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A New Approach To Safety Assessment At Gated Highway-Rail Grade Crossings

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A NEW APPROACH TO SAFETY ASSESSMENT AT GATED HIGHWAY-RAIL GRADE CROSSINGS

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A NEW APPROACH TO SAFETY ASSESSMENT AT GATED HIGHWAY-RAIL GRADE CROSSINGS

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A significant number of pedestrians and bicyclists (i.e., non-motorists) use the roadway system in the U.S. Research pertaining to the safety of them, especially their safety at highway-rail grade crossings (HRGCs), has drawn much attention in the past decade, and remains an important issue of safety research. Yet, the majority of existing research has examined non-motorist safety at intersections or motorist safety at HRGCs separately. Such research has related primarily to exploring relationships between safety countermeasures (e.g., engineering devices, education, enforcement, etc.) and crash frequency/severity, using different quantitative analysis approaches. A primary limitation of these studies is that few have focused on identifying impact factors associated with non-motorist safety at HRGCs or explicit assessment of educational activity's safety effect on non-motorist safety at HRGCs, by concentrating on undiluted effects of educational activity only.

The current research selected a two-quadrant HRGC in the City of Fremont, Nebraska for data collection. A median barrier device was installed at this HRGC in 2006. Restorative maintenance was performed from April 1st to 18th, 2011. In addition, an educational activity was implemented at this HRGC on September 29th and 30th, 2011 to explore its impact on HRGC safety. Based on these two issues, the current research consisted of data

collection at the HRGC before and after maintenance, and before and after the educational activity.

Following the preliminary analysis and statistical modeling of the collected data, it was concluded that: 1) pedestrians and bicyclists could be treated as one group during analysis, defined as "non-motorists" in terms of the similarity between their crossing violation frequencies, 2) the total motorist violation frequency increased with more violation opportunities, higher traffic volume, group crossing, non-nighttime period, and more crossing trains, 3) the total non-motorist violation frequency increased with higher traffic volume, group crossing, train stoppage, non-nighttime period, and gate malfunction, 4) regarding the influence of median barrier maintenance on the motorist safety, there was no statistically significant change in motorist's type 2 and 4 violations before and after the maintenance, 5) educational activity alone was effective toward reducing non-motorists' type 2 violations at the HRGC during a short-term period.

DEDICATION

To the memory of my dear father: I wish you could feel my love and enjoy the happiness with me at this moment. Also to my beloved mom: I could not have accomplished this achievement without your support.

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Finishing a Ph.D. dissertation is a tough process. It is a job that is impossible to accomplish without the assistance of others. Doubtless I would like to show my appreciation to some of the people who worked with me on this project over the past four years, as well as some of the individuals who were studying and working with me as research assistants at the Mid-America Transportation Center (MATC) at University of Nebraska-Lincoln.

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TABLE OF CONTENTS

LIST OF FIGURES

LIST OF TABLES

CHAPTER 1

INTRODUCTION

1.1 BACKGROUND

The number of trips made by walking and bicycling has increased steadily over time in the U.S. The benefits of these two transportation modes compared to motorized transportation include reduced air pollution, improved personal health, the mitigation of traffic congestion, enhanced quality of life, and cost savings (Turner et al. 2006; District Department of Transportation 2009; University of North Carolina 2011). However, pedestrian and bicyclist crashes involving fatalities and high-level injuries are a serious problem (Zegeer et al. 2002; Zegeer et al. 2009; Federal Highway Administration 2011). In 2009, 4,092 pedestrians were killed, and estimated 59,000 were injured, in reported traffic crashes across the U.S. These figures represent 12 % of all fatalities and 3% of all injuries reported in traffic crashes (National Highway Traffic Safety Administration's National Center for Statistics and Analysis 2009). In addition, 630 pedal cyclists (i.e., bicyclists and other pedal-based vehicle users) were killed and 51,000 were injured in motor vehicle traffic crashes in 2009. These accounted for 2% of all motor vehicle traffic fatalities and 2% of all individuals injured in traffic crashes (National Highway Traffic Safety Administration's National Center for Statistics and Analysis 2009). Overall, the safety of pedestrians and bicyclists is an important topic, and its importance will continue to grow as trips made by utilizing these two modes increase in the future.

While differences exist between pedestrians and bicyclists, these groups were combined as one group in this research, and labeled as “non-motorists.” Long-term statistics on non-motorist fatalities and injuries are available from the National Highway Traffic Safety Administration (NHTSA) in its annual Traffic Safety Facts (National Highway Traffic Safety Administration’s National Center for Statistics and Analysis 2009). Figure 1.1 shows pedestrian and bicyclist yearly fatalities for 2000-2009, while figure 1.2 presents pedestrian and bicyclist yearly injuries during the same period. Overall, many more pedestrians are killed and injured each year than are bicyclists. Lately, the trend of pedestrian fatalities and injuries appears to be declining, while no obvious changes are evident in the case of bicyclists.

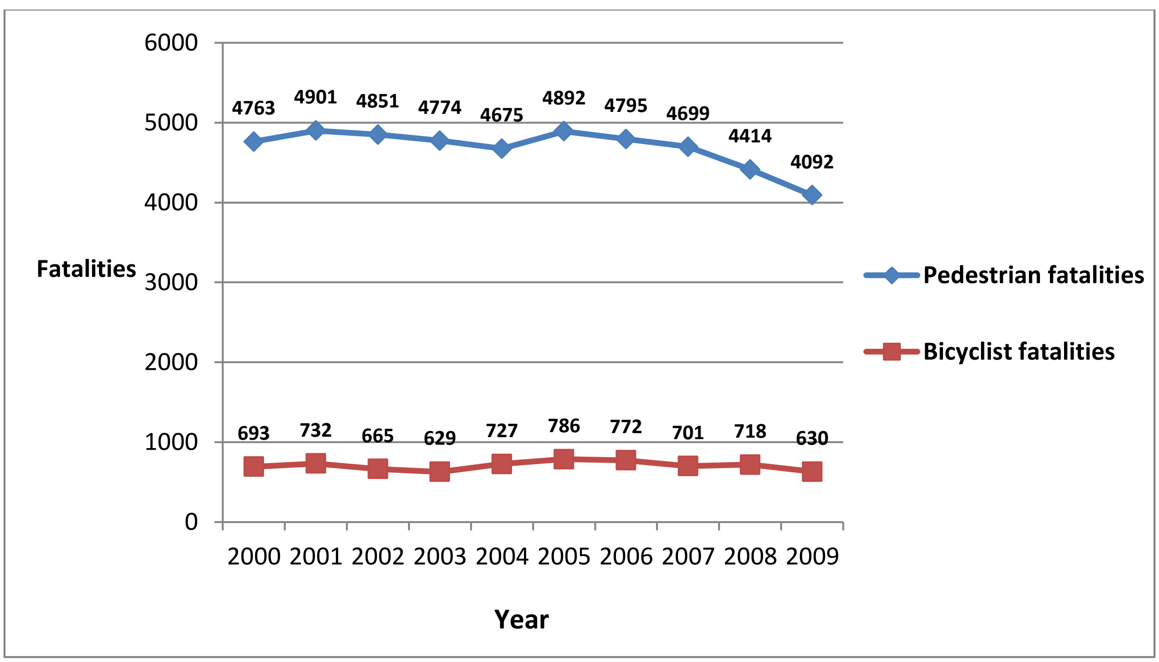

FIGURE 1.1 Non-motorist traffic crash fatalities in the U.S. (2000-2009)

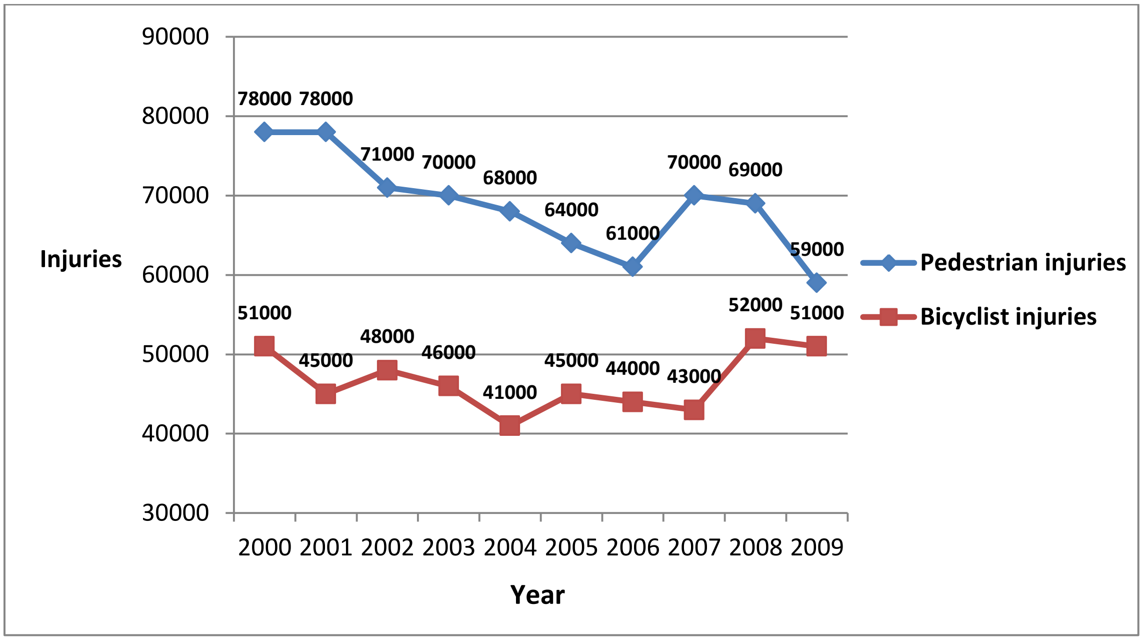

FIGURE 1.2 Non-motorist traffic crash injuries in the U.S. (2000-2009)

Concerning crash costs, the U.S. Department of Transportation (US DOT) estimated the national impact of highway crashes to be $230.6 billion, representing 2.3% of the GDP in the year 2000 (New York City Department of Transportation 2011). Moreover, in 2005 the National Safety Council (NSC) estimated the comprehensive cost of pedestrian fatalities to be more than $18.7 billion, and the cost of bicyclist fatalities to be more than $3 billion. The costs of non-fatal injuries were estimated at $3.4 billion for pedestrians and $2.4 billion for bicyclists during the same year (University of North Carolina 2011).

A review of safety statistics at highway-rail grade crossings (HRGCs) in the U.S. indicated that in 2009 there occurred 1,896 incidents, resulting in 247 deaths and 705 injuries. An HRGC is defined as the intersection where a highway crosses a railroad at-grade (Federal Railroad Administration 2011). In terms of non-motorist safety at HRGCs, figures 1.3 and 1.4 present fatality and injury records from 1999 to 2010. These statistics were obtained from the Federal Railroad Administration (FRA) online database, available at http:// safetydata.fra.dot.gov/officeofsafety/ (accessed on Feb. 20th, 2011).

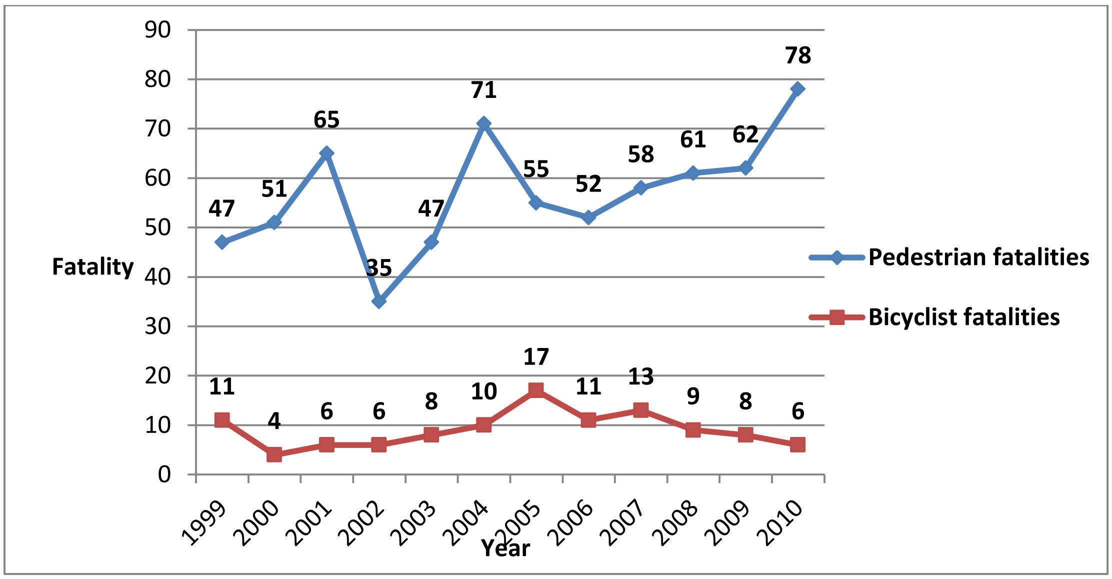

FIGURE 1.3 Non-motorist crash fatalities at HRGCs in the U.S. (1999-2010)

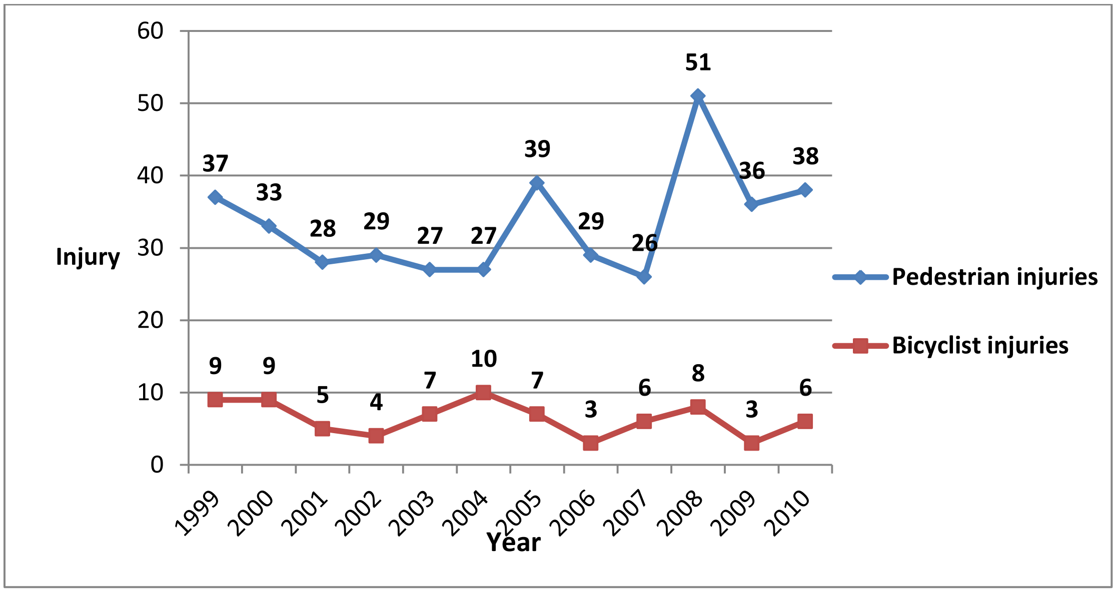

FIGURE 1.4 Non-motorist crash injuries at HRGCs in the U.S. (1999-2010)

Based on figures 1.3 and 1.4, the trend for non-motorist crashes over time at HRGCs displays two characteristics: 1) all four lines fluctuated in terms of frequency; however, the frequencies of bicyclist fatalities and injuries were relatively stable, 2) the frequencies of pedestrian fatalities and injuries changed significantly, displaying an obvious increasing trend in toward of pedestrian fatalities.

While the safety of non-motorists has received attention in the literature, relatively few studies have focused on non-motorist-involved crashes at HRGCs. Considering the large number of HRGCs in the U.S. (there were 147,681 public and 94,583 private HRGCs in 2005), as well as the high-speed rail projects planned for the near future (Federal Railroad Administration 2011), the safety of non-motorists at

HRGCs warrants more attention. The next section provides the problem statement for the research presented herein.

1.2 PROBLEM STATEMENT

Literature reviewed and presented in chapter 2 shows that HRGC safety can be assessed by different methods, such as the Peabody-Dimmick Formula, the New Hampshire Index, and the US DOT Accident Prediction Formula. These methods have certain limitations, including their use of a limited number of parameters for safety estimation, the use of decades-old data in model estimations, and a reliance on reported HRGC crashes, which are rare events. Further, these HRGC safety assessment methods do not include measures of pedestrian and bicyclist traffic, instead relying solely on train and roadway vehicular traffic. Disregarding non-motorist traffic at HRGCs having significant pedestrian and bicyclist traffic can result in the over-estimation of safety. There are also relatively few studies available concerning the effectiveness of educational activities on the HRGC-related safety of pedestrians and bicyclists. Therefore, there is a need to study HRGC safety by taking into consideration not only motorists, but non-motorists, as well. Similarly, there is a need to assess the impact of educational activities on the safety of non-motorists at HRGCs.

This research investigated gate violations for crossing users at a dual-quadrant gated HRGC located in Fremont, Nebraska. The reason for focusing on violations rather than crashes was that violations are more numerous, relatively easy to record using video technology, and have a connection with crashes at HRGCs (Abraham et al. 1998). The research involved the estimation of models of gate violations by motorists, pedestrians, and bicyclists, based on utilizing actual traffic encountered during train crossings, as well as an assessment of an educational activity focused on improving the safety of non-motorists at the Fremont HRGC. The reason for investigating the impact of educational activity was because it is more viable than engineering-based countermeasures (usually expensive) and enforcement-based activities (usually expensive but also unpopular amongst the public).

1.3 RESEARCH OBJECTIVES

The goal of this research is to better understand HRGC safety by considering not only motorists, but also pedestrians and bicyclists. Specific objectives are: 1) the estimation of count-based models for motorist and non-motorist violations at a selected HRGC, and 2) the assessment of changes in violations at the selected HRGC in response to an educational activity focused on improving non-motorists' safety.

1.4 ORGANIZATION OF THE DISSERTATION

This dissertation is organized into five chapters. Chapter 1 presents an introduction to the background of the study, the problem statement, and research objectives. Chapter 2 reviews pertinent literature related to this research, including studies of motorist safety at HRGCs, studies of non-motorist safety on highways, and modeling approaches for safety assessments. Chapter 3 describes the data collection/reduction process and preliminary data analysis (i.e., descriptive statistics). Chapter 4 presents the statistical model estimation and model explanation in terms of gate violations for both motorists and non-motorists, as well as the assessment of the effect of the educational activity on non-motorist safety at a select HRGC. Chapter 5 includes conclusions and suggestions for future research on HRGC safety. References and appendices are available at the end of this dissertation.

CHAPTER 2

LITERATURE REVIEW

2.1 INTRODUCTION

This literature review consists of three major sections: 1) studies on motorist safety at HRGCs; 2) studies on non-motorist safety on the highway system; and 3) a discussion of specific modeling approaches to safety. A summary of the main findings from the literature review is available at the end of this chapter.

2.2 MOTORIST SAFETY AT HRGCS

Three aspects of motorist safety are discussed in this section: 1) the evaluation of countermeasures based on engineering, education, and enforcement (i.e., the "triple Es"), 2) analysis of specific safety-related parameters, and 3) the identification of factors associated with safety.

2.2.1 Evaluation of the "Triple Es" of Safety Countermeasures

Collisions between motor vehicles and trains are the most common type of crashes at HRGCs. The focus of safety enhancement has been on countermeasures labeled as the "triple Es" (i.e., engineering, education, and enforcement) as three methods of dealing with motorist safety issues surrounding HRGCs (Ogden 2007). Various safety measures in terms of the “triple Es” have been adopted at different HRGCs for safety enhancement. These are discussed below.

2.2.1.1 Engineering design based countermeasures for motorists

To date, many researchers have evaluated the effectiveness of different safety-related engineering designs at HRGCs. Yeh and Multer (2007) reviewed literature concerning driver behavior at HRGCs observed from 1990 to 2006; the authors then addressed a series of engineering design issues related to motorist safety, arriving at the summary conclusion that engineering-related countermeasures could pertain to roadway signs, pavement markings, and active control devices (e.g., flashing lights and gates at HRGCs).

For sign evaluation, Zwahlen and Schnell (1999) adopted two new crossbuck designs at 3,833 passive crossings in four Ohio rail corridors, also utilizing a section of unused Ohio University airport runway to conduct experiments. The two designs were: 1) buckeye crossbuck equipped with red yield legend and retroreflective side panels, and 2) standard improved crossbuck equipped with reflectorized wooden post and double-sided microprismatic sheeting. By collecting video data among rail corridors, the researchers conducted a simple frequency comparison relative to driver compliance behaviors under the use of traditional versus new crossbuck designs. Historical crash data obtained from the Public Utilities Commission Database in Ohio was also used for comparison. The authors concluded that the new design helped to reduce driver noncompliance. Moreover, a survey questionnaire provided to assess user acceptance also indicated that respondents preferred the new design.

Millegan et al. (2009) evaluated the safety-related effectiveness of stop signs at public passive HRGCs (lacking gates, flashing lights, warning bells, etc.) nationwide, using Federal Railroad Administration (FRA) data. The data were in two sets: grade crossing inventory (i.e., attributes of crossings and crossing environment) and grade crossing crash history (i.e., crash frequencies and associated factors). The two datasets were combined using a shared variable labeled crossing identification number—a unique identification number assigned to each HRGC. This study covered 26 years of crash history beginning with 1980 for 7,394 crossings that were upgraded from crossbuck-only sign to stop sign control. Simple comparisons were made of annual vehicle-involved crash rates before and after stop sign control. Negative binomial (NB) regression modeling was used to identify the effect of stop signs. An analysis of significant crash risk factors was also conducted. The authors reported that annual crash rates were consistently higher during the crossbuck-only period compared to the period after the installation of stop signs. Moreover, the NB model showed the positive effect of stop signs on safety at HRGCs. Several factors associated with the increase of crash frequencies at HRGCs were listed, including annual average daily traffic (AADT), percentage of trucks, number of daily trains, number of highway lanes, number of rail tracks, and presence of adjacent industrial areas. The study also indicated that stop signs were more effective with multiple tracks, lower train speeds, lower motor vehicle and train volumes.

Pavement marking is another engineering measure for improving safety at HRGCs. Stephens and Long (2003) tested a new type of pavement marking called “25-ft X shape box.” The box was painted on the pavement on the downstream side of the roadway, slightly past the rail track. The outline was a 25 ft. square with “X” painted on the inside. The box could show motorists whether there was sufficient space to accommodate vehicles beyond the track (useful in the case of a vehicular queue past the crossing, perhaps due to a traffic signal). This design was expected to assist motorists in making correct track-crossing decisions. After painting at three locations on urbanized arterials in Fort Lauderdale, Florida and three rural sites in Barberville, Florida, the authors used Analysis of Variance (ANOVA) to test the resulting safety effects and identify safety-related factors. Results indicated that the application of the design at rural HRGCs significantly reduced motorists’ hazardous stopping behavior both in the short- and long-term periods. However, little benefit was found at urban HRGCs.

Various traffic control facilities and active warning devices have been installed and evaluated at HRGCs in the past. Khattak (2007, 2009), and Khattak and McKnight (2008) studied the safety impact of installing median barriers at gated HRGCs in the cities of Waverly and Fremont, Nebraska. The median barriers prevented motorists from going around closed gates. Three types of unsafe maneuvers were studied: vehicles going around closed gates or passing under gates that were in motion, U-turns, and backing up in the lanes (Khattak 2007). After the installation of flexible rubber and plastic barriers at two different locations, and the collection of before-and-after observational data by video cameras, the authors reported improvement in safety due to installation of the barrier.

Khattak and McKnight (2008) examined motorists' behaviors at a gated HRGC under three different scenarios: before barrier installation, after installation of partially extended barriers short of the gates, and after the installation of barriers fully extended to the gates. The NB regression model was adopted. Modeling results showed a 37% reduction in passing around gates after installation of partially extended barriers short of the gates, in comparison to compared to before barrier installation. In addition, the authors reported that passing around gates increased with longer durations of road closure due to the passage of trains, but decreased under adverse weather conditions.

Khattak (2009) compared unsafe maneuvers at HRGCs in two different cities, reporting that risky driver maneuvers at HRGCs were location-specific, but that the order of response to the installation of barriers in the two locations was fairly similar.

Regarding active warning devices, Gent et al. (2000) evaluated the overall safety at HRGCs with installed automated-horn systems in Ames, Iowa, while also evaluating the effectiveness of these systems at reducing levels of annoyance among nearby residents. The system warned HRGC users via two stationary horns mounted at the HRGCs. When the system was activated, a strobe light began flashing to warn approaching locomotive engineers to avoid sounding the train horn. The authors administered a survey to assess crossing users' and nearby residents' responses to the new device. Results of the survey showed that 92% of locomotive engineers rated the crossings as "safer" or "about the same" in comparison to the crossings lacking such a device. About 78% of motorists preferred the new system over traditional train horns in terms of safety. Moreover, 71% of the nearby residents had positive attitudes toward the new system.

2.2.1.2 Education and enforcement based countermeasures for motorists

The US DOT Grade Crossing Action Plan (Federal Railroad Administration 2011) and the 2004 Secretary's Action Plan on Highway-Rail Crossing Safety and Trespass Prevention (US Department of Transportation 2011) identified education and enforcement as key actions toward reducing motorist incidents at HRGCs.

Richards and Heathington (1988) conducted surveys in Tennessee to evaluate motorists' comprehension of HRGC traffic control devices and traffic regulations. The questionnaire survey was administered to 176 drivers and to 35 city police officers. The survey gathered input on driver recognition and understanding of common grade crossing traffic control devices, including signs, pavement markings, flashing light signals, gates, and train whistles, as well as driver perceptions of train capabilities and operating requirements. Driver education was also included in the survey in order to estimate its effect on safety. The study found that most drivers indicated a need for increased education in addition to grade separations and installation of gates and flashing lights.

According to Bowman et al. (1998), in April 1996 the state of Alabama Legislature, with the passage of Act 503, directed the Alabama Department of Transportation (ALDOT) to conduct a comprehensive study of highway-rail grade crossings in the state, and to recommend methods to drastically reduce the number of vehicle-train crashes. In response to Act 503, the Multimodal Bureau of ALDOT developed a plan of action comparing Alabama's grade crossing crash history with that of the rest of the nation and the southeastern states, in order to identify the prevalent characteristics, perceived safety needs, and the type of railroad professionals required to decrease vehicle-train crashes and crash severity. The Bureau compiled a list of recommendations and outlined the activities required for their implementation. The resulting plan discussed the engineering, economic, education, enforcement, and emotional impediments to increasing rail-highway intersection safety, and presented a broad range of realistic countermeasures. Operation Lifesaver education was recommended, to be delivered through mass media, brochures distributed at all state driver’s license locations, and the spread of information via newsletters.

A study by Mok and Savage (2005) disaggregated the improvement of safety at highway-rail intersections into the constituent causes of collisions and fatalities. Negative binomial regressions were conducted on a pooled dataset for 49 states that was gathered from 1975 to 2001. The analysis concluded that the development of the Operation Lifesaver public education campaign in the 1970s and early 1980s attributed to approximately 1/7 of the reduction in the number of collisions at HRGCs experienced since 1975. In another study by Savage (2006), a Negative binomial regression was used to estimate whether variations in Operation Lifesaver activity across states and from year-to-year in individual states were related to the number of collisions and fatalities at crossings. Annual data on 46 states from 1996 to 2002 were used. It was found that increasing the amount of educational activities reduced the number of collisions, but the effect of education on the number of fatalities could not be concluded with statistical certainty.

To explore the safety-related effects of education and enforcement, Sposato et al. (2006) conducted an evaluation at three gated HRGCs equipped with flashing warning devices in Arlington Heights, Illinois between July 1, 2003 and October 31, 2004. The objective of this study was to evaluate the effectiveness of an enhanced crossing safety education and enforcement program established by the Illinois Commerce Commission (ICC). After selecting HRGCs at three locations in Arlington Heights, a series of educational and enforcement activities was conducted over a 12-month period. The main activities included safety inserts with utility bills, radio and television public service announcements, poster campaigns, train station public address announcements, community enrollment and involvement in the Officer on the Train program, increased Operation Lifesaver presentations throughout the community, and police presence at the crossings. These activities were expected to efficiently inform motorists that it was illegal and dangerous to disobey traffic safety laws and crossing warning devices, and to provide information to help them make better decisions at HRGCs. During the three periods, including the 12-month phase necessary to enact these programs, as well as the two months before and two months after conducting the countermeasures, video cameras were used to capture three types of motorist violations. The violations included: 1) traversed the crossing while the lights were flashing but before the gates descended (Type 1 violation); 2) traversed the crossing during gate descent or ascent (Type 2 violation); and 3) traversed the grade crossing after the gates were fully deployed (Type 3 violation). Findings indicated 23 % and 71 % reductions in Type 2 and Type 3 violations, with a 15% noted increase for Type 1 violations.

Carroll and Warren (2002) investigated the safety effectiveness of an automatic photo enforcement system at HRGCs in California, Illinois, North Carolina, Florida, and Texas. This system used a red light to warn motorists at crossings, and captured a picture of a driver’s face and license plate if a red light violation was detected. After reviewing picture and violation information, police officers or other officials mailed tickets to vehicle owners in cases in which it was clear that the motorist ran the red light. Results showed that violations at California HRGCs were reduced by 36–92 % using photo enforcement, while crashes reduced by 70 %. Moreover, a 47–51 % reduction in violations was observed in Illinois, and a 78 % reduction in violations was recorded in North Carolina. The authors concluded that the use of photo enforcement was effective in modifying unsafe driver behavior.

2.2.2 Analysis of Specific Safety-Related Parameters

Moon and Coleman (1999) collected two-day video data at two four-quadrant HRGCs in Hartford and McLean, respectively, along the Chicago-St. Louis high-speed rail corridor in October, 1996 and July, 1997. At each crossing, three zones were marked to represent different distances from the rail tracks at which drivers approached the crossing. Vehicle travel times (for single vehicles) and time headways (for vehicle platoons) among the zones were recorded to calculate approach speed. Hypothesis testing of differences in mean values of speed among the zones showed that there was a definite tendency to reduce speed when vehicles approached HRGCs. Furthermore, the speed profiles of vehicle platoons were lower than the speed profiles of single vehicles at both study sites.

Estes and Rilett (2000) and Cho and Rilett (2003) investigated train arrival and crossing times at four HRGCs along the Wellborn corridor in College Station, Texas, using two prediction technologies. The Wellborn corridor is composed of the Union Pacific rail line, a parallel arterial highway, and several urban and rural streets intersecting both the rail line and the highway. For the study in 2000, the authors collected data on train instantaneous speed and direction of approach using Doppler microwave radar detectors mounted on traffic signal poles near three different HRGCs. A digital camera was placed at one HRGC to verify the presence of trains in the corridor. The entire process was conducted from February to July in 1999, and 823 northbound trains were observed and recorded. Cluster analysis was used to categorize approaching trains into four groups: strong deceleration, mild deceleration, constant speed, and mild acceleration. After classification, multiple linear regressions were used to predict arrival and crossing times based on speed profiles. Results showed that predicted train arrival time was within ±20 seconds of true arrival time. This value was half that of the error of values obtained from traditional prediction methods, such as the use of active warning device controllers to detect a train's presence when it passes a particular point on the track.

For the study in 2003, the authors chose the same monitoring devices and locations to collect data on 683 northbound trains from April to September in 2001. A Modular Artificial Neural Network (MAAN) design was used to group the train speed profiles and then forecast train arrival times. The results were more accurate than the prediction results obtained from multiple regression modeling and traditional prediction methods (i.e., 29.7 % and 46 % improvement was observed, respectively).

2.2.3 Identification of Safety-Associated Factors

Multiple researchers have investigated safety-associated factors related to vehicle and train operation, HRGC geometry, or HRGC environment. Oh et al. (2006) identified factors associated with vehicle-train crashes at HRGCs in Korea using statistical models. They also examined crash prediction models for HRGC safety, including the Peabody Dimmick Formula, the New Hampshire Index, and the US DOT Accident Prediction Formula. Some disadvantages of these models, such as their lack of descriptive capabilities, their complexity, and their declining accuracy over time were cited by the authors. Data on 162 crossings between 1998 and 2002 were obtained from the Korean National Railroad Accident Database. Results indicated that the number of vehicle-train crashes increased when average daily traffic volume, daily train volume, and time duration between the activation of warning signals and the activation of gates increased, and when crossings were located near commercial areas. Crashes decreased when a speed hump was present at the crossing to slow motor vehicle traffic. After comparing their model to the USDOT Accident Prediction Formula, the authors reported that several predictors differed across the models. In the US DOT model, type of highway surface and the presence of stop signs and pavement markings were significant factors affecting crash frequency. However, these factors were not found to be significant in the model estimated using Korean data.

Hu et al. (2010) tested statistical models to find the association between vehicle-train collisions at HRGCs and related factors in Taiwan. After obtaining crash and inventory data for 1995-1997 from the Taiwan Railway Administration (TRA) and Ministry of Transportation and Communications (MOTC), 35 factors were selected to fit the NB model. According to the results, the number of daily trains, AADT, and the number of tracks were significantly and positively associated with the number of collisions, while the crossing length was significantly and negatively associated with crash frequency. An HRGC equipped with a physical median at the highway side experienced fewer traffic collisions than did an HRGC lacking highway separation. The authors also conducted an analysis involving the marginal effect of AADT on the probability of crash occurrence. The results showed that the probability of a crash occurrence increased as AADT increased.

Kallberg et al. (2002) collected field observation data on 360 HRGCs at five main railway links in Finland from 1999 to 2000. The data included sight distance, presence of warning devices or crossing signs, vertical profiles of the road near crossings, road conditions, crossing photographs, and train approach speeds. A total of 34 variables were chosen for modeling, while crossing times for automobiles, general trucks, and trailer trucks were computed. Typical crossing times for the three types of vehicles were 3.5 to 4 s, 5.6 to 6.4 s, and 14 to 16 s, while the average train crossing time was 11.3 s. The collected data and statistical calculations identified vehicle and train crossing times as the factors associated with safety. The suggested measures to improve safety at HRGCs included improving sight distances by clearing vegetation, conducting crossing bans for trailer trucks, adding speed limits for trains, and trains' frequent use of whistles.

2.3 NON-MOTORIST SAFETY ON THE HIGHWAY SYSTEM

Non-motorists on the highway system primarily consist of pedestrians and bicyclists. Compared to pedestrians, relatively few published documents were found on bicyclist safety. Some studies combined pedestrians and bicyclists. An account of findings from the literature is presented below in two categories: evaluation of "triple E" countermeasures for non-motorists, and identification of safety-associated factors for non-motorists.

2.3.1 Evaluation of the "Triple Es" of Safety Countermeasures for Non-Motorists

2.3.1.1 Engineering design-based countermeasures for non-motorists

Similar to engineering designs for motorist safety at HRGCs, the typical devices used for the safety of non-motorists in traffic include various traffic signals and warning systems. Scott et al. (2008) examined the effectiveness of optimized Accessible Pedestrian Signals (APS) for providing street crossing information to blind pedestrians in Portland, Oregon, and Charlotte, North Carolina. The APS devices consisted of a pushbutton unit with integrated speakers and a beacon speaker on top of pedestrian signal head. Sixteen pedestrians participated in each city, and each pedestrian was assigned to travel four short routes that required nighttime crossings at two complex, unfamiliar intersections. Results compared before-and-after APS installation showed numerous improvements following APS installation. For example, the installation resulted in a nearly 2 s reduction in starting delay, which offered additional time for pedestrians to complete the crossing maneuver. In addition, only 13 % of participants in each city were unable to finish crossing in time, compared to 44–50 % who were unable to cross in time prior to APS installation.

Nambisan et al. (2009) introduced automatic pedestrian detection devices and smart lighting deployed at the site at Charleston Boulevard in Las Vegas, Nevada. The automatic pedestrian detection device could detect pedestrian presence near the crosswalk, then increase the illumination time of the crosswalk with the aid of smart lighting. The selected location had several safety problems; for example, pedestrians often did not wait for acceptable traffic gaps, or motorists did not yield to crossing pedestrians. A before-and-after study and corresponding statistical analysis were performed. The authors collected data for both the before and after scenarios on weekdays during mornings and evenings between 7:00-9:00am and 4:00-7:00pm. The recorded data included whether pedestrians looked to the left and right when crossing, whether the crosswalk was used correctly, whether motorists yielded and vehicles stopped upstream of the crosswalk, whether pedestrians were trapped on the roadway and whether significant pedestrian delay existed. The results obtained by Nambisan et al. (2009) showed that, after deployment of smart lighting, the number of pedestrians correctly using the crosswalk and carefully observing both directions increased. The percentage of motorists yielding to pedestrians also increased, as did vehicle stopping distance from pedestrians. Further, the proportion of trapped pedestrians decreased, and a significant reduction of pedestrian delay was noted, accompanied by a slight rise in vehicular delay. The authors concluded that the tested devices improved visibility for both motorists and pedestrians, and increased motorist compliance and pedestrian safe crossing behaviors.

Shurbutt et al. (2009) examined the effect of LED Rectangular Rapid-Flash Beacons (RRFBs) on motorists' yielding to pedestrians in multilane crosswalks. This countermeasure consisted of a standard pedestrian warning sign and two attached rectangular yellow LED flashers, which flashed in a wigwag sequence. The flashers could be activated by the push of a button, while an audible message warned pedestrians to wait for vehicles to stop before initiating the crossing maneuver. Four pedestrian crossings were utilized in St. Petersburg, Florida, and four signs with beacons were installed at each crosswalk. Additionally, three crosswalks each, in Illinois and Washington, D.C. were used to test location-specific features and long-term influences of RRFBs. A total of 20 pedestrians were involved in field experiments to test several variables, including the percentage of yielding motorists, yielding distance, and whether drivers in the yielding queue passed or attempted to pass vehicles stopped in front of them. Results showed that RRFBs produced a higher percentage of vehicles yielding to pedestrians and longer yielding distances at multilane, uncontrolled crosswalk locations. This effect was increased by installing additional beacons on the median island. Further, the numbers of vehicle in the yielding queue that passed or attempted to pass the vehicles stopped in front of them decreased significantly. Upon comparing the variables above to the traditional yellow flashing beacon, the RRFB was found to be more effective.

Fitzpatrick and Park (2009) evaluated the safety-related effectiveness of the High-Intensity Activated Crosswalk (HAWK) device installed at multiple sites in Tucson, Arizona. This device included an overhead red-yellow-red beacon, stop signs on the minor streets, marked crosswalks on the major streets, pedestrian pushbuttons with supplemental educational plaques, and pedestrian signal indications with interval countdown displays. The before-and-after evaluation utilized the Empirical Bayes (EB) method. The crash data from November, 1999 to February, 2008 were provided by the city of Tucson. The analysis spanned 36 months for each before and after period, a two-month installation period, and a two-month device learning period. It was concluded that pedestrian crashes reduced in the range of 51–59.2 % at the city's multiple HAWK installation sites.

Ellis and Houten (2009) identified and evaluated a series of engineering countermeasures to reduce pedestrian deaths and injuries along eight high-crash corridors in Miami–Dade County, Florida. A total of 14 engineering countermeasures were implemented. These measures included pedestrian pushbuttons, pedestrian yield signs, pedestrian zone signs, speed trailers, RRFB, offset stop lines, and several traffic signal improvements such as reduced minimum green time, lead pedestrian intervals, and countdown pedestrian signals. Statistical analysis of these mixed engineering measures showed that countywide pedestrian crash rates reduced in the range of 13.3 – 49.5% at different selected sites within the county.

2.3.1.2 Education and enforcement countermeasures for non-motorists

Countermeasures involving education and enforcement have been studied for their impact on non-motorist safety in traffic. Britt et al. (1995) evaluated the effect of enforcement of the crosswalk law in Seattle, Washington. The enforcement program included four campaigns: 1) a citywide focus from summer 1990 to fall 1991, 2) a neighborhood focus from September, 1992 to January, 1993, 3) a second neighborhood focus from July to October, 1993, and 4) intersection-specific enforcement from May to June, 1994. These campaigns focused mainly on drivers' compliance when approaching a crosswalk (e.g., stoppage behind the crosswalk line). Results of the study showed that the first campaign, which was conducted at 12 crosswalks in Seattle, did not improve vehicles' compliance. The second and third campaigns were conducted at 12 crosswalks in five neighborhoods with marked and unmarked crosswalks. The study detected a modest increase in vehicle compliance, and the amount of compliance at marked crosswalks was nine times that of compliance at unmarked crosswalks. Enforcement did not display significant benefits at locations with higher traffic volumes. Some other factors, such as speed limit, road surface conditions, pedestrian volumes, the presence of single or grouped vehicles, and the intensity of enforcement, may have impacted the change in vehicle compliance. Finally, the forth campaign verified that the compliance behaviors were location-specific.

In New Zealand, Lobb et al. (2001) evaluated a program of educational and environmental (access prevention) interventions designed to reduce the incidence of illegal and unsafe crossing of the rail corridor at a suburban station in Auckland, New Zealand. After the program of interventions was completed, the proportion of individuals crossing the rail corridor by walking across the tracks directly, rather than using the nearby overbridge, decreased substantially. Three months later, the decrease was even greater. However, the educational and environmental interventions were introduced simultaneously, so the effects of each could not be separated; nor could other unmeasured factors be ruled out. Anonymous surveys administered immediately before and 3 months after the interventions indicated that, while awareness of the illegality of walking across the tracks had increased slightly, the perceived risk had not changed. This suggests that the educational interventions may have had less effect than the access prevention measures.

In their study, Lobb et al. (2003) introduced another comprehensive intervention program that mixed communications/public safety awareness, education, and punishment. The evaluation of this program's effect on safety was conducted in a collaborative effort by New Zealand's Auckland City Council, Tranz Rail (the national railway company), and the University of Auckland. An inner city rail platform adjacent to a private boys' secondary school in Auckland was selected for evaluation. The platform included some safety crossing devices, such as a paved crossing and fences. The intervention program was carried out over eight weeks from February to September, 2000. For public awareness, a large billboard was placed near the platform, with a picture of a thinking schoolboy and a safety-related warning message. Over a four-week period, the educational portion included a discussion with pupils, a general educational statement, and follow-up activities related to crossing safety. The punishment portion, which consisted of continuous and intermittent punishments, mainly involved a possible Friday detention administered by teacher upon observing students crossing unsafely. The unsafe crossing behaviors before and after this intervention program were recorded. Two surveys inquiring on safety-related questions were also administered before and after the application of the intervention. Using chi-square tests, the analysis concluded that there was a significant decrease in unsafe crossing following the implementation of the program. Comparisons between different portions of program showed that unsafe crossing reduced between the communication and education portions, and even more so between the education and continuous punishment portions. However, no significant changes were found between continuous and intermittent punishments. Upon applying Multivariate Analysis of Variance (MANOVA) and correlational analysis, the survey conclusions indicated that correct responses increased following the program. This study verified the positive effect of the intervention program as a whole, and demonstrated that the punishment of unsafe behavior was much more effective than education and communication.

Gates et al. (2009) conducted a large-scale before-and-after evaluation of a pedestrian safety educational program designed for and delivered to elementary and middle school students at 16 participating schools in Detroit, Michigan. The program was developed to educate children on proper street-crossing, with an emphasis on path selection and initiation of crossing maneuvers in terms of the traffic conditions and signal display. Informational presentations were made in school cafeterias or auditoriums between May, 2008 and January, 2009. Field observation of students' street-crossing behavior near the school before and after the informational presentations was conducted.

In addition, a pre- and post- examination that tested attending children on how to cross the street correctly was carried out. The results showed that, among the 10 schools selected for observation, there was a decrease in violation rates ranging from 2.42 % to 18.3 % in night schools. There was also a significant, 4.44 % decrease in overall violation rates. Furthermore, an overall 23.2 % increase in the rate of correct pre- and post-examination responses was found. Both analyses suggested that the educational program could improve the safety of child pedestrians.

The Public Education and Enforcement Research Study (PEERS) was a collaborative effort between the Federal Railroad Administration, the Illinois Commerce Commission, and several communities in Illinois. Sposato et al. (2006) reported on crossing safety in the Arlington Heights, Illinois community, where education and enforcement activities targeted at reducing violations at grade crossings were undertaken. Three gated HRGCs in this community saw an overall reduction in violations of 30.7% between the pre-test to post-test period. The largest reduction of 71.4% was reported for the most risky type of violation—traversing the crossing after the gates were fully deployed in a horizontal position. Overall highway user behavior became safer, and pedestrians, especially commuters, were the group most impacted by the PEERS program.

Another study by Horton (2011) pertaining to the PEERS program implemented in the Macomb community in Illinois showed that overall grade crossing violations were not reduced from the pre-test to the post-test period. Grade crossing violations continued at the same rate, or increased, throughout the tenure of PEERS. The reasons for the diverse success levels of the PEERS program in Arlington Heights and Macomb were attributed to differences in the population characteristics (Macomb had a higher turnover in the student population), differences in highway users at HRGCs (Macomb saw a majority violations committed by motorists), and differences in wait times at HRGCs (Macomb had higher wait times). Another reason cited was differences in the implementation of the PEERS program: Macomb's implementation was oriented toward passive activities to reach wider portion of the community, compared to Arlington Height's aggressive activities focused at the crossings. The author recommended the development of a report on best practices and guidance on the proper design of a successful crossing safety education and enforcement program.

2.3.2 Identification of Safety-Associated Factors

Kim and Yamashita (2008) applied multiple correspondence analysis technology to explore the relationship between select variables in terms of pedestrian-involved traffic collisions in Hawaii. This method mainly examined data in a contingency table. The data used in the study were collected from a police-reported crash database collected by the state department of transportation from 2002-2006. Seven variables, including fault, gender, age, injury, time of day, land use, and whether or not the crash occurred at an intersection, were utilized in the analysis. Results showed that: 1) drivers were 13.8 times more likely than pedestrians to be classified as at-fault when involved in pedestrian crashes in Hawaii; 2) men were more likely than women to commit errors or dangerous actions, while children (i.e., 17 years and younger), compared to adults (i.e., 18-65 years old) or seniors (i.e., over 65 years of age) were more likely to be at fault as pedestrians; 3) seniors were more likely to be seriously injured than other age groups, and 4) crashes in residential areas appeared to be more likely than in nonresidential areas. The authors suggested that greater efforts in terms of enforcement and education should be directed toward drivers instead of pedestrians, and toward children and seniors, and that separate strategies for pedestrian safety in residential and nonresidential areas were needed.

Moudon et al. (2008) collected pedestrian-involved collision data on state routes in King County, Washington. Collision data recorded from 1999 to 2004 and data on the road characteristics (e.g., number of lanes, number of traffic signals, average annual daily traffic [AADT]) were obtained from the Transportation Data Office of the Washington State DOT and the Puget Sound Regional Council, respectively. The data were mainly used to analyze the relationship between occurrences of pedestrian-motor vehicle collisions along state routes and environmental characteristics. Binomial logit model results showed that the likelihood of a collision occurrence was strongly correlated with the presence of crosswalks with or without traffic signals, the number of roadway lanes, and the presence of nearby retail outlets. Other significant factors included the number of traffic signals, street block size, AADT, posted vehicle speed, bus ridership, and the number of residential units; all of these variables increased the likelihood of collisions. The authors suggested that engineering approaches to safety should be complemented by education- and enforcement-based measures. Moreover, facilities in areas with concentrations of retail outlets should become the targets of safety programs in the future.

2.4 MODELING APPROACHES FOR SAFETY STUDIES

A variety of modeling approaches have been adopted in safety studies focusing on motorists at HRGCs and non-motorists in traffic. The following section presents a review of models for: 1) counts of vehicle-train collisions at HRGCs, 2) counts of vehicle collisions in traffic; and 3) injury severity of pedestrian-only collisions in traffic.

2.4.1 Models for Counts of Vehicle-Train Collisions at HRGCs

Hauer and Persaud (1987) estimated a safety equation that was a linear combination of crossing crash history combined with the mean crash experience of similar crossings. Since information was used from two sources, each was given a weight to reflect its impact on the safety estimate. This weight depended on the variance-to-mean ratio of the expected number of crashes (represented by “M”) at HRGCs. The authors illustrated an example in terms of 10-year crash data at a single-track, crossbuck-equipped HRGC and a large group of similar crossings that were equipped with crossbucks or flashers and located in rural or urban areas. The Generalized Linear Interactive Modeling (GLIM) software package was used to estimate the mean value of M and the variance-to-mean ratio for similar crossings by inputting values of AADT and the total number of through trains per day. Next, the estimated equation was used to evaluate the safety effect of three warning devices at HRGCs. Results of this effort showed that the equation offered an effective way to estimate vehicle-train crash frequency at HRGCs. In addition, the safety evaluation of warning devices performed using this method showed that conversions from crossbucks to flashers, from crossbucks to gates, and from flashers to gates reduced the chances of an HRGC crash by 51, 69 and 45 %, respectively (Hauer and Persaud 1987).

Austin and Carson (2002) reviewed HRGC crash prediction methods and models. These included the Peabody-Dimmick formula, the New Hampshire Index, the National Cooperative Highway Research Program (NCHRP) Hazard Index, and the US DOT Accident Prediction formula. Because the Peabody-Dimmick formula was developed using crash data from rural HRGCs in 29 states in 1941, the non-representative sampling of HRGCs and aged predefined protection coefficient (which represented the relation between warning device presence and crash factors and can be found in figures in the *Railroad-highway grade crossing handbook*) hindered its validity for widespread application. The New Hampshire Index is somewhat similar to the Peabody-Dimmick formula in that it utilizes a simplified multiplicative form, but the index uses a different protection coefficient. Application of this method is difficult because of the variation in protection coefficient values and the striking dissimilarity between results for different states. Application of the US DOT Accident Prediction formula is complex, involving three stages of application, and its results decline in crash prediction accuracy over time.

Finally, the above formulas lack descriptive capabilities due to their utilization of a limited number of explanatory variables, and they do not take into account the hazard contribution from pedestrians and bicyclists at HRGCs. After collecting data on 1,538 vehicle-train crashes at HRGCs from six states (California, Montana, Texas, Illinois, Georgia, and New York) from January, 1997 through December, 1998, Austin and Carson estimated Poisson and NB models. The authors noted several benefits of the NB model: 1) a simplified estimation process; 2) a comparable supporting data requirement; and 3) facilitated interpretation of both the magnitude and direction of the effect of the factors found to significantly influence HRGC crash frequencies. The authors also reported that crash frequency increased with a greater number of nightly through trains, a greater number of main track lines and traffic lanes, higher maximum timetable train speeds, greater AADT, and paved highway. In addition, the presence of gates and highway traffic signals reduced HRGC crash frequency.

McCollister and Pflaum (2007) presented a logit model to predict the probabilities of unsuccessful crossing maneuvers that result in a vehicle-train crash characterized by injury or fatality. Output from the model was compared to output from the FRA, which can be found directly on the FRA's official website. The researchers collected HRGC inventory data and crash records spanning from 1991 and 2001 from the FRA online database. The authors' estimated model had better measures of effectiveness than those of the FRA model. Factors associated with the probability of crash occurrence at HRGCs were identified: a higher number of warning devices, a greater number of through trains at night, a greater number of switching trains per day, and higher train speeds were associated with a higher probability of crashes, fatalities, and injuries at HRGCs. In contrast, greater traffic volume and a greater percentage of trucks in the traffic were associated with a decreased probability of crashes.

In order to provide useful information for economically conducting safety improvements at HRGCs in Canada, Saccomanno et al. (2004) developed a risk-based model to identify HRGC blackspots, which represented specific crossings that had the highest risk of HRGC collisions. The authors combined two datasets, the Collision Occurrence Data RODS and the Inventory Data Set IRIS provided by Transport Canada and the Transportation Safety Board of Canada (TSB). A total of 826 collisions on 720 crossings that occurred between 1997 and 2001 were selected for model calibration and validation. Collision frequency and collision severity models were estimated. After demonstrating the consequences of collisions with collision severity scores, defined as the weighted sum of different types of consequences, NB regression was utilized to develop risk-based models and predict collisions at HRGCs in Canada. By ranking crossings according to prediction results and historical records, the top 22 crossings based on both risk elements were listed and illustrated on a map. The authors concluded that collision frequency was associated with traffic exposure (i.e., log of the cross product of AADT and daily number of trains), train speed, road speed, road surface width, and the number of tracks. Additionally, factors associated with collision severity included train speed, the number of tracks, track angle, the number of vehicles, and the number of involved persons. The identified blackspots were found to cluster in Saskatchewan, Ontario and Quebec, which, respectively, represented urban and rural areas.

Park and Saccomanno (2005) presented a study that demonstrated an advanced statistical model for safety-associated factor identification at HRGCs. The authors developed a model using a tree-based data mining method that was able to discover meaningful correlations in attributes among model variables. Using the collected data from the RODS/IRIS database in Canada, 13 factors were applied to develop a hierarchical Poisson regression tree for reflecting interactions in the prediction models within five classifiers. These classifiers represented interactions among the explanatory factors. Then an NB model was used to predict collision frequency at HRGCs. The conclusions indicated that the reliability of the collision prediction model was significantly improved by adding classifiers, in comparison to the model lacking interactions. This model also showed that the effect of specific safety countermeasures at HRGCs varied based on classifiers including highway class, track angle, posted road speed, track type, and surface width.

Saccomanno and Lai (2005) developed another collision prediction model using the same RODS/IRIS database. Statistical Package for the Social Sciences (SPSS) was used for the analysis of data on 10,449 crossings to yield four significant orthogonal factors. These factors explained about 60 % of the variance in the original dataset using 12 input variables. After the estimation of factor scores, five clusters representing similar geometric and traffic attributes were found by cluster analysis. Then an NB model was estimated; it showed that the process of predicting the number of collisions following a countermeasure can take place in two ways: 1) the number of collisions can be directly obtained from the prediction model if the countermeasures have been specified in the model, and 2) can be indirectly obtained by estimating factor scores and change in cluster membership with the introduction of the countermeasures.

2.4.2 Safety-Related Models on Count of Vehicle Collisions in the Roadway System

Glauz et al. (1985) aimed to establish a relationship between traffic crashes and traffic conflicts (or violations), which have a higher observable frequency. A traffic conflict was defined as an observable situation in which two or more road users approached each other in space and time to such an extent that there was a risk of collision if their movements remained unchanged. The authors collected data on12 different types of traffic conflicts at 46 urban intersections located in the greater Kansas City metropolitan area from 1979 to 1981. The authors compared the expected crash rate as predicted by traffic conflict data with the expected crash rate as predicted by historical crash data using crash/conflict ratios. After abandoning some intersections that had very few conflicts and infrequent occurrences of crashes, the authors randomly selected two intersections for each of four intersection classes. Then they used the remaining 38 locations to compute crash/conflict ratios with three-year crash data and four-day observed conflict data, computing expected crash rates using these ratios along with the conflict data from selected eight intersections. These expected crash rates were compared to the expected crash rates based on actual crashes. Results indicated good agreement between the two expected rates. The authors concluded that conflicts were nearly as good as crashes toward predicting expected crashes for certain types of intersection, and as such, were good surrogates of crashes.

Lord et al. (2005) balanced statistical fit and theory among Poisson, NB, and zero-inflated (i.e., with excess zeros recorded for the dependent variable) regression models toward the prediction of motor vehicle crashes. The objective of the study was to make an intelligent choice for modeling motor vehicle crash data from amongst several available modeling approaches. After assuming a dual-state (safe and unsafe) data-generating process of crashes, the authors utilized a Bernoulli process with unequal probability of independent events. According to the authors, four conditions led to excess zeros in crash data, including: 1) sites with a combination of low crash exposure, high heterogeneity, or high-risk categorization, 2) analyses conducted with small time or spatial scales, 3) data with a relatively high percentage of missing or misreported crashes, and 4) crash models with omitted important variables. Moreover, their simulation results verified the empirical crash data from existing zero-inflated modeling results. Additionally, the negative binomial distribution was found to provide a superior statistical fit than the Poisson distribution for sites with medium crash exposure. Finally, some theoretically defensible solutions for modeling crash data with excess zeros were addressed, including changing the spatial or time scale of analyses involving unobserved heterogeneity terms in NB and Poisson models, improving the set of explanatory variables, and applying small-area statistical methods.

2.4.3 Safety-Related Models on Injury Severity of Pedestrians Only in Traffic

Sze and Wong (2007) analyzed data involving crash environment profiles, casualty injury profiles, and vehicle involvement profiles obtained from the Traffic Accident Database System (TRADS) maintained by the Hong Kong Police Force and Transport Department. A total of 73,746 pedestrian casualties occurring in Hong Kong between 1991 and 2004 were used to predict pedestrian injury severity. In a binary logistic regression model, the probability of fatality or severe injury over slight injury (KSI) was used to represent the dependent variable. Explanatory variables, such as gender, age, location, pedestrian action, time, traffic congestion, road type, and lane number were extracted from the above three profiles. Results of the estimated model showed that factors lowering the risk of pedestrian fatality and severe injury included being male and below 15 years of age, being on an overcrowded or obstructed sidewalk, and being involved in a daytime crash on a road section with severe or moderate congestion. Factors that led to a higher risk of pedestrian fatality and severe injury included being over 65, sustaining a head injury, the crash occurring at the crossing or within 15 m of a crosswalk, the crash occurring on a road section with a speed limit above 50 kilometers per hour (km/h), signalized intersections, and two or more lanes. In addition, pedestrian injury risk underwent a decreasing trend from 1991 to 2004, perhaps due to remedial measures, road safety campaigns, pedestrianization, and traffic-calming strategies.

Eluru et al. (2008) reviewed studies on non-motorist injury severity in U.S. traffic crashes, finding: 1) the logistic regression was widely used when injury severity was studied in a binary format, while the ordered response model was commonly used when injury severity was recorded in multiple ordered categories; 2) there were no studies examining injury severity of both pedestrians and bicyclists; 3) few studies had considered attributes of the driver of the motored vehicle in terms of pedestrian injury severity. The authors presented a Mixed Generalized Ordered Response Logit Model (MGORL) structure for modeling severity data, which was sourced from the 2004 General Estimated System (GES). For the ordinal scale of crashes in GES, five levels were recorded, including no injury, possible injury, non-incapacitating injury, incapacitating injury, and fatal injury. This model allowed heterogeneity in the effects of contributing factors due to moderating influence of unobserved factors. Moreover, it allowed flexibility in capturing the effects of explanatory variables on each ordinal category in which injury severity was recorded. The authors reported the MGORL model to be superior to the common ordered response logit model based on a comparison of measures of fit. Moreover, the MGORL presented the elasticity effect (the percentage change in the probability of an injury severity category due to a change in a variable from 0 to 1) between pedestrians and bicyclists. Eluru et al. (2008) concluded that the general pattern and magnitude of elasticity effects of variables on injury severity was similar across these two categories. Several statistically significant associated factors were identified as influencing non-motorist injury severity. They included the age of the individual (elderly were more injury-prone), the speed limit on the roadway (higher speed limits led to more severe injuries), the location of crashes (those at signalized intersections were less severe compared to those elsewhere), and time-of-day (darker periods led to more severe injuries).

Kim et al. (2008) developed a heteroskedastic multivariate model of pedestrian injury severity. This model was mainly used to explore the relationship between the variance of unobserved pedestrian characteristics and a specific variable, age. After collecting police-reported pedestrian-vehicle crash data from North Carolina for the years 1997-2000, a total of 5,808 observations were used for modeling. Four injury outcomes were presented as the dependent variable: fatal, incapacitating, non-incapacitating, and possible or no injury. Results showed that pedestrian age induced heteroskedasticity across individual pedestrians, and affected the probability of fatal injury, especially for ages over 65 years. The probability of pedestrian fatal injury increased with increasing pedestrian age, male drivers, and intoxicated drivers. It also increased with the involvement of traffic signs, commercial areas, darkness, sport utility vehicle (SUV) and truck crashes, freeways, two-way divided roadways, speeding-involved crashes, and off-roadway crashes. The probability of pedestrian fatality decreased with increasing driver age, as well as the involvement of the pm traffic peak, traffic signal control, inclement weather, curved roadways, crosswalks, and walking along the roadway.

Finally, Jang et al. (2010) investigated the relationship between the level of injury in pedestrian crashes and various associated factors in San Francisco, California using an ordered probit model. The authors collected 2002-2007 pedestrian crash data on public roadways from the Statewide Integrated Traffic Records System (SWITRS) of San Francisco. A total of 5,084 pedestrian crashes including five levels of pedestrian crash injury as dependent variables and 25 explanatory variables were used for modeling. The five levels of injury were: property damage only, slight injury, visible injury, severe injury, and fatal injury. The explanatory variables mainly covered four categories, including pedestrian characteristics, driver characteristics, characteristics of the environment, and crash features. Based on modeling results the authors concluded that injury levels tended to increase with older pedestrians (older than 65 years), alcohol consumption, cell phone use, the time period occurring between midnight and 6 a.m., weekends, precipitation, proceeding straight vehicle movements, and larger vehicle involvement.

2.5 SUMMERY

In summary, this review of the literature revealed multiple sources of information on the safety of motorists at HRGCs and the safety of non-motorists in traffic, while relatively fewer documents were uncovered on pedestrian and bicyclist safety at HRGCs. Engineering, education, and enforcement were found to be the main categories of countermeasures used for improving safety on highways and HRGCs. Statistical models like the Poisson, negative binomial, and logit models were found useful for safety prediction and associated factor identification. Moreover, several published studies on the effectiveness of educational activities in improving HRGC safety were reviewed. Most of the reviewed studies evaluated the effects of educational activities along with other activities (e.g., enforcement or access prevention); therefore, the effects of educational activities could not be separated from those of the other activities.

The reviewed literature shows that there is a need to evaluate the safety of HRGC users by using appropriate and sufficient amounts of data alongside relevant statistical modeling techniques. Further, there is a need to evaluate the effects of an educational activity alone on the safety of non-motorists at HRGCs.

CHAPTER 3

DATA COLLECTION AND PRELIMINARTY DATA ANALYSIS

3.1 INTRODUCTION

Data for this study were collected at the dual-quadrant 'M' Street HRGC in Fremont, NE (fig. 3.1). This location was chosen because of the presence of sufficient trains, vehicles, pedestrians, and bicyclists, as well as granting of permission by the city of Fremont to install data collection devices at the HRGC. This crossing had two train tracks and used dual-quadrant protection gates, flashing lights, and median barriers on the intersecting roadway on both sides of the tracks. According to the US DOT crossing inventory information, the estimated average vehicular daily traffic at this HRGC in 1996 was 1,315, with 4% trucks. Average train traffic was estimated at 11 trains per day, although many more trains per day were observed during data collection. The maximum timetable train speed was 25 mph at this crossing, while the speed limit on the roadway was also 25 mph.

Flexible plastic and rubber barriers were installed along the median at this HRGC in 2006. The barriers were intended to prevent motorists from going around lowered gates when trains were at or near crossings. However, at the start of data collection, the barriers were in substandard condition due to abuse from vehicles, including snow plows, and also from the effects of weather (fig. 3.2). Barrier maintenance was performed by the city of Fremont from April 1st to 18th in 2011 to restore its condition (fig. 3.3).

FIGURE 3.1 The HRGC in Fremont, NE

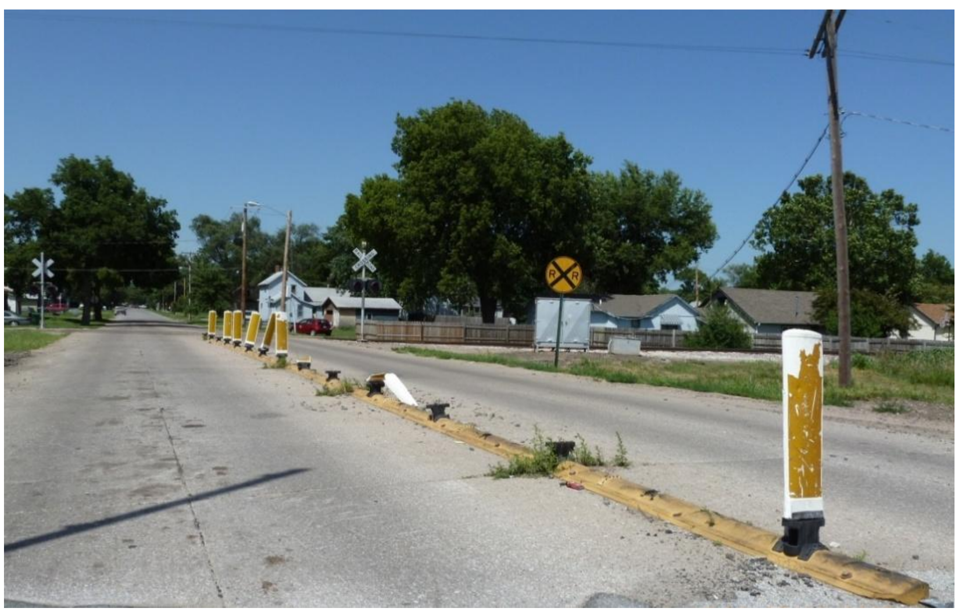

FIGURE 3.2 Condition of the median barriers prior to maintenance

FIGURE 3.3 Barrier condition after maintenance

An educational activity focusing on non-motorists was undertaken at this HRGC on September 29th and 30th in 2011, in order to examine its impact on non-motorists' HRGC safety. Data were collected before and after maintenance work (dataset 1), as well as before and after the educational activity (dataset 2). This chapter provides information on the process of data collection and reduction, as well as the preliminary data analysis.

3.2 VARIABLE DESCRIPTION

Motorists, pedestrians, and bicyclists encountered at the HRGC were individually observed during the data collection periods via recorded video, and pertinent data was extracted to a spreadsheet. A train crossing event was defined by the elapsed time between the onset and cessation of flashing lights at the HRGC. The extracted variables were aggregated for each train crossing event to obtain counts of different variables occurring in each. For example, the count of pedestrians encountered during a train crossing event was obtained by adding the number of pedestrians observed at the HRGC during the train crossing. Table A in appendix A lists the original variables that were subsequently aggregated to obtain the count variables that are listed in table 3.1. Both tables also list crossing event characteristics such as time elapsed between the onset and cessation of flashing gate lights, train stoppage on the tracks, and gate malfunctions.

TABLE 3.1 Variables Used for Data Analysis

Variable	Label/Description	Coding/Units
EVENT	Series number of each train crossing event at HRGC	Integer (1, 2…)
DATE	Date of observation for each train crossing event	Year, Month, Day
PERIOD	Indicator variable for time period before and after educational activity implementation	0 = before activity implementation 1 = after activity implementation
V_TYPE	Categorical variable for vehicle types	0 = passenger car, 1 = pickup truck, 2=van, 3=SUV, 4=single unit truck, 5=semi-trailer truck, 6=school bus, 7=motorcycle, 8=tractor or other farm vehicle, 9=others
N_VIO	Number of gate violations per train crossing event by HRGC users	Integer (0, 1, 2…)
N_OPP	Number of violation opportunities per train crossing event available to HRGC users	Integer (0, 1, 2…)
N_VEH_VIO	Number of gate violations per train crossing event by motor vehicles	Integer (0, 1, 2…)
N_PED_VIO	Number of gate violations per train crossing event by pedestrians	Integer (0, 1, 2…)
N_BIC_VIO	Number of gate violations per train crossing event by bicyclists	Integer (0, 1, 2…)
N_NM_VIO	Number of gate violations per train crossing event by non-motorists	Integer (0, 1, 2…)

Table 3.1. continued

N_VEH_OPP	Number of gate violation opportunities per train crossing event available to motor vehicles	Integer (0, 1, 2…)
N_PED_OPP	Number of gate violation opportunities per train crossing event available to pedestrians	Integer (0, 1, 2…)
N_BIC_OPP	Number of gate violation opportunities per train crossing event available to bicyclists	Integer (0, 1, 2…)
N_NM_OPP	Number of gate violation opportunities per train crossing event available to non-motorists	Integer (0, 1, 2…)
N_V1	Number of V1 gate violations per train crossing event by all cross users	Integer (0, 1, 2…)
N_V2	Number of V2 gate violations per train crossing event by all cross users	Integer (0, 1, 2…)
N_V3	Number of V3 gate violations per train crossing event by all cross users	Integer (0, 1, 2…)
N_V4	Number of V4 gate violations per train crossing event by all cross users	Integer (0, 1, 2…)
N_OPP V1	Number of V1 gate violation opportunities per train crossing event available to all cross users	Integer (0, 1, 2…)
N_OPP V2	Number of V2 gate violation opportunities per train crossing event available to all cross users	Integer (0, 1, 2…)
N_OPP V3	Number of V3 gate violation opportunities per train crossing event available to all cross users	Integer (0, 1, 2…)
N_OPP V4	Number of V4 gate violation opportunities per train crossing event available to all cross users	Integer (0, 1, 2…)
N_VEH_V1	Number of V1 gate violations per train crossing event by motor vehicles	Integer (0, 1, 2…)
N_VEH_V2	Number of V2 gate violations per train crossing event by motor vehicles	Integer (0, 1, 2…)
N_VEH_V3	Number of V3 gate violations per train crossing event by motor vehicles	Integer (0, 1, 2…)
N_VEH_V4	Number of V4 gate violations per train crossing event by motor vehicles	Integer (0, 1, 2…)
N_VEH_OPP V1	Number of V1 gate violation opportunities per train crossing event available to motor vehicles	Integer (0, 1, 2…)
N_VEH_OPP V2	Number of V2 gate violation opportunities per train crossing event available to motor vehicles	Integer (0, 1, 2…)
N_VEH_OPP V3	Number of V3 gate violation opportunities per train crossing event available to motor vehicles	Integer (0, 1, 2…)

Table 3.1. continued

N_VEH_OPP V4	Number of V4 gate violation opportunities per train crossing event available to motor vehicles	Integer (0, 1, 2…)
N_PED_V1	Number of V1 gate violations per train crossing event by pedestrians	Integer (0, 1, 2…)
N_ PED_V2	Number of V2 gate violations per train crossing event by pedestrians	Integer (0, 1, 2…)
N_ PED_V3	Number of V3 gate violations per train crossing event by pedestrians	Integer (0, 1, 2…)
N_ PED_V4	Number of V4 gate violations per train crossing event by pedestrians	Integer (0, 1, 2…)
N_ PED_OPP V1	Number of V1 gate violation opportunities per train crossing event available to pedestrians	Integer (0, 1, 2…)
N_ PED_OPP V2	Number of V2 gate violation opportunities per train crossing event available to pedestrians	Integer (0, 1, 2…)
N_ PED_OPP V3	Number of V3 gate violation opportunities per train crossing event available to pedestrians	Integer (0, 1, 2…)
N_ PED_OPP V4	Number of V4 gate violation opportunities per train crossing event available to pedestrians	Integer (0, 1, 2…)
N_BIC_V1	Number of V1 gate violations per train crossing event by bicyclists	Integer (0, 1, 2…)
N_ BIC_V2	Number of V2 gate violations per train crossing event by bicyclists	Integer (0, 1, 2…)
N_ BIC_V3	Number of V3 gate violations per train crossing event by bicyclists	Integer (0, 1, 2…)
N_ BIC_V4	Number of V4 gate violations per train crossing event by bicyclists	Integer (0, 1, 2…)
N_ BIC_OPP V1	Number of V1 gate violation opportunities per train crossing event available to bicyclists	Integer (0, 1, 2…)
N_ BIC_OPP V2	Number of V2 gate violation opportunities per train crossing event available to bicyclists	Integer (0, 1, 2…)
N_ BIC_OPP V3	Number of V3 gate violation opportunities per train crossing event available to bicyclists	Integer (0, 1, 2…)
N_ BIC_OPP V4	Number of V4 gate violation opportunities per train crossing event available to bicyclists	Integer (0, 1, 2…)
N_N_V1	Number of V1 gate violations per train crossing event by non-motorists	Integer (0, 1, 2…)
N_N_V2	Number of V2 gate violations per train crossing event by non-motorists	Integer (0, 1, 2…)
N_N_V3	Number of V3 gate violations per train crossing event by non-motorists	Integer (0, 1, 2…)

Table 3.1 continued

N_N_V4	Number of V4 gate violations per train crossing event by non-motorists	Integer (0, 1, 2…)
N_N_OPP V1	Number of V1 gate violation opportunities per train crossing event available to non-motorists	Integer (0, 1, 2…)
N_N_OPP V2	Number of V2 gate violation opportunities per train crossing event available to non-motorists	Integer (0, 1, 2…)
N_N_OPP V3	Number of V3 gate violation opportunities per train crossing event available to non-motorists	Integer (0, 1, 2…)
N_N_OPP V4	Number of V4 gate violation opportunities per train crossing event available to non-motorists	Integer (0, 1, 2…)
GROUP	Indicator variable for presence of users in groups (i.e., more than one user present at the same time)	0 = individual user, 1 = group
V_TRAFFIC	Number of motor vehicles encountered per train crossing event (includes vehicles in queue and those that departed after gate violation)	Integer (0, 1, 2…)
B_TRAFFIC	Number of bicyclists encountered per train crossing event (includes bicyclists in queue and those that departed after gate violation)	Integer (0, 1, 2…)
P_TRAFFIC	Number of pedestrians encountered per train crossing event (includes pedestrians in queue and those that departed after gate violation)	Integer (0, 1, 2…)
NM_TRAFFIC	Number of non-motorists encountered per train crossing event (P_TRAFFIC+B_TRAFFIC)	Integer (0, 1, 2…)
N_U_TURN	Number of vehicle’s U-turn at HRGC	Integer (0, 1, 2…)
N_B_UP	Number of vehicle’s backup at HRGC	Integer (0, 1, 2…)
WEEKEND	Indicator variable for train crossing event on a weekend (Saturday or Sunday)	0 = event on weekdays, 1 = event on weekend
DAY	Days of a week	Monday, Tuesday,…Sunday
G_DOWN	Elapsed time between the onset and cessation of flashing lights at the HRGC	Seconds
T_ARRIVAL	Elapsed time between the onset of flashing lights and train arrival at the crossing	Seconds
N_TRAINS	Number of crossing trains	Integer (0, 1, 2…)
SIMULTANEOUS	Indicator variable for simultaneous crossing of trains	0 = non-simultaneous, 1 = simultaneous
STOP	Indicator variable for train stoppage at the crossing	0 = non-stop, 1 = stop

Table 3.1 continued

WEATHER	Categorical variable for weather condition at the time of train crossing	0 = clear, 1=fog, 2=wet pavement, 3=rain, 4=snow
LIGHT	Categorical variable for light condition at the time of train crossing	0 = nighttime, 1=daytime, 2=dawn or dust, 3=dark or cloudy, 4=others
G_MALF	Indicator variable for gate malfunction when no train arrived	0 = non-malfunction, 1 = malfunction

HRGC gate violations by users were categorized into four types: violation type 1 (V1) implied passing under descending gates; violation type 2 (V2) implied passing around fully lowered gates; violation type 3 (V3) was passing under ascending gates; and violation type 4 (V4) was passing around fully lowered gates between successive trains. Figures 3.4 and 3.5 display two examples of V1 and V2 violations, respectively, engaged in by motorists. Opportunities available to HRGC users for engaging in different types of gate violations were monitored and recorded during data collection. For example, a pedestrian's opportunity to engage in V2 was recorded if at the time of the pedestrian's arrival the gates were fully lowered and the train was not yet at the crossing. Counts for motorists, pedestrians, and bicyclists per train crossing event were maintained in the database.

FIGURE 3.4 Motorist engaged in a type 1 gate violation

FIGURE 3.5 Motorist engaged in a type 2 gate violation

Video time stamp was used to calculate the time interval between the onset and cessation of flashing lights at the HRGC, as well as the period between the onset of flashing lights and train arrival at the crossing. The weather at the time of train crossing, the presence of daylight conditions, train stoppage on the crossing, and any gate malfunctions were also recorded in the dataset.

3.3 DATASETS AND EDUCATIONAL ACTIVITY

Dataset 1 was collected in March and April, 2011, during which time the city of Fremont performed maintenance on the median barriers (from April 1st to the 18th). The dilapidated barriers were restored by replacing damaged elements, and a guide sign indicating the presence of the barriers were erected at the site. Data collected in March pertained to the before-maintenance period, while data collected after 18th in April related to the after-maintenance period.

Dataset 2, regarding gate violations by non-motorists and crossing event characteristics, was collected in 28 days prior to and in 28 days following an educational activity focused on reducing non-motorists' gate violations at the Fremont HRGC. The two-day (7:00 am-7:00 pm) educational activity was conducted on September 29th and 30th in 2011. Operation Lifesaver educational materials were used in this activity to raise awareness of HRGC safety among non-motorists. Operation Lifesaver was a non-profit organization involved in public awareness activities to improve HRGC safety. The materials used in the activity included printed matter (pamphlets, flyers, and brochures, etc.), DVDs with HRGC safety videos, and logo merchandise with HRGC safety messages (e.g., baseball caps, hand fans, mugs, and duffel bags). Figure 3.6 shows examples of the materials used in the activity, while figure 3.7 shows the materials distribution. Safety videos were played at the HRGC for visitors, and were distributed to non-motorists for later home-viewing. During the two-day educational activity, most of the regular non-motorist users of the HRGC were contacted and advised of the HRGC safety issue. A higher-than-usual amount of non-motorist traffic was observed at this location during the educational activity, which was the result of HRGC users spreading information about the activity throughout the community via word-of-mouth.

FIGURE 3.6 Sample educational materials distributed at the HRGC

FIGURE 3.7 Distribution of educational materials at the HRGC

In this study, dataset 1 and 2 together were used for identifying safety-related factors at HRGCs concerning motorists and non-motorists, respectively. Moreover, dataset 1 and 2 together were used for safety effect assessment of median barrier maintenance for motorists while dataset 2 only was used for safety effect assessment of educational activity for non-motorists.

3.4 Preliminary Data Analysis

3.4.1 Descriptive Statistics for Dataset 1

Dataset 1 has a total of 1,748 observations, of which 1,266 were collected in 31 days prior to barrier maintenance and 482 were collected in 12 days following barrier maintenance. Table 3.2 presents the frequencies of select variables and table 3.3 displays descriptive statistics. The descriptive statistics for all variables are reported in appendix B.

Table 3.2 shows that total motorist violation frequency increased after median barriers' maintenance. A review of the statistics of the four types of violations in appendix B shows that type V3 increased substantially following maintenance, while there were relatively small changes in the frequency of the other three types of violations.

Table 3.3 verifies the increase in the total frequency of motorist violations following median barrier maintenance, coinciding with a decrease in the total frequency of motorists' opportunities to violate. Both vehicle traffic volume and the number of crossing trains increased slightly. Among the four types of violations, type V3 displayed a significant increase following median barrier maintenance, while opportunity type 2 displayed a significant decrease during that time period.

TABLE 3.2 Variable Frequency (Percentage) Statistics for Dataset

Variable Description	Observation Frequency in Before Time Period (%) n=1266	Observation Frequency in After Time Period (%) n=482
Number of violations (N_VEH_VIO)		
Zero	591(46.7)	144 (29.9)
One	493(38.9)	202(41.9)
Two	155(12.2)	114(23.7)
Three or more	27(2.2)	22(4.5)
Weather Condition (WEATHER)		
Clear	1176(92.9)	428(88.8)
Fog	17(1.3)	0(0)
Wet pavement	20(1.6)	0(0)
Rain	0(0)	32(6.6)
Snow	47(3.7)	22(4.6)
Snow pavement	6(0.5)	0(0)
Light condition (LIGHT)		
Night time	597(47.2)	107(22.2)
Daytime	175(13.8)	112(23.2)
Dawn or dusk	48(3.8)	62(12.9)
Dark or cloudy	446(35.2)	201(41.7)

Table 3.2 continued

Violation with group (GROUP)		
Yes	770 (60.8)	328(68.0)
No	496(39.2)	154(32.0)
Number of violation opportunities (N_OPP)		
One	237(18.7)	172(35.7)
Two	433(34.2)	227(47.1)
Three	171(13.5)	54(11.2)
Four	327(25.8)	20(4.1)
Five or more	98(7.8)	9(1.9)
Weekend (WEEKEND)		
Yes	320(25.3)	132(27.4)
No	946(74.7)	350(72.6)
Number of crossing trains (N_TRAINS)		
Zero	36(2.8)	12(2.5)
One	1148(90.7)	414(85.9)
Two or more	82(6.5)	56(11.6)
Train's simultaneous crossing (SIMULTANEOUS)		
Yes	65(5.1)	41(8.5)
No	1201(94.9)	441(91.5)
Train stoppage (STOP)		
Yes	47(3.7)	19(3.9)
No	1219(96.3)	463(96.1)
Gate malfunction (G_MALF)		
Yes	32(2.5)	14(2.9)
No	1234(97.5)	468(97.1)

TABLE 3.3 Descriptive Statistics of Numerical Variables for Dataset 1

Variable Description	Descriptive Statistics in Before Time Period			Descriptive Statistics in After Time Period			Total Mean Value	Total Standard Deviation Value
	Min./ Max. value	Mean	Std. Dev.	Min./ Max. value	Mean	Std. Dev.		
Number of Violations (N_VEH_VIO)	0/5	0.70	0.79	0/5	1.04	0.88	0.80	0.825
Number of Violation opportunities (N_OPP)	1/16	2.75	1.43	1/6	1.90	0.91	2.51	1.364
Vehicle traffic volume (V_TRAFFIC)	1/66	7.19	7.77	1/50	7.80	8.14	7.36	7.872
Time (second) between the start and the end of flashing lights (G_DOWN)	27/2232	325.21	171.23	24/825	296.23	123.50	317.21	159.981
Time (second) between the start of flashing lights and train arrival (T_ARRIVAL)	24/672	56.71	31.30	27/217	51.38	21.79	55.20	29.023
Number of crossing trains (N_TRAINS)	0/2	1.04	0.30	0/2	1.09	0.37	1.05	0.322
Number of violations type 1 per train crossing event (N_VEH_V1)	0/4	0.16	0.41	0/3	0.09	0.31	0.14	0.391
Number of violations type 2 per train crossing event (N_VEH_V2)	0/4	0.02	0.17	0/3	0.02	0.17	0.02	0.173
Number of violations type 3 per train crossing event (N_VEH_V3)	0/3	0.52	0.65	0/4	0.93	0.77	0.63	0.708

Table 3.3 continued

Number of violations type 4 per train crossing event (N_VEH_V4)	0/4	0.01	0.15	0/1	0.00	0.05	0.01	0.131
Number of type 1 violation opportunities per train crossing event (N_VEH_OPP1)	0/4	0.16	0.42	0/3	0.12	0.37	0.15	0.408
Number of type 2 violation opportunities per train crossing event (N_VEH_OPP2)	0/6	1.05	0.88	0/3	0.17	0.47	0.80	0.881
Number of type 3 violation opportunities per train crossing event (N_VEH_OPP3)	0/5	1.52	0.63	0/4	1.59	0.59	1.54	0.619
Number of type 4 violation opportunities per train crossing event (N_VEH_OPP4)	0/8	0.01	0.26	0/4	0.01	0.20	0.01	0.246

In this case, gate violation counts for pedestrians and bicyclists were assumed Poisson distributed. Przyborowski et al. (1940) introduced a method to conduct homogeneity test of two Poisson distributed count samples. This approach can be used by an online statistical tool to determine the difference in the mean of gate violation frequencies between pedestrians and bicyclists (available at http://www.stattools.net/Twocounts_Pgm.php). The null hypothesis (H_o) was that there was no difference in the mean frequency of gate violations between pedestrians and bicyclists, while the alternative hypothesis (H_a) was that the two means were statistically different.

Table 3.4 presents the results of the homogeneity test. As displayed in the table, p-values of V1, V2, V3, V4 and total violation comparisons were 0.194, 0.084, 0.002, 0.033, and 0.499, respectively. The table shows that there was no statistically significant difference in gate violation frequencies between pedestrians and bicyclists, except in the case of type V3 and V4. Overall, it appears reasonable to combine both bicyclists and pedestrians into one group, identified as the non-motorist group for further analysis.

TABLE 3.4 Comparison of Pedestrian and Bicyclist Gate Violation Based on Poisson distribution

Violation Type	Pedestrian Violation (n=470)		Bicyclist Violation (n=395)		P Value
	Sum of Violations	Sample Size	Sum of Violations	Sample Size	
V1	48	470	29	395	0.194
V2	220	470	219	395	0.084
V3	189	470	110	395	0.002
V4	2	470	9	395	0.033
Total	459	470	367	395	0.499

3.4.2 Descriptive Statistics for Dataset 2

Dataset 2 comprised of 522 observations, of which 280 were collected before the educational activity and 242 were collected after the educational activity. The results of the descriptive statistics are shown in tables 3.5-3.10. Tables 3.5, 3.7 and 3.9 present frequency statistics, while tables 3.6, 3.8 and 3.10 present descriptive statistics. Appendix C provides tables that report frequency statistics for all variables contained in dataset 2.

TABLE 3.5 Pedestrian-Related Variable Frequency (Percentage) Statistics

Variable Description	Observation Frequency in Before Time Period (%) n=151	Observation Frequency in After Time Period (%) n=162
Number of pedestrian violations (N_PED_VIO)		
Zero	59(39.1)	47(29.0)
One	72(47.7)	78(48.1)
Two	16(10.6)	21(13.0)
Three or more	4(2.6)	16(9.9)
Day of Week (DAY)		
Monday	29(19.2)	29(17.9)
Tuesday	27(17.9)	21(13.0)
Wednesday	21(13.9)	13(8.0)
Thursday	17(11.3)	29(17.9)
Friday	17(11.3)	15(9.3)
Saturday	19(12.6)	22(13.6)
Sunday	21(13.8)	33(20.3)
Weather Condition (WEATHER)		
Clear	140(92.7)	160(98.8)
Fog	0(0)	0(0)
Wet pavement	5(3.3)	2(1.2)

Table 3.5 continued

Rain	0(0)	0(0)
Snow	0(0)	0(0)
Snow pavement	0(0)	0(0)
Light condition (LIGHT)		
Night time	21(13.9)	33(20.4)
Non-nighttime	130(86.1)	129(79.6)
Violation with group (GROUP)		
Yes	44(29.1)	53(32.7)
No	107(70.9)	109(67.3)
Number of pedestrian violation opportunities (N_PED_OPP)		
One	46(30.5)	66(40.7)
Two	74(49.0)	61(37.7)
Three	2(1.3)	11(6.8)
Four	23(15.2)	10(6.2)
Five or more	6(4.0)	14(8.6)
Weekend (WEEKEND)		
Yes	40(26.5)	55(34.0)
No	111(73.5)	107(66.0)
Number of crossing trains (N_TRAINS)		
Zero	3(2.0)	9(5.6)
One	132(87.4)	131(80.9)
Two or more	16(10.6)	22(13.5)
Train's simultaneous crossing (SIMULTANEOUS)		
Yes	10(6.6)	15(9.3)
No	141(93.4)	147(90.7)
Train stoppage (STOP)		
Yes	11(7.3)	6(3.7)

Table 3.5 continued

No	140(92.7)	156(96.3)
Gate malfunction (G_MALF)		
Yes	3(2.0)	9(5.6)
No	148(98.0)	153(94.4)

TABLE 3.6 Descriptive Statistics of Pedestrian-Related Numerical Variables

Variable Description	Descriptive Statistics in Before Time Period			Descriptive Statistics in After Time Period			Total Mean Values	Total Std. Dev. Values
	Min./ Max. value	Mean	Std. Dev.	Min./ Max. value	Mean	Std. Dev.		
Number of Violations (N_PED_VIO)	0/5	0.78	0.799	0/5	1.08	1.021	0.94	0.932
Number of Violation opportunities (N_PED_OPP)	1/10	2.21	1.422	1/8	2.15	1.547	2.18	1.486
Time (second) between the start and the end of flashing lights (G_DOWN)	79/2870	340.72	275.308	57/2811	329.11	255.536	334.8	264.95
Time (second) between the start of flashing lights and train arrival (T_ARRIVAL)	24/144	50.16	16.984	26/117	50.55	17.950	50.36	17.450
Number of crossing trains (N_TRAINS)	0/2	1.09	0.345	0/5	1.11	0.568	1.10	0.473
Number of violations type 1 (N_PED_V1)	0/2	0.11	0.409	0/4	0.10	0.481	0.11	0.447
Number of violations type 2 (N_PED_V2)	0/5	0.30	0.653	0/4	0.59	0.861	0.45	0.779

Table 3.6 continued

Number of violations type 3 (N_PED_V3)	0/3	0.36	0.605	0/4	0.39	0.750	0.38	0.683
Number of violations type 4 (N_PED_V4)	0/0	0.00	0.000	0/0	0.00	0.000	0.00	0.000
Number of type 1 violation opportunities (N_PED_OPP1)	0/2	0.12	0.415	0/4	0.10	0.423	0.10	0.419
Number of type 2 violation opportunities (N_PED_OPP2)	0/5	1.11	0.884	0/4	1.13	1.064	1.12	0.980
Number of type 3 violation opportunities (N_PED_OPP3)	0/5	0.97	0.852	0/4	0.91	0.993	0.94	0.927
Number of type 4 violation opportunities (N_PED_OPP4)	0/2	0.01	0.163	0/2	0.02	0.191	0.02	0.178

TABLE 3.7 Bicyclist-Related Variable Frequency (Percentage) Statistics

Variable Description	Observation Frequency in Before Time Period (%) n=160	Observation Frequency in After Time Period (%) n=134
Number of bicyclist violations (N_BIC_VIO)		
Zero	48(30.0)	28(20.9)
One	85(53.1)	87(64.9)
Two	22(13.8)	15(11.2)
Three or more	5(3.1)	4(3.0)
Day of Week (DAY)		
Monday	16(10.0)	31(23.1)
Tuesday	34(21.3)	18(13.4)
Wednesday	22(13.8)	17(12.7)
Thursday	13(8.1)	17(12.7)
Friday	28(17.5)	10(7.5)
Saturday	26(16.3)	20(14.9)
Sunday	21(13.1)	21(15.7)
Weather Condition (WEATHER)		
Clear	152(95.0)	130(97.0)
Fog	0(0)	0(0)
Wet pavement	8(5.0)	2(1.5)
Rain	(0)	2(1.5)
Snow	(0)	0(0)
Snow pavement	(0)	0(0)
Light condition (LIGHT)		
Night time	25(15.6)	47(35.1)
Non-nighttime	135(84.4)	87(64.9)
Violation with group (GROUP)		
Yes	33(20.6)	17(12.7)
No	127(79.4)	117(87.3)
Number of bicyclist violation opportunities (N_BIC_OPP)		

Table 3.7 continued

One	66(41.3)	75(56.1)
Two	71(44.4)	50(37.3)
Three	3(1.9)	3(2.2)
Four	12(7.5)	3(2.2)
Five or more	8(4.9)	3(2.2)
Weekend (WEEKEND)		
Yes	48(30.0)	41(30.6)
No	112(70.0)	93(69.4)
Number of crossing trains (N_TRAINS)		
Zero	3(1.9)	2(1.5)
One	144(90.0)	114(85.1)
Two or more	13(8.1)	18(13.4)
Train's simultaneous crossing (SIMULTANEOUS)		
Yes	10(6.3)	14(10.4)
No	150(93.7)	120(89.6)
Train stoppage (STOP)		
Yes	10(6.9)	12(9.0)
No	149(93.1)	122(91.0)
Gate malfunction (G_MALF)		
Yes	3(1.9)	2(1.5)
No	157(98.1)	132(98.5)

TABLE 3.8 Descriptive Statistics of Bicyclist-Related Numerical Variables

Variable Description	Descriptive Statistics in Before Time Period			Descriptive Statistics in After Time Period			Total Mean Values	Total Std. Dev.
	Min./ Max. Value	Mean	Std. Dev.	Min./ Max. Value	Mean	Std. Dev.		
Number of Violations (N_BIC_VIO)	0/6	0.92	0.851	0/5	0.99	0.756	0.95	0.808
Number of Violation opportunities (N_BIC_OPP)	1/8	1.96	1.273	1/8	1.60	0.959	1.80	1.153
Time (second) between the start and the end of flashing lights (G_DOWN)	51/2027	315.04	201.708	24/1808	344.29	232.625	328.2	215.87
Time (second) between the start of flashing lights and train arrival (T_ARRIVAL)	23/237	50.74	22.612	24/224	55.46	26.875	52.89	24.711
Number of crossing trains (N_TRAINS)	0/2	1.06	0.311	0/5	1.16	0.532	0.63	0.569
Number of violations type 1 (N_BIC_V1)	0/2	0.12	0.343	0/1	0.04	0.190	0.08	0.286
Number of violations type 2 (N_BIC_V2)	0/6	0.47	0.760	0/5	0.74	0.775	0.59	0.777
Number of violations type 3 (N_BIC_V3)	0/4	0.31	0.673	0/4	0.19	0.508	0.25	0.605
Number of violations type 4 (N_BIC_V4)	0/2	0.03	0.207	0/2	0.02	0.193	0.03	0.201
Number of type 1 violation opportunities (N_BIC_OPP1)	0/2	0.13	0.374	0/1	0.04	0.190	0.09	0.307
Number of type 2 violation opportunities (N_BIC_OPP2)	0/6	1.06	0.837	0/5	1.06	0.744	1.06	0.794

Table 3.8 continued

Number of type 3 violation opportunities (N_BIC_OPP3)	0/4	0.72	0.794	0/4	0.48	0.646	0.61	0.739
Number of type 4 violation opportunities (N_BIC_OPP4)	0/2	0.05	0.246	0/2	0.02	0.193	0.04	0.223

TABLE 3.9 Non-Motorist Variable Frequency (Percentage) Statistics

Variable Description	Observation Frequency in Before Time Period (%) n=280	Observation Frequency in After Time Period (%) n=242
Number of non-motorist violations (N_NM_VIO)		
Zero	90(32.1)	56(23.2)
One	135(48.2)	128(52.9)
Two	40(14.3)	40(16.5)
Three	12(4.3)	10(4.1)
Four or more	3(1.1)	8(3.3)
Day of Week (DAY)		
Monday	39(13.9)	46(19.0)
Tuesday	53(18.9)	33(13.7)
Wednesday	38(13.6)	26(10.7)
Thursday	27(9.6)	44(18.2)
Friday	44(15.7)	23(9.5)
Saturday	41(14.6)	26(10.7)
Sunday	38(13.4)	44(18.2)
Weather Condition (WEATHER)		
Clear	267(95.4)	236(07.5)
Fog	0(0)	0(0)
Wet pavement	13(4.6)	4(1.7)

Table 3.9 continued

Rain	0(0)	2(0.8)
Snow	0(0)	0(0)
Snow pavement	0(0)	0(0)
Light condition (LIGHT)		
Night time	44(15.7)	65(26.9)
Non-nighttime	236(84.3)	177(73.1)
Violation with group (GROUP)		
Yes	73(26.1)	61(25.2)
No	207(73.9)	181(74.8)
Number of non-motorist violation opportunities (N_NM_OPP)		
One	95(33.9)	108(44.6)
Two	123(43.9)	89(36.8)
Three	12(4.3)	12(5.0)
Four	27(9.6)	16(6.6)
Five	3(1.1)	3(1.2)
Six	13(4.7)	7(2.9)
Seven or more	7(2.5)	7(2.9)
Weekend (WEEKEND)		
Yes	80(28.6)	70(28.9)
No	200(71.4)	172(71.1)
Number of crossing trains (N_TRAINS)		
Zero	12(4.3)	10(4.1)
One	200(71.4)	202(83.5)
Two or more	68(24.3)	30(12.4)
Train's simultaneous crossing (SIMULTANEOUS)		
Yes	17(6.1)	22(9.1)
No	263(93.9)	220(90.9)
Train stoppage (STOP)		

Table 3.9 continued

Yes	20(7.1)	15(6.2)
No	260(92.9)	227(93.8)
Gate malfunction (G_MALF)		
Yes	4(1.4)	10(4.1)
No	276(98.6)	232(95.9)

TABLE 3.10 Descriptive Statistics of Non-Motorist Numerical Variables

Variable Description	Descriptive Statistics in Before Time Period			Descriptive Statistics in After Time Period			Total Mean Values	Total Std. Dev.
	Min./ Max. Value	Mean	Std. Dev.	Min./ Max. Value	Mean	Std. Dev.		
Number of Violations (N_NM_VIO)	0/7	0.96	0.942	0/8	1.14	1.050	1.044	0.997
Number of Violation opportunities (N_NM_OPP)	1/14	2.30	1.736	1/11	2.07	1.602	2.193	1.677
Time (second) between the start and the end of flashing lights (G_DOWN)	51/2870	320.90	237.713	27/2811	330.72	239.185	320.356	238.214
Time (second) between the start of flashing lights and train arrival (T_ARRIVAL)	23/237	50.29	20.472	14/224	553.06	22.590	51.545	21.482
Number of crossing trains (N_TRAINS)	0/2	1.08	0.314	0/5	1.11	0.512	1.090	0.417
Number of violations type 1 (N_NM_V1)	0/3	0.13	0.412	0/4	0.08	0.373	0.105	0.395
Number of violations type 2 (N_ NM _V2)	0/7	0.44	0.827	0/7	0.73	0.963	0.575	0.904
Number of violations type 3 (N_ NM _V3)	0/4	0.37	0.691	0/4	0.33	0.710	0.352	0.700
Number of violations type 4 (N_ NM _V4)	0/2	0.02	0.157	0/1	0.00	0.064	0.011	0.123
Number of type 1 violation opportunities (N_NM_OPP1)	0/3	0.14	0.430	0/4	0.08	0.373	0.111	0.405

Table 3.10 continued

Number of type 2 violation opportunities (N_NM_OPP2)	0/7	1.20	1.056	0/9	1.20	1.135	1.201	1.093
Number of type 3 violation opportunities (N_NM_OPP3)	0/7	0.92	1.002	0/4	0.78	0.950	0.857	0.980
Number of type 4 violation opportunities (N_NM_OPP4)	0/2	0.03	0.213	0/2	0.02	0.157	0.025	0.189

Due to the short duration of the educational activity (2 days), it was assumed that any effects of this activity on non-motorist's gate violations would be short-lived. Thus, the before and after educational activity data were limited to one week before and one week after the educational activity and were extracted from dataset 2. The total number of observations in this case was 97, of which 49 were collected during the week prior to the educational activity (i.e., September 22nd -28th, 2011), while 48 were collected during the week following the educational activity (i.e., October 1st -7th, 2011). Table 3.11 presents a simple comparison of the means of the two types of non-motorists' gate violations across the one-week periods occurring before and after the educational activity; it also presents information on the available opportunities for engaging in V1 and V2 type violations during the two time periods. On average, fewer V1 violations were observed per train crossing event at the HRGC after the educational activity (0.02 versus 0.18). The reduction in mean V1 violations per train crossing event was 88.65%, and a student's t-statistic value of 2.45 for comparing the before and after means was statistically significant at the 5% level of significance (a critical t-statistic value of 1.96

was used for establishing statistical significance at the 5% level). Therefore, on average, V1 violations reduced in the period following the educational activity. This appeared to be an important finding until the variable representing the number of opportunities for V1 violations (N_N_OPP_V1) was reviewed, which showed a reduction of 88.65% in opportunities for violations during the period following the educational activity.

It is clear that fewer opportunities were available for engaging in V1 violations in the period following the educational activity. In fact, non-motorists availed every V1 opportunity that was available. In light of this information, the educational activity cannot be credited with reducing non-motorists' V1 violations, despite the observance of a statistically significant reduction associated with the post-educational activity period. That reduction was due to fewer available opportunities. Opportunities for V1 violations are governed by non-motorists' arrival timings at the HRGC, and for unknown reasons there were fewer available in the period following the educational activity. This finding underscores the need to take into account available opportunities for violations in before-after comparisons to avoid incorrectly assigning credit to safety-improving measures.

TABLE 3.11 Comparisons of Gate Violations and Violation Opportunities

Variable	Brief description	Period	Mean per event	Std. Dev.	Percent change	t-statistic
N_N_V1	Count of non-motorists passing under descending HRGC gates	Before	0.18	.44	-88.65	2.45
		After	0.02	.14		
N_N_V2	Count of non-motorists passing around fully lowered HRGC gates	Before	0.51	.68	-38.75	1.49
		After	0.31	.62		
N_N_OPP_V1	Count of opportunities for non-motorists to engage in type V1 violations	Before	0.18	.44	-88.65	-
		After	0.02	.14		
N_N_OPP_V2	Count of opportunities for non-motorists to engage in type V2 violations	Before	1.12	.92	31.78	-
		After	1.47	.98		

The before-after comparison of mean V2 violations per train crossing event showed a reduction of 38.75%, while an increase of 31.78% in opportunities for V2 violations was recorded in the period after educational activity. Thus, V2 violations reduced despite an increase in opportunities to engage in such violations in the period after the educational activity. However, the t-statistic for the simple comparison of before and after means was not statistically significant ($1.49 < 1.96$). This comparison did not account for other variables that may have affected the occurrence of V2 violations.

CHAPTER 4

MODEL ESTIMATION

4.1 MODELING HRGC GATE VIOLATIONS

Counts of gate violations in datasets 1 and 2 consisted of non-negative integers that are best modeled with Poisson and Negative Binomial regression models (Washington et al. 2011). The Poisson distribution approximates rare-event count data, such as crashes and gate violations at HRGCs. In a Poisson regression model, the probability of a certain HRGC (i) having y_i violation crossings per year (where y_i is a non-negative integer) is given by,

$$P(y_i) = \frac{EXP(-\lambda_i)\lambda_i^{y_i}}{y_i!} \tag{4.1}$$

where,

> $P(y_i)$ is the probability of HRGC i having y_i violation crossings per year, and
>
> λ_i is the Poisson parameter for HRGC i, which is equal to HRGC i's expected number of violation crossings per year, $E(y_i)$.

Poisson regression models are estimated by specifying the Poisson parameter λ_i as a function of explanatory variables. For example, in this case, the explanatory variables may include weather condition, light condition, time period, weekend, vehicle volume, and so on. The most common relationship between the explanatory variables and the Poisson parameter is the log-linear model,

$$\lambda_i = EXP\ \ \beta x_i \tag{4.2}$$

where,

x_i is a vector of explanatory variables,

and β is a vector of estimable parameters.

This model can be estimated by standard maximum likelihood methods.

A property of the Poisson distribution is that the mean and variance of the frequency of violation crossings at an HRGC should be equal, implying $E\ y_i\ = VAR\ y_i$. The data are said to be under dispersed if $E\ y_i\ > VAR\ y_i$ or over dispersed if $E\ y_i\ < VAR\ y_i$. Parameter estimates may be biased if corrective measures are not taken when under- or over dispersion is encountered (Hilbe 2011; Washington et al. 2011). In the case of over dispersion, which is usually more common than under dispersion, the Negative Binomial model can be used, as it relaxes the Poisson requirement of mean and variance equality. The Negative Binomial model is derived by rewriting equation 4.2 such that, for each HRGC

$$\lambda_i = EXP\ \ \beta x_i + \varepsilon_i \tag{4.3}$$

where,

$EXP\ \ \varepsilon_i$ is a Gamma-distributed disturbance term with mean 1 and variance α.

The addition of this term allows the variance to differ from the mean, as shown below:

$$VAR(y_i) = E(y_i)[1 + \alpha E(y_i)] = E(y_i) + \alpha E(y_i)^2 \qquad (4.4)$$

The Poisson regression model is regarded as a limiting model of the Negative Binomial regression model because α approaches 0, meaning that the selection between these two models is dependent on the value and statistical significance of α. The parameter α is referred to as the over dispersion parameter. Statistical significance of the α parameter in an estimated model indicates the appropriateness of the Negative Binomial regression. For the test of model fit, rho-squared value and chi-squared value are used to measure the goodness-of-fit of developed models. Rho-squared value is a statistical measure of how well the regression line approximates the real data points; usually it ranges from 0 to 1. A rho-squared value of 1.0 indicates that the regression line perfectly fits the data. The chi-squared value is used to test a null hypothesis stating that the frequency distribution of certain events observed in a sample are consistent with a particular theoretical distribution. The model fit is better with a lager chi-squared value. In addition, marginal value is used to find the change in the dependent variable in the model that is associated with a unit change in a specific independent variable when other independent variables do not change. These three values (i.e., Rho-squared value, chi-squared value, and marginal value) were presented in the following statistical prediction models.

4.2 MOTORIST AND NON-MOTORIST GATE VIOLATIONS AT HRGCS

Combination of dataset 1 and 2 was used to investigate variables associated with motorist and non-motorist gate violations. Different types of motorist/non-motorist gate violation frequencies per train crossing event were the dependent variables for which Poisson and negative binomial models were estimated to identify factors associated with those dependent variables. NLOGIT (version 4.0) was used for model estimation.

Table 4.1, 4.2. and 4.3 present the estimated Poisson model for counts of motorists' total gate violations (N_VEH_VIO), type 1 and 3 gate violations, (N_VEH_V1V3), and types 2 and 4 gate violations (N_VEH_V2V4). The model equations were:

$$\lambda_{N\_VEH\_VIO} = e^{0.229*\mathrm{GROUP}+0.133*\mathrm{N\_VEH\_OPP}+0.013*\mathrm{V\_TRAFFIC}+0.138*\mathrm{N\_TRAINS}+0.255*\mathrm{LIGHT}-1.079} \quad (4.5)$$

$$\lambda_{N\_VEH\_V1V3} = e^{0.286*\mathrm{GROUP}+0.071*\mathrm{N\_VEH\_OPP}+0.179*\mathrm{V\_TRAFFIC}+0.110*\mathrm{N\_TRAINS}+0.242*\mathrm{LIGHT}-0.989} \quad (4.6)$$

$$\lambda_{N\_VEH\_V2V4} = e^{0.390*\mathrm{N\_VEH\_OPP}+0.007*\mathrm{T\_ARRIVAL}+0.299*\mathrm{N\_TRAINS}-5.740} \quad (4.7)$$

TABLE 4.1 Poisson Model for Motorists' Gate Violations (N_VEH_VIO)

Independent Variable	Estimated Coefficient	*t*-Value	Mean Value	Marginal Value
(GROUP), indicator variable for gate violation group (0=individual passing, 1=group passing) (GROUP)	0.229	5.210	0.657	0.190
(N_VEH_OPP), number of total violation opportunities	0.133	10.870	2.259	0.110
(V_TRAFFIC), vehicle volume including vehicles in queue and violated	0.013	4.779	5.379	0.011
(N_TRAINS), number of crossing trains	0.138	3.072	1.053	0.115
(LIGHT), indicator variable for light condition (0=night time, 1=non-night-time)	0.255	6.617	0.627	0.212
Constant	-1.079	-18.074	-	-0.896

Model summary statistics:
Number of observations=4199
Log likelihood=-4605.476
Restricted log likelihood=-4875.574
Chi-squared statistic=540.195, and
P-value for chi-squared statistics=.000

TABLE 4.2 Poisson Model for Motorists' V1 and V3 Violations (N_VEH_V1V3)

Independent Variable	Estimated Coefficient	*t*-Value	Mean Value	Marginal Value
(GROUP) indicator variable for gate violation group (0=individual passing, 1=group passing)	0.286	6.342	0.657	0.229
(N_VEH_OPP) number of total violation opportunities	0.071	4.816	2.259	0.057
(V_TRAFFIC) vehicle volume including vehicles in queue and violated	0.179	6.031	5.379	0.014
(N_TRAINS) number of crossing trains	0.110	2.290	1.053	0.088
(LIGHT) indicator variable for light condition (0=night time, 1=non-night-time)	0.242	6.156	0.627	0.194
Constant	-0.989	-15.057	-	-0.791

Model summary statistics:
Number of observations=4199
Log likelihood=-4563.681
Restricted log likelihood=-4755.385
Chi-squared statistic=383.409, and
P-value for chi-squared statistics=.000

TABLE 4.3 Poisson Model for Motorist's V2 and V4 Violations (N_VEH_V2V4)

Independent Variable	**Estimated Coefficient**	***t*-Value**	**Mean Value**	**Marginal Value**
(N_VEH_OPP) number of total violation opportunities	0.390	13.767	2.265	0.0073
(T_ARRIVAL) time between light flashing and train arrival	0.007	10.214	53.020	0.0001
(N_TRAINS) number of crossing trains	0.299	1.959	1.090	0.0006
Constant	-5.740	-30.303	-	-0.1182

Model summary statistics:
Number of observations=4039
Log likelihood=-361.169
Restricted log likelihood=-583.754
Chi-squared statistic=445.169, and
P-value for chi-squared statistics=.000

From tables 4.1 to 4.3, the p-values for the chi-squared statistics were all less than 0.05, which implies that each model has at least one statistically significant variable. In tables 4.1-4.3, the positive values of the estimated coefficients represent the increase in violation frequency with the corresponding variables, and vice versa, for the negative estimated coefficients. Even though not all of the following independent variables were statistically significant (i.e., with t-values less than 1.96 at the 5% level of significance), it is still meaningful to show the relationships between violation frequency and various impact factors (Khattak et al. 2002; Hauer 2004). In these models, the variable with the t-value less than 1.96 is N_TRAINS in table 4.3.

In table 4.1, the total frequency of motorist violations increased with more violation opportunities and higher traffic volumes. These relationships are easy to understand using human judgment: a higher number of approaching vehicles increases the number of violation opportunities, and henceforth, the actual occurrence of violations. It was also found that the total motorist violation frequency increased with group crossing, the non-nighttime period, and more crossing trains. One explanation for these relationships, perhaps, is that following vehicles would like to conduct the same maneuvers as front vehicles in a crossing group, even though these crossing maneuvers would be violations. Moreover, poor lighting conditions at night may draw attention away from motorists as they pass the HRGC, compared to good lighting conditions during the day time. Thirdly, more crossing trains would produce longer motorist waiting times, which could lead to the occurrence of type 3 and type 4 violations. For the marginal value, it shows that how violation frequency changes with a unit change in a specific independent variable when all other independent variables are held at their means. For example, in this model, a 1% increase in traffic volume and crossing trains at the HRGC increased violations by 1.1% and 11.5%, respectively.

In table 4.2, the frequency of motorists' combined type 1 and 3 violations, which have similar characteristics, increased with group crossing, more violation opportunities, higher traffic volume, more train crossing, and the non-nighttime period. The associated factors are the similar to the previous model for reasons previously explained.

In table 4.3, it can be seen that the frequency of motorists' combined type 2 and type 4 violations (again, similar violation types) increased with more violation opportunities and more train crossings. These relationships are easy to explain using human judgment; however, the number of train crossings did not impact the violation frequency significantly at the 5% level of significance. It was also found that violation frequency increased with longer train arrival times. One possible explanation is that longer train arrival times allotted available time for vehicles to go around the fully descended gates.

Table 4.4, 4.5, and 4.6 present the estimated Poisson model for counts of non-motorists' total gate violations (N_NM_VIO), violation type 1 and 3 gate violations (N_NM_V1V3), and violation type 2 and 4 gate violations (N_NM_V2V4). . The model equations are:

$$\lambda_{N\_NM\_VIO} = e^{0.488*\mathrm{GROUP}+0.061*\mathrm{NM\_TRAFFIC}+0.282*\mathrm{STOP}+0.217*\mathrm{LIGHT}+0.624*\mathrm{G\_MALF}-0.491} \quad (4.8)$$

$$\lambda_{N\_NM\_V1V3} = e^{0.325*\mathrm{GROUP}+0.141*\mathrm{N\_NM\_OPP}+0.208*\mathrm{WEEKEND}-1.284} \quad (4.9)$$

$$\lambda_{N\_NM\_V2V4} = e^{0.449*\mathrm{GROUP}+0.077*\mathrm{NM\_TRAFFIC}+0.402*\mathrm{N\_TRAINS}+0.590*\mathrm{STOP}+1.630*\mathrm{G\_MALF}-1.489} \quad (4.10)$$

TABLE 4.4 Poisson Model for Non-Motorist Total Violations (N_NM_VIO)

Independent Variable	Estimated Coefficient	*t*-Value	Mean Value	Marginal Value
(GROUP) indicator variable for gate violation group (0=individual passing, 1=group passing)	0.488	5.798	0.277	0.504
(NM_TRAFFIC) non-motorist volume including non-motorists in queue and violated	0.061	5.622	1.870	0.063
(STOP) indicator variable for train stoppage at crossing (0=non-stop, 1=stop)	0.282	2.206	0.076	0.291
(LIGHT) indicator variable for light condition (0=night time, 1=non-night-time)	0.217	2.285	0.776	0.223
(G_MALF) indicator variable for gate malfunction without train arrival (0=non-malfunction, 1=malfunction)	0.624	3.417	0.020	0.645
Constant	-0.491	-5.316	-	-0.507

Model summary statistics:

Number of observations=736

Log likelihood=-883.616

Restricted log likelihood=-948.693

Chi-squared statistic=130.153, and
P-value for chi-squared statistics=.000

TABLE 4.5 Poisson Model for Non-Motorist V1 and V3 Violations (N_NM_V1V3)

Independent Variable	Estimated Coefficient	*t*-Value	Mean Value	Marginal Value
(GROUP) indicator variable for gate violation group (0=individual passing, 1=group passing)	0.325	2.525	0.275	0.130
(N_NM_OPP) number of total violation opportunities	0.141	6.434	2.176	0.079
(WEEKEND) indicator variable for weekend (0=non-weekend, 1=weekend)	0.208	1.856	0.290	0.092
Constant	-1.284	-14.556	-	-0.634

Model summary statistics:

Number of observations=766

Log likelihood=-675.447

Restricted log likelihood=-715.072
Chi-squared statistic=79.251, and
P-value for chi-squared statistics=.000

TABLE 4.6 Poisson Model for Non-Motorist V2 and V4 Violations (N_NM_V2V4)

Independent Variable	Estimated Coefficient	*t*-Value	Mean Value	Marginal Value
(GROUP) indicator variable for gate violation group (0=individual passing, 1=group passing)	0.449	3.931	0.277	0.252
(NM_TRAFFIC) non-motorist volume including non-motorists in queue and violated	0.077	5.878	1.870	0.043
(N_TRAINS) number of crossing trains	0.402	4.194	1.102	0.215
(STOP) indicator variable for train stoppage at crossing (0=non-stop, 1=stop)	0.590	3.849	0.076	0.332
(G_MALF) indicator variable for gate malfunction without train arrival (0=non-malfunction, 1=malfunction)	1.630	7.467	0.020	0.901
Constant	-1.489	-10.997	-	-0.824

Model summary statistics:
Number of observations=736
Log likelihood=-703.366
Restricted log likelihood=-768.662
Chi-squared statistic=130.593, and
P-value for chi-squared statistics=.000

Tables 4.4, 4.5, and 4.6 present the Poisson model results for non-motorist violations at the Fremont HRGC. From tables 4.4 to 4.6, the Chi-square tests for the three models indicated that at least one variable each was significant in the models. Some variables with t-values less than 1.96 were retained in the models as they still provided some useful information between the variables and violation frequencies. In these models, the variable with the t-value less than 1.96 was WEEKEND in table 4.5.

In table 4.4, it can be seen that the total frequency of non-motorist violations increased with higher traffic volume. It is possible that a higher number of approaching vehicles may have increased violation opportunities, and, correspondingly, the actual number of violations. In addition, it also the total frequency of non-motorist violations may increase with group crossing, train stoppage at the crossing, nighttime period, and gate malfunction. The reasons were listed as follows: First, a non-motorist in a group, when passing an HRGC, likely wishes to copy the actions of other violators (e.g., walking around the gates). Second, train stoppage at the crossing may increase the waiting time of non-motorists at the HRGC, increasing the opportunity for type 2 and violations. Third, non-motorists may be less cautious when crossing during good lighting conditions during day. Finally, gate malfunctions may confuse the judgment of non-motorists as they attempt to pass the HRGC, urging them to ignore the flashing warning lights and cross unsafely.

In Table 4.5, the frequency of combined type 1 and type 3 non-motorist violations (which have similar characteristics), increased with group crossing and more violation opportunities. The associated factors were similar to the previous model. The explanations for these relationships can potentially be explained using reasons previously mentions. Moreover, the two violations increased during weekend periods. One plausible explanation is that there may have been more non-motorist exposures as a result of weekend recreational activities, increasing the opportunity for crossing violations at the HRGC. However, the 'weekend' variable did not impact the violation frequency statistically significantly at the 5% level of significance.

In Table 4.6, the frequency of combined types 2 and 4non-motorist violations frequency of combination of type 2 and 4 (similar in nature) increased with group crossing, higher traffic volume, and more train crossing. It was also found that violation frequency may have increased with train stoppage at the crossing and gate malfunction, for reasons previously mentioned.

Motorist data in both dataset 1 and dataset 2 were combined and used to statistically evaluate the effects on safety of the median barrier maintenance performed between April 1st and April 18th, 2011. This data was used independently because non-motorists usually went across this HRGC along the sidewalks. Moreover, the barriers were installed on roadways, and therefore had no effect on improving safety among non-motorists.

From video footage, the installation of median barrier mainly helped to mitigate unsafe crossing of the violation types 2 and 4. Motorists conducting these two types of violations could abuse the plastic barriers and go around the fully descended gates. Prior to barrier maintenance, the barriers were badly damaged, producing more opportunities for motorists to violate the gates. Thus, only the violation frequency of the combination of types 2 and 4 was tested by statistical models to explore the safety effect of median barrier maintenance. Following the analysis using the Negative Binomial regression model, the result indicated that there was no statistically significant change in motorist's type 2 and 4 violation frequency before and after median barrier maintenance. The model is presented in appendix D in this dissertation.

4.3 EDUCATIONAL ACTIVITY ASSESSMENT

Educational activity assessment was based on analyzing one week before and one week after V2 violations only because this type of violation was deemed most dangerous and pertinent to correction via an educational activity. The descriptive statistics showed that V1 violations reduced in the after period accompanied by an equal reduction in opportunities for V1 violations and therefore were not considered in this analysis. V3 violations were not taken into account because they were deemed unaffected by the educational activity while there were no V4 violations recorded in the one week before and one week after periods.

Counts of V2 gate violations by non-motorists at HRGCs during train crossing events were modeled using the Poisson regression model (i.e., the dependent variable was N_NM_V2). Differences in the before and after educational activity periods were judged by inclusion of an indicator variable named "Period" in the model specification. The Poisson model was appropriate to use since the mean of N_NM_V2 in the dataset was 0.41 violations per train crossing event, with a variance of 0.43 violations per train crossing event squared. These two values were fairly close; therefore the Poisson model was used for the analysis of dataset 2.

Table 4.7 presents the estimated Poisson model for counts of N_NM_V2. The model equation is:

$$\lambda_{N\_NM\_V2} = e^{-0.92*PERIOD+0.80*N\_N\_OPP\_V2-0.58*NM\_TRAFFIC+0.01*T\_ARRIVAL-1.36*N\_TRAINS-0.07} \quad (4.11)$$

A positive coefficient in the above equation shows that counts of V2 violations increased with increasing values of the independent variable, while a negative coefficient indicates that V2 violations decreased with increasing values of the variable. The coefficients in the model were statistically tested using a student's t-test to assess whether they were different than zero (see table 4.7). The coefficient for the variable Period was negative and statistically significant at the 5% level of significance, showing that V2 violations decreased in the period after the educational activity. The marginal value for the variable Period showed that V2 violations reduced by 0.37 violations per train crossing event in the period following the educational activity.

The coefficient for variable N_N_OPP_V2, representing opportunities available to non-motorists to engage in V2 violations, was positive and statistically significant, showing that greater opportunities for V2 violations were accompanied by higher counts of V2 violations. The coefficient for non-motorist traffic (NM_Traffic) was also statistically significant, but the negative sign indicated that higher traffic was associated with lower counts of V2 violations. This may be due to a tendency to engage in unsafe behavior when no one else is around. Greater elapsed time between the onset of flashing lights and train arrival at the crossing (T_ARRIVAL) was associated with higher counts of V2 violations, but the variable was statistically not significant. The variable representing the number of trains during an event (N_TRAINS) was negatively associated with counts of V2 violations, but this variable, too, was statistically not significant.

TABLE 4.7 Estimated Poisson Model for Count of V2 per Train Crossing Event (N_NM_V2)

Variable	Brief description/coding	Estimated coefficient	t-statistic	Mean	Marginal value
PERIOD	0 if before educational activity, 1 if after educational activity	-0.92	-2.55	0.49	-0.37
N_N_OPP_V2	Count of opportunities for non-motorists to engage in type V2 violations	0.80	3.88	1.29	0.32
NM_TRAFFIC	Non-motorist traffic	-0.58	-2.79	1.26	-0.23
T_ARRIVAL	Elapsed time between onset of flashing lights and train arrival at the crossing	0.01	1.41	52.05	0.00
N_TRAINS	Number of passing trains	-1.36	-1.84	1.13	-0.54
CONSTANT	Constant in the model	-0.07	-0.08	-	-0.03

Model summary statistics:
Number of observations=96
Chi-squared statistic=21.58, and
P-value for chi-squared statistics=.000

Other variables available in the database were tried in the model specification, but their inclusion did not improve the model. In summary, modeling results showed that after accounting for opportunities, counts of V2 violations per train crossing event reduced in the period after the educational activity was undertaken at the HRGC.

CHAPTER 5

CONCLUSIONS AND FUTURE STUDY

5.1 CONCLUSIONS

The safety of motorists, pedestrians, and bicyclists has received consideration from researchers, but the focus mostly has been on highway segments and intersections. There is relatively less knowledge available in the published literature regarding the safety of these groups at HRGCs. Of the available knowledge, much more is focused on motor vehicle operators than pedestrians and bicyclists. With increasing rail and highway traffic, the issue of safety at HRGCs will become more important. The goal of this research was to better understand the safety of HRGCs by considering not only motorists, but also pedestrians and bicyclists.

Specific objectives were: 1) the estimation of count-based models for motorist and non-motorist gate violations, and 2) the assessment of change in violations at the selected HRGC in response to an educational activity focused on improving non-motorists' safety at HRGCs. Gate violation data were collected and analyzed for these two objectives. Data on pedestrians and bicyclists were combined for the purpose of analysis due to the absence of any significant differences in violations between these two crossing user groups. Based on the analysis, the following conclusions were reached:

For the first objective, motorists' gate violation frequencies were found to increase with a greater number of violation opportunities and higher highway and rail traffic volume. Gate violation frequencies were higher if other users were present at the HRGC, as well as during non-nighttime periods. Non-motorist gate violations increased with greater highway traffic volume, the presence of others at the HRGC, train stoppage on the crossing, non-nighttime periods, and gate malfunctions. Additionally, this research did not find a statistically significant difference in motorists' type 2 and 4 violations prior to and following median barrier maintenance.

In terms of the second objective, the educational activity was effective toward improving non-motorists' safety at the HRGC. Many jurisdictions are hesitant to increase enforcement due to budget constraints, and access reduction measures (e.g., closure of HRGCs or conversion of at-grade HRGCs to grade-separated HRGCs) are not popular in many communities. However, this conclusion shows that jurisdictions can rely on educational activities to improve non-motorist safety when budgetary or political considerations make other options less appealing. The availability of educational materials from Operation Lifesaver made the process more expedient. The successful safety improvement in this study demonstrated the effectiveness of educational activities targeted at HRGCs, rather than at other locations or activities intended for the whole community. This research underscored the need to account for violation opportunities in before-and-after comparisons in HRGC gate violation studies, in order to avoid incorrectly assigning safety change credit to measures undertaken in hopes of improving safety. Also, it is possible that educational activity may be contaminated by the fact that crossing users became aware of the installed camera. This factor may impact the educational activity's evaluation results for non-motorist safety at HRGCs.

For the research contribution, this study provided an approach to assess HRGC safety based on more common HRGC gate violations rather than crashes. In addition, this study identified safety-related factors at HRGCs pertinent to both motorists and non-motorists. Finally, this study indicated the need to collect non-motorist safety information at HRGCs.

5.2 FUTURE STUDY

The educational activity undertaken did not have any measured effect on the relatively less dangerous V1 violations (passing under descending gates). Non-motorists used all opportunities for V1 violations that were available to them, although for unknown reasons, fewer were available in the period following the educational activity. Two questions are noteworthy for future investigation: what factors are responsible for the availability of fewer or more V1 violation opportunities in a period of time, and what interventions might reduce or eliminate such violations by non-motorists? Answers to these questions will help with measures aimed at improving HRGC safety.

This research utilized only one HRGC for data collection; it is possible that HRGC users in different geographic areas may behave differently. Therefore, gate violation data at HRGCs could be collected at multiple locations and tested for the identification of safety impact factors. The results could then be compared to detect location-related characteristics impacting safety. New educational activities, especially activities focused on children, could be designed and evaluated and safety material could be developed and learned. For example, school HRGC safety presentations and activities, as well as commercials and posters in public, could be conducted to test their effects on safety. In addition, long-term (e.g., one year) educational activities concerning non-motorists could be implemented to compare their effects to short-term (e.g., one week) educational activities.

Limitations of the examined education research activity included the use of a single HRGC and a relatively small sample of observed non-motorists. Wider geographic coverage and larger sample sizes may reveal more insights and provide more generalizable results. Also, for future studies, the measurement of violation opportunities should be an essential consideration of the study design.

Pedestrian and bicyclist data were combined in this study to conduct non-motorist gate violation analysis, due to similar violation counts. Future studies may consider evaluating pedestrian-only and bicyclist-only gate violation models. Finally, model estimations may be improved by considering safety-related factor interactions in the model specifications and the considering other dependent variables such as violation rates, e.g., violation count per violation opportunity or violation count per unit time period during train crossing event.

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APPENDIX A

TABLE A. Variables Used for Individual Violation Data Analysis

Variable	Label/Description	Coding/Units
EVENT	Series number of each crossing user behavior at HRGC	Integer (1, 2…)
DATE	Date of observation for each train crossing event	Year, Month, Day
PA_CAR	Indicator variable for passenger car	0=other vehicle, 1=passenger car
VIOLATION	Indicator variable for violations	0=no violation, 1=violation
VEH_V1	Indicator variable for type 1 violation by a vehicle	0=no type 1 violation by a vehicle, 1=type 1 violation by a vehicle
VEH_V2	Indicator variable for type 2 violation by a vehicle	0= no type 2 violation by a vehicle, 1=type 2 violation by a vehicle
VEH_V3	Indicator variable for type 3 violation by a vehicle	0=no type 3 violation by a vehicle, 1=type 3 violation by a vehicle
VEH_V4	Indicator variable for type 4 violation by a vehicle	0=no type 4 violation by a vehicle, 1=type 4 violation by a vehicle
PED_V1	Indicator variable for type 1 violation by a pedestrian	0=no type 1 violation by a pedestrian, 1=type 1 violation by a pedestrian
PED_V2	Indicator variable for type 2 violation by a pedestrian	0= no type 2 violation by a pedestrian, 1=type 2 violation by a pedestrian
PED_V3	Indicator variable for type 3 violation by a pedestrian	0=no type 3 violation by a pedestrian, 1=type 3 violation by a pedestrian
PED_V4	Indicator variable for type 4 violation by a pedestrian	0=no type 4 violation by a pedestrian, 1=type 4 violation by a pedestrian
BIC_V1	Indicator variable for type 1 violation by a bicyclist	0=no type 1 violation by a bicyclist, 1=type 1 violation by a bicyclist
BIC_V2	Indicator variable for type 2 violation by a bicyclist	0=no type 2 violation by a bicyclist, 1=type 2 violation by a bicyclist
BIC_V3	Indicator variable for type 3 violation by a bicyclist	0=no type 3 violation by a bicyclist, 1=type 3 violation by a bicyclist
BIC_V4	Indicator variable for type 4 violation by a bicyclist	0=no type 4 violation by a bicyclist, 1=type 4 violation by a bicyclist

Table A. continued

NM_V1	Indicator variable for non-motorist violation type 1	0=non-violation, 1=violation
NM_V2	Indicator variable for non-motorist violation type 2	0=non-violation, 1=violation
NM_V3	Indicator variable for non-motorist violation type 3	0=non-violation, 1=violation
NM_V4	Indicator variable for non-motorist violation type 4	0=non-violation, 1=violation
V1	Indicator variable for violation type 1	0=non-violation, 1=violation
V2	Indicator variable for violation type 2	0=non-violation, 1=violation
V3	Indicator variable for violation type 3	0=non-violation, 1=violation
V4	Indicator variable for violation type 4	0=non-violation, 1=violation
T_PERIOD1	Time period of barrier maintenance	0= before maintenance, 1=after maintenance
T_PERIOD2	Time period of educational awareness activity	0= before education, 1=after education
CHILD	Indicator variable for child	0=adult, 1= child
GROUP	Indicator variable for a group of crossing users	0=individual, 1= group
VEH_OPP V1	Indicator variable for vehicle violation opportunity type 1	0=non-opportunity, 1= opportunity
VEH_OPP V2	Indicator variable for vehicle violation opportunity type 2	0=non-opportunity, 1= opportunity
VEH_OPP V3	Indicator variable for vehicle violation opportunity type 3	0=non-opportunity, 1= opportunity
VEH_OPP V4	Indicator variable for vehicle violation opportunity type 4	0=non-opportunity, 1= opportunity
PED_OPP V1	Indicator variable for pedestrian violation opportunity type 1	0=non-opportunity, 1= opportunity
PED_OPP V2	Indicator variable for pedestrian violation opportunity type 2	0=non-opportunity, 1= opportunity
PED_OPP V3	Indicator variable for pedestrian violation opportunity type 3	0=non-opportunity, 1= opportunity
PED_OPP V4	Indicator variable for pedestrian violation opportunity type 4	0=non-opportunity, 1= opportunity
BIC_OPP V1	Indicator variable for bicyclist violation opportunity type 1	0=non-opportunity, 1= opportunity
BIC_OPP V2	Indicator variable for bicyclist violation opportunity type 2	0=non-opportunity, 1= opportunity
BIC_OPP V3	Indicator variable for bicyclist violation opportunity type 3	0=non-opportunity, 1= opportunity
BIC_OPP V4	Indicator variable for bicyclist violation opportunity type 4	0=non-opportunity, 1= opportunity
NM_OPP V1	Indicator variable for non-motorist violation opportunity type 1	0=non-opportunity, 1= opportunity

Table A. continued

NM_OPP V2	Indicator variable for non-motorist violation opportunity type 2	0=non-opportunity, 1= opportunity
NM_OPP V3	Indicator variable for non-motorist violation opportunity type 3	0=non-opportunity, 1= opportunity
NM_OPP V4	Indicator variable for non-motorist violation opportunity type 4	0=non-opportunity, 1= opportunity
OPPOR1	Indicator variable for violation opportunity type 1	0=non-opportunity, 1= opportunity
OPPOR2	Indicator variable for violation opportunity type 2	0= non-opportunity, 1= opportunity
OPPOR3	Indicator variable for violation opportunity type 3	0= non-opportunity, 1= opportunity
OPPOR4	Indicator variable for violation opportunity type 4	0= non-opportunity, 1= opportunity
V_TRAFFIC	Vehicle volume (including vehicles in queue and violated)	Integer (0, 1, 2…)
B_TRAFFIC	Bicyclist volume (including bicyclists in queue and violated)	Integer (0, 1, 2…)
P_TRAFFIC	Pedestrian volume (including pedestrians in queue and violated)	Integer (0, 1, 2…)
NM_TRAFFIC	Non-motorist volume (including non-motorists in queue and violated)	Integer (0, 1, 2…)
WEEKEND	Indicator variable for train crossing event on a weekend (Saturday or Sunday)	0 = event on weekdays, 1 = event on weekend
DAY	Days of a week	Monday, Tuesday,…Sunday
G_DOWN	Elapsed time between the onset and cessation of flashing lights at the HRGC	seconds
T_ARRIVAL	Elapsed time between the onset of flashing lights and train arrival at the crossing	seconds
N_TRAINS	Number of crossing trains	Integer (0, 1, 2…)
SIMULTANEOUS	Indicator variable for simultaneous crossing of trains	0 = non-simultaneous, 1 = simultaneous
STOP	Indicator variable for train stoppage at the crossing	0 = non-stop, 1 = stop
WEATHER	Categorical variable for weather condition at the time of train crossing	0 = clear, 1=fog, 2=wet pavement, 3=rain, 4=snow
LIGHT	Categorical variable for light condition at the time of train crossing	0 = nighttime, 1=daytime, 2=dawn or dust, 3=dark or cloudy, 4=others
G_MALF	Indicator variable for gate malfunction when no train arrived	0 = non-malfunction, 1 = malfunction

[A] Violation type 1 is passing under descending gates, violation type 2 is passing around fully lowered gates, violation type 3 is passing under ascending gates, and violation type 4 is passing around fully lowered gates between successive trains (Khattak and Luo 2011). [V]iolation opportunity types are the correspondence of violation types. For example, violation opportunity type 1 is the opportunity for violation type 1 occurrence.

APPENDIX B

TABLE B. Full Statistical Description for Median Barrier Maintenance

Variable Description	Observation Frequency in Before Time Period (%) n=1266	Observation Frequency in After Time Period (%) n=482
Number of violations (N_VEH_VIO)		
Zero	591(46.7)	144 (29.9)
One	493(38.9)	202(41.9)
Two	155(12.2)	114(23.7)
Three or more	27(2.2)	22(4.5)
Day of Week (DAY)		
Monday	163(12.9)	35(7.3)
Tuesday	200(15.8)	71(14.7)
Wednesday	202(16.0)	82(17.0)
Thursday	214(16.9)	80(16.6)
Friday	167(13.2)	82(17.0)
Saturday	174(13.7)	89(18.5)
Sunday	146(11.5)	43(8.9)
Weather Condition (WEATHER)		
Clear	1176(92.9)	428(88.8)
Fog	17(1.3)	0(0)
Wet pavement	20(1.6)	0(0)
Rain	0(0)	32(6.6)
Snow	47(3.7)	22(4.6)
Snow pavement	6(0.5)	0(0)
Light condition (LIGHT)		
Night time	597(47.2)	107(22.2)
Daytime	175(13.8)	112(23.2)
Dawn or dusk	48(3.8)	62(12.9)
Dark or cloudy	446(35.2)	201(41.7)
Passenger car involvement (P_CAR)		
Yes	603(47.6)	243(50.4)
No	663(52.4)	239(49.6)

Table B. continued

Violation with group(GROUP)		
Yes	770 (60.8)	328(68.0)
No	496(39.2)	154(32.0)
Number of violation opportunities (N_OPP)		
One	237(18.7)	172(35.7)
Two	433(34.2)	227(47.1)
Three	171(13.5)	54(11.2)
Four	327(25.8)	20(4.1)
Five or more	98(7.8)	9(1.9)
Weekend (WEEKEND)		
Yes	320(25.3)	132(27.4)
No	946(74.7)	350(72.6)
Number of crossing trains (N_TRAINS)		
Zero	36(2.8)	12(2.5)
One	1148(90.7)	414(85.9)
Two or more	82(6.5)	56(11.6)
Train's simultaneous crossing (SIMULTANEOUS)		
Yes	65(5.1)	41(8.5)
No	1201(94.9)	441(91.5)
Train stoppage (STOP)		
Yes	47(3.7)	19(3.9)
No	1219(96.3)	463(96.1)
Clear weather (CLEAR)		
Yes	1176(92.9)	428(88.8)
No	90(7.1)	54(11.2)
Daytime (D_TIME)		
Night time	597(47.2)	107(22.2)
Non-Night time	669(52.8)	375(77.8)

Table B. continued

Gate malfunction (G_MALF)		
Yes	32(2.5)	14(2.9)
No	1234(97.5)	468(97.1)
Number of violation type 1 (N_V1)		
Zero	1084(85.6)	445(92.3)
One	167(13.2)	34(7.1)
Two or more	15(1.2)	3(0.6)
Number of violation type 2 (N_V2)		
Zero	1242(98.1)	476(98.8)
One or more	24(1.9)	6(1.2)
Number of violation type 3 (N_V3)		
Zero	717(56.6)	155(32.2)
One	447(35.3)	207(42.9)
Two or more	102(8.1)	120(24.9)
Number of violation type 4 (N_V4)		
Zero	1263(99.8)	481(99.8)
One or more	3(0.2)	1(0.2)
Number of type 1 violation opportunities (N_OPP1)		
Zero	1079(85.2)	427(88.6)
One	170(13.4)	51(10.6)
Two or more	17(1.4)	4(0.8)
Number of type 2 violation opportunities (N_OPP2)		
Zero	392(31.0)	417(86.5)
One	475(37.5)	54(11.2)
Two	360(28.4)	7(1.5)
Three or more	39(3.1)	4(0.8)
Number of type 3 violation opportunities (N_OPP3)		
Zero	41(3.2)	5(1.0)
One	565(44.6)	203(42.1)

Table B. continued

Two	621(49.1)	260(53.9)
Three or more	39(3.1)	14(3.0)
Number of type 4 violation opportunities (N_OPP4)		
Zero	1260(99.5)	478(99.2)
One or more	6(0.5)	4(0.8)
Vehicle's U-Turn (U_TURN)		
Yes	6(0.5)	5(1.0)
No	1260(99.5)	477(99.0)
Vehicle's backup (B_UP)		
Yes	47(3.7)	11(2.3)
No	1219(96.3)	471(97.7)

APPENDIX C

Full Statistical Description for Educational Activity

TABLE C.1. Pedestrian-Related Variable Frequency (Percentage) Statistics for Educational Activity Case

Variable Description	Observation Frequency in Before Time Period (%) n=151	Observation Frequency in After Time Period (%) n=162
Number of pedestrian violations (N_PED_VIO)		
Zero	59(39.1)	47(29.0)
One	72(47.7)	78(48.1)
Two	16(10.6)	21(13.0)
Three or more	4(2.6)	16(9.9)
Day of Week (DAY)		
Monday	29(19.2)	29(17.9)
Tuesday	27(17.9)	21(13.0)
Wednesday	21(13.9)	13(8.0)
Thursday	17(11.3)	29(17.9)
Friday	17(11.3)	15(9.3)
Saturday	19(12.6)	22(13.6)
Sunday	21(13.8)	33(20.3)
Weather Condition (WEATHER)		
Clear	140(92.7)	160(98.8)
Fog	0(0)	0(0)
Wet pavement	5(3.3)	2(1.2)
Rain	0(0)	0(0)
Snow	0(0)	0(0)
Snow pavement	0(0)	0(0)
Light condition (LIGHT)		
Night time	21(13.9)	33(20.4)
Non-nighttime	130(86.1)	129(79.6)
Violation with group (GROUP)		
Yes	44(29.1)	53(32.7)

Table C.1 continued

No	107(70.9)	109(67.3)
Age (AGE)		
Adult	129(85.4)	141(87.0)
Children	14(9.3)	18(11.1)
Missed information	8(5.3)	3(1.9)
Number of pedestrian violation opportunities (N_PED_OPP)		
One	46(30.5)	66(40.7)
Two	74(49.0)	61(37.7)
Three	2(1.3)	11(6.8)
Four	23(15.2)	10(6.2)
Five or more	6(4.0)	14(8.6)
Weekend (WEEKEND)		
Yes	40(26.5)	55(34.0)
No	111(73.5)	107(66.0)
Number of crossing trains (N_TRAINS)		
Zero	3(2.0)	9(5.6)
One	132(87.4)	131(80.9)
Two or more	16(10.6)	22(13.5)
Train's simultaneous crossing (SIMULTANEOUS)		
Yes	10(6.6)	15(9.3)
No	141(93.4)	147(90.7)
Train stoppage (STOP)		
Yes	11(7.3)	6(3.7)
No	140(92.7)	156(96.3)
Gate malfunction (G_MALF)		
Yes	3(2.0)	9(5.6)
No	148(98.0)	153(94.4)
Number of pedestrian violations type 1 (N_PED_V1)		

Table C.1 continued

Zero	139(92.1)	152(93.8)
One	7(4.6)	6(3.7)
Two or more	5(3.3)	4(2.5)
Number of pedestrian violations type 2 (N_PED_V2)		
Zero	115(76.2)	96(59.3)
One	29(19.2)	46(28.4)
Two or more	7(4.6)	20(12.3)
Number of pedestrian violations type 3 (N_PED_V3)		
Zero	105(69.5)	117(72.2)
One	38(25.2)	33(20.4)
Two or more	8(5.3)	12(7.4)
Number of pedestrian violations type 4 (N_PED_V4)		
Zero	151(100.0)	162(100.0)
Number of type 1 vehicle violation opportunities (N_PED_OPP1)		
Zero	138(91.4)	153(94.4)
One	8(5.3)	6(3.7)
Two or more	5(3.3)	3(1.9)
Number of type 2 vehicle violation opportunities (N_PED_OPP2)		
Zero	29(19.2)	46(28.4)
One	89(58.9)	78(48.1)
Two	26(17.2)	16(9.9)
Three or more	7(4.7)	22(13.6)
Number of type 3 vehicle violation opportunities (N_PED_OPP3)		
Zero	45(29.8)	65(40.1)
One	74(49.0)	64(39.5)
Two	27(17.9)	19(11.7)

Table C.1 continued

Three or more	5(3.3)	14(8.7)
Number of type 4 vehicle violation opportunities (N_PED_OPP4)		
Zero	150(99.3)	159(98.1)
One or more	1(0.7)	3(1.9)

TABLE C.2. Bicyclist-Related Variable Frequency (Percentage) Statistics for Educational Activity Case

Variable Description	**Observation Frequency in Before Time Period (%) n=160**	**Observation Frequency in After Time Period (%) n=134**
Number of bicyclist violations (N_BIC_VIO)		
Zero	48(30.0)	28(20.9)
One	85(53.1)	87(64.9)
Two	22(13.8)	15(11.2)
Three or more	5(3.1)	4(3.0)
Day of Week (DAY)		
Monday	16(10.0)	31(23.1)
Tuesday	34(21.3)	18(13.4)
Wednesday	22(13.8)	17(12.7)
Thursday	13(8.1)	17(12.7)
Friday	28(17.5)	10(7.5)
Saturday	26(16.3)	20(14.9)
Sunday	21(13.1)	21(15.7)
Weather Condition (WEATHER)		
Clear	152(95.0)	130(97.0)
Fog	0(0)	0(0)
Wet pavement	8(5.0)	2(1.5)
Rain	(0)	2(1.5)
Snow	(0)	0(0)
Snow pavement	(0)	0(0)

Table C.2 continued

Light condition (LIGHT)		
Night time	25(15.6)	47(35.1)
Non-nighttime	135(84.4)	87(64.9)
Violation with group (GROUP)		
Yes	33(20.6)	17(12.7)
No	127(79.4)	117(87.3)
Age		
Adult	108(67.5)	78(58.2)
Children	42(26.3)	50(37.3)
Missed information	10(6.2)	6(4.5)
Number of bicyclist violation opportunities(N_BIC_OPP)		
One	66(41.3)	75(56.1)
Two	71(44.4)	50(37.3)
Three	3(1.9)	3(2.2)
Four	12(7.5)	3(2.2)
Five or more	8(4.9)	3(2.2)
Weekend (WEEKEND)		
Yes	48(30.0)	41(30.6)
No	112(70.0)	93(69.4)
Number of crossing trains (N_TRAINS)		
Zero	3(1.9)	2(1.5)
One	144(90.0)	114(85.1)
Two or more	13(8.1)	18(13.4)
Train's simultaneous crossing (SIMULTANEOUS)		
Yes	10(6.3)	14(10.4)
No	150(93.7)	120(89.6)
Train stoppage (STOP)		
Yes	10(6.9)	12(9.0)
No	149(93.1)	122(91.0)
Gate malfunction (G_MALF)		

Table C.2 continued

Yes	3(1.9)	2(1.5)
No	157(98.1)	132(98.5)
Number of bicyclist violations type 1 (N_BIC_V1)		
Zero	142(88.8)	129(96.3)
One	17(10.6)	5(3.7)
Two or more	1(0.6)	0(0)
Number of bicyclist violations type 2 (N_BIC_V2)		
Zero	101(63.1)	54(40.3)
One	47(29.4)	66(49.3)
Two or more	12(7.5)	14(10.4)
Number of bicyclist violations type 3 (N_BIC_V3)		
Zero	125(78.1)	113(84.3)
One	25(15.6)	19(14.2)
Two or more	10(6.3)	2(1.5)
Number of bicyclist violations type 4 (N_BIC_V4)		
Zero	156(97.5)	132(98.5)
One or more	4(2.5)	2(1.5)
Number of type 1 bicyclist violation opportunities (N_BIC_OPP1)		
Zero	141(88.1)	129(96.3)
One	17(10.6)	5(3.7)
Two or more	2(1.3)	0(0)
Number of type 2 bicyclist violation opportunities (N_BIC_OPP2)		
Zero	31(19.4)	21(15.7)
One	101(63.1)	92(68.7)
Two	19(11.9)	16(11.9)
Three or more	9(5.6)	5(3.7)

Table C.2 continued

Number of type 3 bicyclist violation opportunities (N_BIC_OPP3)		
Zero	71(44.4)	78(58.2)
One	70(43.8)	50(37.3)
Two	13(8.1)	5(3.7)
Three or more	6(3.7)	1(0.8)
Number of type 4 bicyclist violation opportunities (N_BIC_OPP4)		
Zero	153(95.6)	132(98.5)
One or more	7(4.4)	2(1.5)

APPENDIX D

TABLE D. Poisson Model to Evaluate the Impact of Median Barrier Maintenance for Motorist Type 2 and 4 Violations at Fremont HRGC

Independent Variable	Estimated Coefficient	*t*-Value	Mean Value	Marginal Value
(PERIOD1) indicator variable for March (0=non-March, 1=March)	-0.222	-0.882	0.302	-0.127
(PERIOD2) indicator variable for April (0=non-April, 1=April)	0.389	0.969	0.116	0.035
(PERIOD3) indicator variable for September (0=non-September, 1=September)	0.504	1.741	0.301	-0.034
(N_OPP) number of total violation opportunities	0.451	26.914	2.265	0.066
(T_ARRIVAL) time between light flashing and train arrival	0.007	10.350	53.020	0.001
Constant	-5.735	-21.530	-	-0.638

Note: -=not applicable. Model summary statistics:

Number of observations=4039

Log likelihood=-359.257

Restricted log likelihood=-583.754

Chi-squared statistic=448.993, and

P-value for chi-squared statistics=.000