figure 6.10 Final SEM model

**Statistically significant at 95%; * statistically significant at 90%. Sample size = 660.

Table 6.4 Standardized and unstandardized coefficients for the structural equation model

Latent Variables (measurement model):

		Estimate	Std.Err	Z-value	P(>|z|)	Std.lv	Std.all
Att_safety (F1) =~							
(5=strongly agree, 1=strongly disagree)	Q18a Safety issue at HRGCs is significant	1.000				0.576	0.600
	Q18i Support technology that block cellphone signals	1.066	0.158	6.749	0.000	0.614	0.461
	Q18j Support stronger law enforcement	0.964	0.129	7.496	0.000	0.556	0.502
	Q18l Would like to receive safety info at HRGCs	0.909	0.129	7.024	0.000	0.524	0.447
Att_violate (F2) =~							
(1=strongly agree, 5=strongly disagree)	Q18b Not like to wait for trains to pass	1.000				0.433	0.386
	Q18c Like to accelerate and cross whenever warning devices get activated	1.192	0.139	8.555	0.000	0.516	0.624
	Q18e Regret stopping for trains when there was a chance to cross the tracks before train arrival	1.509	0.178	8.456	0.000	0.654	0.665
	Q18f Like to cross immediately after train passage even though warning devices still active	0.946	0.114	8.299	0.000	0.410	0.596
	Q18h Like to drive around/between lowered gates	0.374	0.047	7.882	0.000	0.162	0.337
Att_obey (F3) =~							
(5=strongly agree, 1=disagree)	Q18d Routinely stop for train devices	1.000				0.533	0.516
	Q18g Ensure warning devices deactivated	0.934	0.076	12.236	0.000	0.498	0.681

	before crossing the tracks						

Perception of local HRGCs (F4) =~							
(1=strongly agree, 5=strongly disagree)	Q1a Perceived excessive delay	1.000				0.556	0.532
	Q1b Perceived unsafe	1.132	0.087	12.987	0.000	0.629	0.738
	Q1c Perceived confusing signs and markings	0.926	0.074	12.511	0.000	0.515	0.757
	Q1d Perceived unreliable train warning devices	1.159	0.093	12.406	0.000	0.644	0.731

Regressions:

		Estimate	Std.Err	Z-value	P(>|z|)	Std.lv	Std.all
Inattentive driving behavior at HRGCs (Q17e_n) ~							
(Low to high scores indicating negative to positive attitudes)	Att_safety (F1)	-3.081	0.739	-4.171	0.000	-1.775	-0.322
	Att_violate (F2)	-10.112	2.086	-4.848	0.000	-4.380	-0.793
	Att_obey (F3)	5.961	1.594	3.740	0.000	3.180	0.576
(1=Yes 0=No)	Use of HRGCs <1 in the past two weeks	-2.467	0.585	-4.220	0.000	-2.467	-0.157
(1=Yes 0=No)	Use of HRGCs >=1 and <=7 in the past two weeks	-0.828	0.449	-1.842	0.065	-0.828	-0.073
(1=Yes 0=No)	Female	1.527	0.408	3.739	0.000	1.527	0.137
(1=Yes 0=No)	Household annual income <30,000	-1.363	0.585	-2.330	0.020	-1.363	-0.095
(Categories: L1=<5yrs, L2=5-15yrs, L3=15-25yrs, L4=25-35yrs, L5=>35yrs	Residency in current city	-0.300	0.163	-1.833	0.067	-0.300	-0.082

Knowledge of safely negotiating at HRGCs (Q8to16cat) ~						

(1= strongly agree, 5=strongly disagree)	Never receive safety info on rail crossing safety (Q1e)	0.164	0.038	4.305	0.000	0.164	0.201
(1=Yes 0=No)	Household annual income >=100,000	0.233	0.116	1.998	0.046	0.233	0.097
(1=Yes 0=No)	Driver age <30	0.435	0.167	2.599	0.009	0.435	0.139
Thresholds:							
	Q8to16cat|t1	-0.586	0.193	-3.042	0.002	-0.586	-0.566
	Q8to16cat|t2	0.117	0.194	0.600	0.548	0.117	0.113
	Q8to16cat|t3	0.919	0.197	4.671	0.000	0.919	0.888

Att_safety (F1) ~							
(Low to high scores indicating negative to positive perceptions)	Perception of local HRGCs (F4)	-0.168	0.060	-2.815	0.005	-0.162	-0.162
(Categories: L1=<5yrs, L2=5-15yrs, L3=15-25yrs, L4=25-35yrs, L5=>35yrs	Residency in current city	0.057	0.022	2.599	0.009	0.099	0.150
(1=Yes 0=No)	Female	0.180	0.059	3.031	0.002	0.312	0.155
(1=Yes 0=No)	Use of HRGCs >=1 and <=7 in the past two weeks	0.133	0.065	2.050	0.040	0.231	0.113
(1=Yes 0=No)	Driver age <30	-0.656	0.115	-5.711	0.000	-1.139	-0.378
(1=Yes 0=No)	Driver age >=30 and <60	-0.286	0.070	-4.097	0.000	-0.496	-0.248
(1=Yes 0=No)	Household annual income <30,000	0.159	0.072	2.206	0.027	0.276	0.107

Att_violate (F2) ~							
(Low to high scores	Perception of local HRGCs (F4)	0.260	0.046	5.688	0.000	0.334	0.334

indicating negative to positive perceptions)							
(Low to high scores indicating negative to positive attitudes)	Att_safety (F1)	0.411	0.074	5.578	0.000	0.547	0.547
(Categories: L1=<18, L2=18-21, L3=21-24, L4=>24)	Knowledge of safely negotiating at HRGCs (Q8to16cat)	0.081	0.022	3.740	0.000	0.186	0.193

Att_obey (F3) ~							
(Low to high scores indicating negative to positive perceptions)	Perception of local HRGCs (F4)	0.284	0.060	4.704	0.000	0.296	0.296
(Low to high scores indicating negative to positive attitudes)	Att_safety (F1)	0.645	0.095	6.786	0.000	0.696	0.696
(Categories: L1=<18, L2=18-21, L3=21-24, L4=>24)	Knowledge of safely negotiating at HRGCs (Q8to16cat)	0.046	0.026	1.755	0.079	0.087	0.090
(1=Yes 0=No)	Driver age <30	0.360	0.085	4.227	0.000	0.674	0.224
(1=Yes 0=No)	Driver age >=30 and <60	0.188	0.055	3.401	0.001	0.352	0.176
(1=Yes 0=No)	Less than high school education	-0.118	0.056	-2.118	0.034	-0.221	-0.086

Perception of local							

HRGCs (F4) ~							
(Categories: L1=<5yrs, L2=5-15yrs, L3=15-25yrs, L4=25-35yrs, L5=>35yrs	Residency in current city	-0.046	0.020	-2.329	0.020	-0.083	-0.125
(1=Yes 0=No)	Less than high school education	-0.115	0.063	-1.814	0.070	-0.207	-0.080
(1=Yes 0=No)	Household annual income <30,000	-0.121	0.067	-1.807	0.071	-0.218	-0.084

The SEM estimates of the variables that are assumed to lead to driver inattentive behavior are different from the multiple linear regression estimates in Chapter 5. The reasons are (1) independent/explanatory variables in the two models are not exactly the same; (2) the latent variables are directly incorporated into the SEM while factor scores are calculated and then used as independent variables in the multiple linear regression; (3) the multiple regression assumes that independent variables are uncorrelated, while SEM assumes that direct or indirect effects or correlations may exist between the independent variables; (4) the multiple regression reveals variables that are associated with drivers' involvement in inattentive driving and those variables are not necessarily the causes of such behavior; on the contrary, SEM assumes the direct effect relations exist (presence of an arrow) or not (absence of an arrow) between the variables and the inattentive behavior and thus have stronger assumptions to test.

The differences between the multinomial logit model results for drivers' knowledge of safely driving at HRGCs as described in Section 6.2 and the SEM estimates for drivers' knowledge can be explained in a similar way. An additional point is that the "lavaan" package actually estimates the ordinal response (recall drivers' knowledge is categorized into four ordinal levels) in SEM using ordered probit regression (though this can be changed to logit). Their thresholds of are all presented in **Table 6.4**.

6.4 SEM Results Interpretation

The interpretation of the SEM results relies on the concepts of direct, indirect, and total effects. A direct effect is the impact that one variable (e.g., exogenous) directly has on another variable (endogenous). For example, gender has a direct effect on a driver's involvement in inattentive driving at HRGCs (female → Q17e-n). An indirect effect represents the effect of one variable on another variable through mediating variables. For example, gender has an indirect effect on inattentive driving through F1 (female → F1 → Q17e-n). The total effect is the summation of the direct and indirect effect. The total effect for gender (female) on involvement in inattentive driving would be the sum of the direct and the indirect effect. **Tables 6.5-6.10** summarize the direct, indirect, and total effects of variables on all related variables revealed by the structural equation model in Section 6.3; the tables also show the 95% confidence intervals for those effects.

Table 6.5 shows that a driver's attitude towards safety issues at HRGCs has a direct effect on his or her involvement in inattentive driving behavior – a driver's more positive attitude reduces inattentive driving. This attitude also has some indirect effects on inattentive driving through affecting the driver's intent to violate or obey rules at HRGCs. The indirect effect is found to have the same sign as the direct effect. Notice the indirect effect in this relation is not significant. In summary, variables that only have direct effects on inattentive driving and can reduce the involvement in inattentive driving include: lower intent to violate rules at HRGCs, greater intent to obey the rules at HRGCs, and smaller frequently of HRGC usage. Variables that only have indirect effects and can reduce the involvement in inattentive driving are: higher perceptions of the safety, reliability, etc., of local HRGCs; older drivers (>=60); higher knowledge of safely negotiating at HRGCs; and a lower educational level. Variables that have both direct and indirect effects and reduce inattentive driving include: occasional HRGC usage (1-7 times per two weeks), male drivers, lower income households (<30k per year), and longer residency in the current city. Notice that gender (female) has opposite direct and indirect effects on inattentive driving – directly, females are more involved in inattentive driving; while indirectly, females have a more positive attitude towards safety issues at HRGCs, which reduces drivers' involvement in inattentive driving. Although the final total effect of "female" is still negative (meaning females are more involved in inattentive driving), the direct effect is mitigated by the opposite indirect effect. In a similar way, when the direct and indirect effects have the same sign, the direct effect gets reinforced.

Table 6.6 shows that safety information dissemination, high household income (>100k per year), and younger drivers only have direct effects on knowledge level and can lead to higher overall knowledge level of safely negotiating HRGCs. Notably, these estimates are based on ordinal probit regression results and thus represent the increase of the probability of knowledge falling into the j category vs. the probability of falling into the j-1 category.

Table 6.7 shows variables that only have direct effects and could improve drivers' attitudes towards safety issues at HRGCs are: female drivers, occasional usage HRGCs (1-7 times per two weeks), older drivers (>=60), and low perceptions of safety, reliability, etc., of local rail crossings. This is reasonable because drivers who perceived their local crossings to be unsafe, unreliable, having excessive delays, or having confusing signs or markings may have a more positive attitude towards improving safety at HRGCs; on the contrary, drivers who think HRGCs are already safe may have negative attitude towards safety issues at HRGCs. One variable that was found to have only indirect effects and could improve attitude towards safety issues is lower educational levels (less than high school). Variables that have both direct and indirect effects and can increase this attitude include: longer residency at current city and low household income (<30k per year).

Similarly, **Table 6.8** shows that drivers' positive attitudes towards safety issues at HRGCs and higher overall knowledge levels of safely negotiating HRGCs have direct effects on and can decrease drivers' intent to violate rules at HRGCs. On the other hand, residency tenure (years) in the current city, lower household income (<30k per year), occasional usage of HRGCs (1-7 times per two weeks), female drivers, and older drivers (>=60 years) have only indirect effects on and could decrease drivers' intent to violate rules at HRGCs. Additionally, perceptions of local HRGCs were found to have both direct (positive) and indirect (negative) effect on drivers' intent to violate rules.

Table 6.9 reveals that drivers' positive attitudes towards safety issues at HRGCs and higher overall knowledge level of safely negotiating at HRGCs have direct effects on and can increase drivers' intent to obey rules at HRGCs. Residency in the current city, low household income (<30k), occasional usage of HRGCs (1-7 times per two weeks), and female drivers indirectly increase drivers' intent to obey rules at HRGCs. Perceptions of local crossings, driver age, and educational level have both direct and indirect effects.

Table 6.10 finds that drivers' perceptions of local crossings are directly affected by residency years in the city, education level, and household income level. Longer residency years, less than a high school education, and lower household income could decrease drivers' perceptions of safety, reliability, etc., of local HRGCs.

Table 6.5 Direct, indirect, and total effects on inattentive driving involvement

Variables	Effect	Estimate	Std.Err	Z-value	P(>|z|)	95% Conf.int	
						Lower	Upper
Att_safety (F1)	Direct	-3.081	0.739	-4.171	0.000	-4.529	-1.633
	Indirect	-0.318	0.607	-0.523	0.601	-1.508	0.872
	Total	-3.399	0.544	-6.245	0.000	-4.465	-2.333
Att_violate (F2)	Direct	-10.112	2.086	-4.848	0.000	-14.201	-6.023
	Indirect	---	---	---	---	---	---
	Total	-10.112	2.086	-4.848	0.000	-14.201	-6.023
Att_obey (F3)	Direct	5.961	1.594	3.740	0.000	2.837	9.085
	Indirect	---	---	---	---	---	---
	Total	5.961	1.594	3.740	0.000	2.837	9.085
Use of HRGCs <1 in the past two weeks	Direct	-2.467	0.585	-4.220	0.000	-3.614	-1.320
	Indirect	---	---	---	---	---	---
	Total	-2.467	0.585	-4.220	0.000	-3.614	-1.320
Use of HRGCs >=1 and <=7 in the past two weeks	Direct	-0.828	0.449	-1.842	0.065	-1.708	0.052
	Indirect	-0.452	0.226	-2.000	0.046	-0.895	-0.009
	Total	-1.280	0.471	-2.716	0.007	-2.203	-0.357
Female	Direct	1.527	0.408	3.739	0.000	0.727	2.327
	Indirect	-0.612	0.211	-2.905	0.004	-1.026	-0.198
	Total	1.075	0.450	2.389	0.017	0.193	1.957
Household annual income <30,000	Direct	-1.363	0.585	-2.330	0.020	-2.510	-0.216
	Indirect	-0.497	0.262	-1.895	0.058	-1.011	0.017
	Total	-1.859	0.604	-3.077	0.002	-3.043	-0.675
Residency in current city	Direct	-0.300	0.163	-1.833	0.067	-0.619	0.019
	Indirect	-0.177	0.081	-2.192	0.028	-0.336	-0.018
	Total	-0.477	0.162	-2.952	0.003	-0.795	-0.159
Perception of local HRGCs (F4)	Direct	---	---	---	---	---	---
	Indirect	-0.367	0.290	-1.267	0.205	-0.935	0.201
	Total	-0.367	0.290	-1.267	0.205	-0.935	0.201
Driver age <30	Direct	---	---	---	---	---	---
	Indirect	4.141	0.657	6.304	0.000	2.853	5.429
	Total	4.141	0.657	6.304	0.000	2.853	5.429
Driver age >=30 and <60	Direct	---	---	---	---	---	---
	Indirect	2.090	0.430	4.858	0.000	1.247	2.933
	Total	2.090	0.430	4.858	0.000	1.247	2.933

Knowledge of safely negotiating at HRGCs (Q8to16cat)	Direct	---	---	---	---	---	---
	Indirect	-0.538	0.143	-3.755	0.000	-0.818	-0.258
	Total	-0.538	0.143	-3.755	0.000	-0.818	-0.258
Less than high school education	Direct	---	---	---	---	---	---
	Indirect	-0.661	0.362	-1.829	0.067	-1.371	0.049
	Total	-0.661	0.362	-1.829	0.067	-1.371	0.049

Table 6.6 Direct, indirect, and total effects on knowledge level of safely negotiating at HRGCs

Variables	Effect	Estimate	Std.Err	Z-value	P(>|z|)	95% Conf.int	
						Lower	Upper
Never receive safety info on rail crossing safety (Q1e)	Direct	0.164	0.038	4.305	0.000	0.090	0.238
	Indirect	---	---	---	---	---	---
	Total	0.164	0.038	4.305	0.000	0.090	0.238
Household annual income >=100,000	Direct	0.233	0.116	1.998	0.046	0.006	0.460
	Indirect	---	---	---	---	---	---
	Total	0.233	0.116	1.998	0.046	0.006	0.460
Driver age <30	Direct	0.435	0.167	2.599	0.009	0.108	0.762
	Indirect	---	---	---	---	---	---
	Total	0.435	0.167	2.599	0.009	0.108	0.762

Table 6.7 Direct, indirect, and total effects on attitude towards safety issues at HRGCs (F1)

Variables	Effect	Estimate	Std.Err	Z-value	P(>|z|)	95% Conf.int	
						Lower	Upper
Perception of local HRGCs (F4)	Direct	-0.168	0.060	-2.815	0.005	-0.286	-0.050
	Indirect	---	---	---	---	---	---
	Total	-0.168	0.060	-2.815	0.005	-0.286	-0.050
Residency in current city	Direct	0.057	0.022	2.599	0.009	0.014	0.100
	Indirect	0.008	0.004	1.841	0.066	0.000	0.016
	Total	0.065	0.022	2.916	0.004	0.022	0.108
Female	Direct	0.180	0.059	3.031	0.002	0.064	0.296
	Indirect	---	---	---	---	---	---

	Total	0.180	0.059	3.031	0.002	0.064	0.296
Use of HRGCs >=1 and <=7 in the past two weeks	Direct	0.133	0.065	2.050	0.040	0.006	0.260
	Indirect	---	---	---	---	---	---
	Total	0.133	0.065	2.050	0.040	0.006	0.260
Driver age <30	Direct	-0.656	0.115	-5.711	0.000	-0.881	-0.431
	Indirect	---	---	---	---	---	---
	Total	-0.656	0.115	-5.711	0.000	-0.881	-0.431
Driver age >=30 and <60	Direct	-0.286	0.070	-4.097	0.000	-0.423	-0.149
	Indirect	---	---	---	---	---	---
	Total	-0.286	0.070	-4.097	0.000	-0.423	-0.149
Household annual income <30,000	Direct	0.159	0.072	2.206	0.027	0.018	0.300
	Indirect	0.020	0.013	1.553	0.120	-0.005	0.045
	Total	0.180	0.072	2.508	0.012	0.039	0.321
Less than high school education	Direct	---	---	---	---	---	---
	Indirect	0.019	0.012	1.548	0.122	-0.005	0.043
	Total	0.019	0.012	1.548	0.122	-0.005	0.043

Table 6.8 Direct, indirect, and total effects on intent of violating rules at HRGCs (F2)

Variables	Effect	Estimate	Std.Err	Z-value	P(>|z|)	95% Conf.int	
						Lower	Upper
Perception of local HRGCs (F4)	Direct	0.260	0.046	5.688	0.000	0.170	0.350
	Indirect	-0.069	0.027	-2.586	0.010	-0.122	-0.016
	Total	0.191	0.039	4.899	0.000	0.115	0.267
Att_safety (F1)	Direct	0.411	0.074	5.578	0.000	0.266	0.556
	Indirect	---	---	---	---	---	---
	Total	0.411	0.074	5.578	0.000	0.266	0.556
Knowledge of safely negotiating at HRGCs (Q8to16cat)	Direct	0.081	0.022	3.740	0.000	0.038	0.124
	Indirect	---	---	---	---	---	---
	Total	0.081	0.022	3.740	0.000	0.038	0.124
Residency in current city	Direct	---	---	---	---	---	---
	Indirect	0.015	0.010	1.479	0.139	-0.005	0.035
	Total	0.015	0.010	1.479	0.139	-0.005	0.035
Household annual income <30,000	Direct	---	---	---	---	---	---
	Indirect	0.042	0.034	1.254	0.210	-0.025	0.109
	Total	0.042	0.034	1.254	0.210	-0.025	0.109
Use of HRGCs >=1 and	Direct	---	---	---	---	---	---
	Indirect	0.055	0.027	2.002	0.045	0.002	0.108

<=7 in the past two weeks	Total	0.055	0.027	2.002	0.045	0.002	0.108
Female	Direct	---	---	---	---	---	---
	Indirect	0.074	0.026	2.857	0.004	0.023	0.125
	Total	0.074	0.026	2.857	0.004	0.023	0.125
Driver age <30	Direct	---	---	---	---	---	---
	Indirect	-0.270	0.055	-4.871	0.000	-0.378	-0.162
	Total	-0.270	0.055	-4.871	0.000	-0.378	-0.162
Driver age >=30 and <60	Direct	---	---	---	---	---	---
	Indirect	-0.118	0.031	-3.760	0.000	-0.179	-0.057
	Total	-0.118	0.031	-3.760	0.000	-0.179	-0.057

Table 6.9 Direct, indirect, and total effects on habit of obeying rules at HRGCs (F3)

Variables	Effect	Estimate	Std.Err	Z-value	P(>|z|)	95% Conf.int	
						Lower	Upper
Perception of local HRGCs (F4)	Direct	0.284	0.060	4.704	0.000	0.166	0.402
	Indirect	-0.108	0.041	-2.648	0.008	-0.188	-0.028
	Total	0.175	0.054	3.245	0.001	0.069	0.281
Att_safety (F1)	Direct	0.645	0.095	6.786	0.000	0.459	0.831
	Indirect	---	---	---	---	---	---
	Total	0.645	0.095	6.786	0.000	0.459	0.831
Knowledge of safely negotiating at HRGCs (Q8to16cat)	Direct	0.046	0.026	1.755	0.079	-0.005	0.097
	Indirect	---	---	---	---	---	---
	Total	0.046	0.026	1.755	0.079	-0.005	0.097
Driver age <30	Direct	0.360	0.085	4.227	0.000	0.193	0.527
	Indirect	-0.423	0.082	-5.128	0.000	-0.584	-0.262
	Total	-0.063	0.098	-0.646	0.518	-0.255	0.129
Driver age >=30 and <60	Direct	0.188	0.055	3.401	0.001	0.080	0.296
	Indirect	-0.184	0.047	-3.921	0.000	-0.276	-0.092
	Total	0.004	0.064	0.055	0.956	-0.121	0.129
Less than high school education	Direct	-0.118	0.056	-2.118	0.034	-0.228	-0.008
	Indirect	-0.020	0.012	-1.635	0.102	-0.044	0.004
	Total	-0.138	0.057	-2.416	0.016	-0.250	-0.026
Residency in current city	Direct	---	---	---	---	---	---
	Indirect	0.029	0.015	1.949	0.051	0.000	0.058
	Total	0.029	0.015	1.949	0.051	0.000	0.058
Household annual	Direct	---	---	---	---	---	---

income <30,000	Indirect	0.081	0.050	1.637	0.102	-0.017	0.179
	Total	0.081	0.050	1.637	0.102	-0.017	0.179
Use of HRGCs >=1 and <=7 in the past two weeks	Direct	---	---	---	---	---	---
	Indirect	0.086	0.041	2.074	0.038	0.006	0.166
	Total	0.086	0.041	2.074	0.038	0.006	0.166
Female	Direct	---	---	---	---	---	---
	Indirect	0.116	0.040	2.875	0.004	0.038	0.194
	Total	0.116	0.040	2.875	0.004	0.038	0.194

Table 6.10 Direct, indirect, and total effects on perceptions of local HRGCs (F4)

Variables	Effect	Estimate	Std.Err	Z-value	P(>|z|)	95% Conf.int	
						Lower	Upper
Residency in current city	Direct	-0.046	0.020	-2.329	0.020	-0.085	-0.007
	Indirect	---	---	---	---	---	---
	Total	-0.046	0.020	-2.329	0.020	-0.085	-0.007
Less than high school education	Direct	-0.115	0.063	-1.814	0.070	-0.238	0.008
	Indirect	---	---	---	---	---	---
	Total	-0.115	0.063	-1.814	0.070	-0.238	0.008
Household annual income <30,000	Direct	-0.121	0.067	-1.807	0.071	-0.252	0.010
	Indirect	---	---	---	---	---	---
	Total	-0.121	0.067	-1.807	0.071	-0.252	0.010

6.5 Chapter Summary

This chapter addressed the third and fourth objectives of the dissertation, which are to investigate drivers' overall knowledge of safely negotiating HRGCs and its impacting factors and to reveal the potential direct and indirect effects between drivers' knowledge, inattentive behavior, demographic factors, and latent factors. Multinomial logit models and structural equation models were used as analysis tools.

The chapter first displayed a series of box-whisker diagrams to show the relations between varied factors and drivers' overall knowledge scores. The latter was found to be higher in groups of people who perceived less delay, more safety, less confusing signs and markings, more reliable warning devices, and more safety information outreach at their local rail crossings. Drivers' overall knowledge scores are higher in groups of people who drive passenger vehicles (instead of pick-ups, trucks, etc.), have lower intent to violate rules and higher intent to obey rules, have no previous accident history at rail crossings, have been a licensed driver for a long time, are younger, have lower educational levels, work in community/social/family and office/administration, and have lower household incomes. Later on, the multinomial logit regression on drivers' overall knowledge confirmed and quantified the statistically significant impacts of safety information outreach, vehicle type, licensed years, driver age, household income, and intent to violate rules at HRGCs on their knowledge of correctly negotiating at HRGCs.

In the structural equation model, a series of direct and indirect effects were assumed based on previous regressions and logical judgement. This theoretical structure was tested using the collected survey data, but resulted in an unacceptable model fit. By removing nonsignificant relations and adding relations with large modification indices (MI) and making sure the removal and addition made sense, the model was modified to one with a good fit, where CFI>0.95 and SRMR<0.08. The SEM model revealed a relatively complete direct and indirect effects flow chart between driver factors and their knowledge, behavior, and intent. The direct, indirect, and total effects the numerous exogenous variables had on the endogenous variables (i.e., drivers' involvement in inattentive driving, overall knowledge level, latent variables of attitude towards safety issues at HRGCs, intent to violate rules and obey rules, and perceptions of local HRGCs) and the causal relations between the endogenous variables were calculated.

CHAPTER 7 SUMMARY, CONCLUSIONS AND FUTURE RESEARCH

The research objectives of the dissertation were (1) to investigate the association between motor vehicle inattentive driving and the severity of drivers' injuries sustained in crashes reported at or near HRGCs; (2) to investigate the association between inattentive drivers' self-reported inattentive driving experiences and a series of factors such as drivers' usage of rail crossings, knowledge of safe driving, attitudes towards safe driving at rail crossings, expectations of encountering trains at rail crossings, previous noncompliance behavior at HRGCs, etc.; (3) to identify driver groups that have lower or higher levels of knowledge of correct rail crossing negotiation; and (4) to investigate the direct and indirect effects between drivers' characteristics and their driving knowledge level as well as their involvement with inattentive driving behavior at HRGCs. The following presents a summary of the research findings, conclusions and recommendations for improving safety at HRGCs; a discussion of the limitations and contributions of this research, and future research directions completes this dissertation.

7.1 Summary

For the first objective, a random parameters binary logit regression model was estimated to investigate two possible outcomes of accidents reported at or near HRGCs – injury or no injury. The analysis utilized the 12-year (2002-2013) accident report data obtained from the Nebraska Department of Roads, which contained 1,133 single-vehicle-single-driver crashes, 890 two-vehicle-two-driver crashes, 90 three-vehicle-three-driver crashes, and another 17 crashes involving more than three vehicles and three drivers. The model quantitatively evaluated the relationship between the crash outcomes (i.e., injury or no injury to drivers) and driver inattentive behavior at HRGCs. The latter was found to be as dangerous as driving under the influence of alcohol or drugs. According to previous research, however, drivers, especially young drivers, tend to perceive inattentive and distracted driving (such as using cellphones) as a normative behavior (Atchley et al., 2012) and thus underestimate the risks of inattentive driving compared to driving under the influence.

To accomplish the second objective, a survey questionnaire for licensed motor vehicle drivers was designed and distributed to a randomly selected household sample in Nebraska. The survey successfully collected 980 questionnaires with useful information. The analysis used a confirmatory factor analysis to identify three latent variables evaluating drivers' intent to violate rules, obey rules, and their attitude towards safety issues at HRGCs. The three latent variables, together with other driver information in the survey were included in a robust multiple linear regression model on drivers' involvement in inattentive driving. The dependent variable (i.e., involvement in inattentive driving) is measured on a continuous scale, which is a score that summarizes drivers' involvement frequencies in different types of inattentive driving listed in the survey. The natural log transformation of the dependent variable and use of robust regression helps improve the model fit and alleviate the influence of outliers. The model found that drivers' gender, age, education, income level, residency years in the current city, use frequency of HRGCs, safety information received, knowledge of safely driving at HRGCs, attitudes towards safety issues at HRGCs, and intent to violate rules at

HRGCs play significant roles in explaining varied degrees of involvement in inattentive driving.

The data used for the third objective is also from the 980 questionnaires collected through the survey. Drivers' overall knowledge of negotiating HRGCs was classified into four levels with "1" indicating a low level of knowledge of negotiating rail crossings and "4" indicating a high level of knowledge. A multinomial logit regression model was estimated. Explanatory variables considered in this analysis largely overlapped with the variables considered in the previous estimated model for inattentive driving. Groups of drivers that are found to have higher overall knowledge scores among other drivers are people who drive passenger vehicles (instead of pick-ups, trucks, special vehicles, etc.), have received more information on safety at HRGCs, are licensed drivers for a long time, are younger, have higher household income, and have lower intent to violate rules at rail crossings. Driver groups with lower knowledge are those with opposite features.

For the fourth objective, a structural equation model revealing direct, indirect and total effects was estimated. Drivers' attitudes towards safety issues and their intent to violate or obey regulations at HRGCs have both direct and indirect effects on drivers' inattentive behavior. No evidence of a direct relationship between drivers' overall knowledge level of safety negotiating HRGCs and inattentive driving was found, but the former indirectly affected the latter through interfering with the drivers' intent to violate/obey regulations. Also, no evidence was found that drivers' perceptions of delay, safety, clarity, and reliability directly affect drivers' inattentive driving behavior, but those factors have indirect effects on inattentive driving by influencing drivers' attitudes towards safety and intent to violate/obey rules. Demographic information of the drivers such as residency years in the current city, income, gender, age, education, and use frequency of rail crossings were found to have some direct or indirect effects on drivers' inattentive behavior that are quantified using the structural equation model.

7.2 Conclusions and Recommendations

Based on the results of the research, the following conclusions are reached.

1. Inattentive driving plays a significant role in contributing to more severe injuries in accidents reported in proximity of HRGCs in Nebraska.
2. Nebraska motor vehicle drivers' personality traits, knowledge levels of negotiating HRGCs and driving experience are associated with inattentive driving at HRGCs.
3. Drivers with lower levels of knowledge of correct HRGC negotiation in Nebraska are: drivers that drive vehicles other than passenger cars, drivers who have received less safety information, have a shorter driving history, are older, have lower income, and have higher intent to violate rules at rail crossings.
4. Nebraska drivers' inattentive driving behavior at HRGCs is directly as well as indirectly affected by their personality traits while drivers' knowledge of correct HRGC negotiation appears to only indirectly affect inattentive driving behavior in the vicinity of HRGCs.

Based on the conclusions, the following recommendations are presented to help with the reduction of inattentive driving and the enhancement of safety at HRGCs:

1. Emphasis should be put on reducing driving inattention and increasing drivers' knowledge of negotiating HRGCs; inattentive driving should be regarded and treated on par with DUI by transportation, law enforcement and other relevant public agencies.

2. Education programs that aim to reduce inattentive driving should focus efforts on female drivers, young drivers, high income drivers, drivers who are new residents in their cities, and drivers who frequently use HRGCs. As well, efforts should be focused on drivers' personality traits, such as enhancement of drivers' positive attitudes towards safety issues and reduction in their intent to violate regulations at HRGCs, as well as to increase drivers' knowledge of correctly negotiating HRGCs.

3. Groups of drivers that should be targeted to enhance drivers' knowledge of safely negotiating HRGCs are elderly drivers, drivers of lower income households, special vehicle drivers, aggressive and novice drivers.

4. Compared to increasing drivers' knowledge, focusing on drivers' personality traits might be a more effective solution to reduce inattentive driving at HRGCs because both direct and indirect relationships were found between the latter two.

Note that all the findings, conclusions and recommendations were based on empirical data that were collected especially for this research and relevant statistical methods were selected. Certain model fit criteria were met and levels of confidence (90% or 95%) were applied in the statistical models to keep results reliable at certain levels based on available data. It is recognized that changing peoples' driving styles is not an easy task and that some drivers may be comfortable trading off a certain level of safety with convenience. Reducing inattentive driving at HRGCs will likely be a protracted process especially considering that there are no effective methods for law enforcement personnel to detect inattentive driving similar to what they use for DUI detection.

7.3 Research Limitations and Contribution

There are several limitations of this research. First, the research used data that pertain to Nebraska only, which limits the generalization of the research findings to the larger driving population. Second, the research used a police-reported crash data, which may have underreported less severe crashes because of not meeting the accident reporting threshold. Third, data collected through the survey pertained to drivers that were aged 19 years or older. Therefore, the research findings and conclusions do not apply to drivers younger than 19 years, who may behave differently than drivers aged 19 years or older.

The research contributed to the body of knowledge of inattentive driving by specifically focusing on the HRGC aspect. HRGCs have features that differentiate them from ordinary highway intersections and the potential involvement of rail equipment significantly increases the risks of casualties and property losses.

This research looks into both the consequence side of and the associated factors side of inattentive driving at HRGCs. The confirmation of the severe consequences of inattentive driving (e.g., leading to more severe driver injuries), the identification of groups of drivers that are more inclined to driving inattentively (e.g., female and young drivers) and groups of drivers that lack proper driving knowledge (e.g., older and special vehicle drivers), the findings of impacts that driver personalities have on inattentive driving, and finally, the direct and indirect effects between all the factors significantly improves the understanding of inattentive driving behavior at HRGCs.

7.4 Future Research

In future research different types of inattentive behavior obtained from police-reported data could be treated differently and investigated in more detail, especially the effects of different types of inattentive behavior on drivers' crash injury severities, provided future crash reports provide such details. This could help to identify priorities for regulations and education.

The current research did not investigate interaction effects that may exist between certain variables included in the estimated models, Therefore, a future investigation of interaction effects between different pairs of variables could possibly lead to additional findings. For example, drivers' gender and types of vehicles driven may likely be associated with each other. The presence of such interactions may have implications for the interpretation of estimated statistical models.

For future research investigating drivers' personality and demographic characteristics that are associated with inattentive driving, questions asking about external factors, such as drivers' perceived social norms, peer pressure, etc., could be added to the survey in addition to the internal factors that are associated with drivers themselves. Those external factors are usually expected to play important roles in explaining people's behavior in social behavioral research. In the planned behavior theory, for instance, people's attitude, subjective norm, and perceived behavior control are said to affect intent and behavior.

The survey results (such as the percentages of inattentive driving behavior) seemed to be more positive than previous observational studies (Ngamdung and DaSilva, 2012, 2013). Drivers are likely underreporting their inattentive behavior (and other unfavorable driving behavior or attitudes). However, surveys are a viable means to study driving behavior, personality, and psychology. The issues with self-reported surveys therefore need to be taken into consideration when using results of the analysis. Thus, for future research it is promising to develop a survey instrument that can more truly reflect drivers' behavior and psychology, such as a combination of surveys and naturalistic observational studies.

Finally, the current research did not focus on the cost-benefit analysis of any relevant safety programs that could potentially reduce inattentive driving and/or increase drivers' knowledge of negotiating HRGCs. Such analysis, however, will be needed in the future to justify that the safety benefits of a proposed program exceed the costs and related training programs remain economically effective.

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APPENDIX A AVAILABLE DATA FIELDS FROM DATASET 1

Accident Case Summary and location data

accident key	accident date	accident location
public/private property	road classification	accident in traffic
intersection-related hwy. no.	one way street/road	railroad involved
railroad crossing number	point of impact - railroad	light condition
road characteristics	road surface type	road surface condition
number of lanes	median type	first harmful event
accident – relation to road	direction	population group
hwy. classification (national)	accident severity	alcohol related
double bottom trailer involved	tractor trailer involved	farm equipment involved
driver less than 25	driver between 13 and 19	school bus involved
motorcycle involved	pedestrian involved	pedalcycle involved
total occupants	total pedestrians	total object owners
total vehicles	total vehicle owners	total drivers
total truck/buses	total injured	total fatalities
city census code	weather condition 1	weather condition 2
contrib. circum. (environment)	contrib. circum. (road cond.)	roadway junction type
school bus related	work zone related	accident location in work zone
work zone type	workers present	latitude
longitude	intersection involved	accident time (military)

Accident Driver Information

accident key	vehicle number	drivers license state
drivers sex	accident location from home	drivers condition
alcohol test performed	accident investigated	drivers birth date
report received date	blood alcohol content	alcohol/drugs suspected
contributing circumstances	citation issued	citation no. 1
citation no. 2		

Accident Injured Occupant and Vehicle Occupant Constraint data

occupant number	occupant the driver	type of restraint
occupant birth date	occupant sex	seating position
occupant ejected/trapped	body part harmed	severity of injury
transported to medical facility	airbag available/deployed	

Accident Non Motorist Injured Pedestrian and Cyclist data

accident key	pedestrian number	pedestrian sex
seating position	body part harmed	severity of injury
transported to medical facility	pedestrian actions	pedestrian condition
alcohol test performed	pedestrian birth date	report received date
blood alcohol content	alcohol/drugs suspected	contributing circumstance 1
contributing circumstance 2	type safety equipment 1	type safety equipment 2
pedestrian location		

Accident Damaged Object data

accident key	object description	object damage amount

Accident Truck and Bus data

accident key	vehicle number	commerce classification
cargo body type	hazardous material placard	hazardous material class code
hazardous material release	issuing state	issuing state
truck width (inches)	gross vehicle weight	

Accident Vehicle data

accident key	vehicle number	vehicle model year
vehicle make	vehicle body style	vehicle id number
direction before accident	vehicle movement	vehicle point of impact
vehicle disposition	most harmful event	vehicle driverless
emergency vehicle	truck/bus involved	something being towed

involved		
government vehicle	owner report received date	investigator damage estimate
driver damage estimate	towed by vehicle number	vehicle license state
vehicle area most damaged	extent of damage	traffic control devise
speed limit	1st event leading to accident	2nd event leading to accident
3rd event leading to accident	4th event leading to accident	

APPENDIX B RAIL CROSSING SAFETY SURVEY

Local Rail Crossings

1. As a motor vehicle driver, please indicate your agreement or disagreement with the following statements.

	Strongly agree	**Agree**	**Neutral**	**Disagree**	**Strongly disagree**
I believe motorist delays at rail crossings in my city (*the city of your residence at the time of this survey*) are excessive.	○	○	○	○	○
I feel unsafe when driving at rail crossings in my city.	○	○	○	○	○
I feel traffic signs and pavement markings at rail crossings in my city are confusing.	○	○	○	○	○
I doubt the reliability of the train warning devices *(e.g., flashing lights, bells, gates, etc.)* at the rail crossings in my city.	○	○	○	○	○
I've never received information on rail crossing safety.	○	○	○	○	○

2. Other comments on rail crossings in my city:

____

Use and Knowledge of Rail Crossings

3. What type of personal motor vehicle do you drive on a daily basis most often?

○ Passenger car

○ Pickup truck

○ Minivan

○ Motorcycle

○ Other *(specify):* _______________

○ Do not drive a personal motor vehicle on a daily basis

4. What type of work or company motor vehicle do you drive on a daily basis most often?

   ○ Passenger car

   ○ Pickup truck

   ○ Minivan

   ○ Motorcycle

   ○ Other *(specify):* ________________

   ○ Do not drive a work or company motor vehicle on a daily basis

5. During the past 14 days, how often did you drive across rail crossings? *For example, if you drive across one rail crossing on your way from home to work and drive back from work to home using the same route on the same day, you drove 2 times across rail crossings.*

   ____________ times during the past 14 days.

6. Which rail crossing did you use most frequently during the past 14 days? *(e.g., crossing at 27th and Highway 2, Lincoln, NE)*

   Railroad crossing location: ___________________

7. Based on your experience, how many trains do you think pass through this crossing *(the crossing you mentioned in Question 6)* on a daily basis?

   _________________ trains pass through on a daily basis.

Questions 8-16 ask your current knowledge driving through a rail crossing.

8. What does a crossbuck sign require a driver to do when approaching a rail crossing?

   ○ Nothing in particular, it's just to let drivers know that there is a rail crossing.

   ○ Yield to train traffic.

   ○ Stop at all the rail crossings and then proceed cautiously.

○ I don’t know.

9. Railroad companies post an emergency 1-800 number at crossings. The purpose of this number is to *(check all that apply):*

☐ Report a malfunctioning gate or lights.

☐ Report trespassing at the crossing.

☐ Report a vehicle or object on the tracks.

☐ I don’t know.

10. What should a motor vehicle driver do when approaching a rail crossing and the crossing lights start flashing?

○ Speed up to cross over to the other side.

○ Stop at the crossing and proceed across if the train is at some distance from the crossing.

○ Stop and wait for the train to cross and only proceed across when the lights cease flashing.

○ I don’t know.

11. What should a motor vehicle driver do if the crossing lights start flashing after he/she has started to cross the tracks?

○ Stop and get out of the vehicle immediately.

○ Proceed across to clear the tracks.

○ Stop and back up to clear the tracks.

○ I don’t know.

12. At a rail crossing that is designated as a Quiet Zone indicated by 

, the train will:

○ Never sound its horn.

○ Not sound its horn during nighttime.

○ Not sound its horn but can do so in emergency situations.

○ I don’t know.

13. What should a motor vehicle driver do if his/her vehicle stalls on a rail crossing?

○ Stay in the vehicle and attempt to drive the vehicle clear of the tracks.

○ Get everyone out immediately and try to push the vehicle off the tracks.

○ Get everyone out and off the tracks immediately then call 911 and the rail 1-800 emergency number.

○ I don't know.

14. Which of the following may be considered a motor vehicle violation at a gated rail crossing? *(Check all that apply)*

☐ Passing under gates that are descending because a train is on its way.

☐ Passing around/between fully-lowered gates.

☐ Passing under gates that are ascending after a train has passed.

☐ I don't know.

15. What should a motor vehicle driver do at a gated rail crossing if the gates do not open after a train has passed?

○ Proceed around/between the gates to the other side as the gates are likely malfunctioning.

○ Wait till the gate is fully open as another train may be on its way.

○ Wait for some other vehicle to start crossing around/between the gates and then follow it.

○ I don't know.

16. Which of the following vehicles must stop at all rail crossings unless the crossing is abandoned, exempted, or a flagman is present? *(Check all that apply)*

☐ A school bus.

☐ A bus carrying passengers.

☐ A commercial vehicle carrying hazardous materials.

☐ I don't know.

Activities and Experiences While Driving Across Rail Crossings

17. Following is a table listing different types of activities that some motor vehicle drivers might do while driving. Please indicate how often you participated in each of the following activities <u>during the past 14 days</u> while driving across rail crossings.

	Always	Often	Sometimes	Rarely	Never
Look left and right to check for trains when approaching a rail crossing.	○	○	○	○	○
Drive across a rail crossing when the train warning devices *(e.g., lights, bells, etc.)* were activated.	○	○	○	○	○
Drive across a rail crossing when the gates were descending, ascending or in a level position.	○	○	○	○	○
Stop and check for trains when there is a STOP sign at the crossing.	○	○	○	○	○
Talk to other passengers in the vehicle while driving across a rail crossing.	○	○	○	○	○
Eat or drink while driving across a rail crossing.	○	○	○	○	○
Talk on a cell phone while driving across a rail crossing *(including using hands-free arrangements).*	○	○	○	○	○
Text or use Apps on a cellphone or other electronic device while driving across a rail crossing.	○	○	○	○	○
Reach for objects inside the vehicle *(e.g., food, phone, map, etc.)* while driving across a rail crossing.	○	○	○	○	○
Adjust any in-vehicle equipment *(e.g., radio, heater/air conditioning, windows, etc.)* while	○	○	○	○	○

driving across a rail crossing.					
Distracted by a person, object or event *(e.g., accident)* outside of the vehicle while driving across a rail crossing.	○	○	○	○	○
Mentally not focused on the driving task while driving across a rail crossing.	○	○	○	○	○
Smoking cigarettes while driving across a rail crossing.	○	○	○	○	○
Other distraction *(e.g., personal grooming)* while driving across a rail crossing.	○	○	○	○	○

18. As a motor vehicle driver, please indicate your agreement or disagreement with the following statements.

	Strongly agree	**Agree**	**Neutral**	**Disagree**	**Strongly disagree**
a. I believe safety is a significant issue at rail crossings.	○	○	○	○	○
b. I do not like to wait for passing trains at rail crossings.	○	○	○	○	○
c. I like to accelerate my vehicle and quickly get across whenever train warning devices get activated.	○	○	○	○	○
d. I routinely stop when train warning devices are active even if I have a chance to cross the tracks before train arrival.	○	○	○	○	○

e. I regret stopping when train warning devices were active and I had a chance to get across before arrival of the train at the crossing.	○	○	○	○	○
f. I like to drive across the tracks after a train has passed even though warning devices may still be active.	○	○	○	○	○
g. I ensure that all warning devices have stopped after the passage of a train before I drive across the tracks.	○	○	○	○	○
h. I like to drive around/between fully lowered gates when I can.	○	○	○	○	○
i. I support technology that will block cellphone signals at rail crossings *(except for emergency calls)* to reduce distracted driving.	○	○	○	○	○
j. I support stronger law enforcement at rail crossings.	○	○	○	○	○
k. I am familiar with Operation Lifesaver.	○	○	○	○	○
l. I would like to receive information on rail crossing safety.	○	○	○	○	○
m. Playing "chicken", intentionally stopping a vehicle on a rail crossing in front of an oncoming train, is fun.	○	○	○	○	○

19. Have you been involved in any accident or near-accident *(evasive maneuvers had to be taken to avoid an accident)* as a motor vehicle driver in the past 3 years in the vicinity *(1/4 mile)* of rail crossings?

○ Yes → Please go to question 20

○ No → Please go to question 23 on page 7

20. Which of the following best describes the type of accident(s) or near accident(s) within 1/4 mile of a rail crossing, you've been involved with as a motor vehicle driver in the past 3 years? *If you've been involved in more than one accident in the past 3 years near a rail crossing, please select all that apply.*

☐ Single-vehicle accident *(i.e., only your vehicle was involved).*

☐ Multi-vehicle accident *(i.e., multiple vehicles were involved).*

☐ Single vehicle near-accident *(i.e., only your vehicle was involved and you had to take an evasive maneuver to avoid an accident).*

☐ Multi-vehicle near-accident *(i.e., multiple vehicles were involved and one or more vehicles took evasive maneuvers to avoid an accident).*

☐ Vehicle-train accident

☐ Vehicle-train near accident *(i.e., you had to take an evasive maneuver to avoid a collision with a train).*

21. In at least one of the accidents or near-accidents, do you believe you or other involved drivers were distracted?

○ Yes → Please go to question 22

○ No → Please go to question 23 on page 7

○ I don't know → Please go to question 23 on page 7

22. Please indicate which of the following activities were involved *(for either yourself or the other driver)* in the accident*(s):*

	Yes	**No**
Talking to other passengers in the vehicle.	○	○
Eating or drinking in the vehicle.	○	○
Talking on a cell phone or other electronic device.	○	○
Texting or using Apps on a cell phone or other electronic device.	○	○

Reaching for objects inside the vehicle (*e.g., food, phone, or map, etc.*)	◯	◯
Distracted by another person, object, or event outside of the vehicle.	◯	◯
Mentally not focused on the driving task.	◯	◯
Smoking cigarettes.	◯	◯
Other distraction (*e.g., personal grooming*).	◯	◯

General Information

Your information will be kept strictly confidential.

23. How long have you lived in your city *(the city of your residence at the time of this survey)*?

    __________ year(s) and____________ month(s)

24. Including yourself, how many adult(s) age 18 and older live in your household?

    Number of adult(s): _______________

25. How long have you been a licensed driver?
    - ◯ Less than a year
    - ◯ 1 – 2 years
    - ◯ 3 – 5 years
    - ◯ 6 – 10 years
    - ◯ More than 10 years

26. What is your gender?
    - ◯ Female
    - ◯ Male
    - ◯ Other

27. What is your age group?
    - ◯ Younger than 20
    - ◯ 20 – 24
    - ◯ 25 – 29
    - ◯ 30 – 34

- ○ 35 – 39
- ○ 40 – 44
- ○ 45 – 49
- ○ 50 – 54
- ○ 55 – 59
- ○ 60 – 64
- ○ 65 – 69
- ○ 70 and older

28. What is your highest level of education?
    - ○ Less than High School
    - ○ High School diploma or equivalent
    - ○ Some college (no degree)
    - ○ Associate's degree
    - ○ Bachelor's degree
    - ○ Master's degree
    - ○ Doctorate degree
    - ○ Other: ___________

29. Which category best describes your primary occupation?
    - ○ Management/Financial
    - ○ Government/Military
    - ○ Student
    - ○ Leisure/Hospitality/Sales/Art
    - ○ Construction/Farming/Technical
    - ○ Healthcare/Legal/Protective Services
    - ○ Transportation/Production
    - ○ Office/Administration
    - ○ Community/Social/Family
    - ○ Computers/Architecture/Engineering/ Science
    - ○ Other: ____________
    - ○ Unemployed/Laid off

○ Retired

30. What is your approximate annual household income (i.e., combined for all household members)?

○ Less than $20,000

○ $20,000 – 29,000

○ $30,000 – 39,999

○ $40,000 – 49,999

○ $50,000 – 59,000

○ $60,000 – 69,999

○ $70,000 – 79,999

○ $80,000 – 89,999

○ $90,000 – 99,999

○ $100,000 – 109,999

○ $110,000 – 119,000

○ $120,000 or higher

31. Please use the space below to provide any comments or feedback.