AN INVESTIGATION OF COLLISIONS AND INJURY SEVERITY LEVELS IN NOVA SCOTIA

by

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Abstract

The social and economic burden imposed on society by road collisions is a major issue in Nova Scotia and across jurisdictions. In Nova Scotia, road safety related injuries are the greatest contributor to the economic and social costs associated with injury, costing an estimated $74 million per year. This thesis study undertakes a comprehensive analysis of over 74,000 collisions in Nova Scotia involving about 208,700 individuals from 2007 to 2011 to characterize collision patterns, including collision frequencies, injury severity outcomes, personal attributes of persons involved, temporal characteristics, and spatial distribution of collisions. Injury severity of two particularly vulnerable road user groups, pedestrians and cyclists, is investigated using alternative ordered response models with an emphasis on understanding the influence of the built environment and land use characteristics on collision outcomes. The investigation reveals that collisions have several patterns of incidence including the age and gender of the road user, the types of injury severity experienced, the month, day, and day of week that collisions occur, and where the collisions occur. The model results suggest that injury severity levels of pedestrians and cyclists are influenced by several road user characteristics, collision characteristics, environmental conditions, and characteristics of the built environment and surrounding land uses. The research offers new insights into the interplay of built environment characteristics on collisions involving pedestrians and cyclists. The thesis contributes to recent advances in the literature that identify the need to incorporate built environment and land use variability in collision and injury severity modeling.

Acknowledgements

This research would not have been possible without the support of many individuals. I would like thank my supervisor, Dr. Muhammad Ahsanul Habib, for his valuable guidance and advice. Many thanks to Ahsan for supporting me in attending conferences in Atlanta and Washington, exposing me to the world of transportation research and broadening my perspectives. I would also like to thank members of the DalTRAC team for sharing the literature and offering peer guidance with the project, and of course, the many non-academic get-togethers we have had over the past year.

I would also like to convey thanks to Service Nova Scotia for providing the data required to complete the study. Thanks to Greg Morrison for his efforts in securing the collision data and undertaking preliminary analysis of the data.

Finally, and most importantly, I would like to express my heartfelt thanks to my family, Katlyn, Aiden, Mom, Dad, and Jess for their understanding and support throughout the duration of the MPS program.

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CHAPTER 1: INTRODUCTION

The economic and social implications of collisions cost an estimated $25 billion per year in Canada (Transport Canada, 2011). In Nova Scotia, road safety related injuries have been identified as the greatest contributor to the human and economic costs associated with injury in the province. Motor vehicle collision injuries cost the province an estimated $74 million per year (Province of Nova Scotia, 2013). A collision can involve any one or combination of road users: pedestrians, cyclists, motorists, and passengers. When a collision occurs, the outcome can be minor or serious, sometimes resulting in death. Road users like pedestrians and cyclists are recognized as vulnerable as collisions involving these users typically result in higher injury severity level outcomes. Road safety issues are a growing concern across jurisdictions, including municipalities within Nova Scotia. Planning and engineering design for road safety has historically been dominated by that for the automobile, but active transportation is increasingly being recognized as an important part of a sustainable transportation system, resulting in increased desire to formulate solutions that consider the safety of these users. Although many factors contribute to the frequency and severity of collisions, we can inform safety countermeasures and policy actions by investigating collision patterns and trends and providing empirically analyzed evidence to collisions.

Effective collision frequency and severity reduction requires an understanding of the factors that affect the likelihood of a collision occurring, as well as the characteristics that may mitigate or exacerbate the level of injury sustained. Although considerable research has been devoted to addressing road safety issues of motorized transportation, relatively little has been directed towards active transportation, which has left significant knowledge and methodology gaps in collision analysis. Many earlier studies focus on collision occurrence/frequency at an aggregate level of analysis while few studies have examined individual-level pedestrian and cyclist injury severity in collisions. Furthermore, few empirical studies have simultaneously investigated injury severity and how it is influenced by the built environment and other land use characteristics. Progress in reducing collision frequency and severity has been minimal in Nova Scotia, especially when considering pedestrians and cyclists.

This thesis addresses several issues regarding road safety in Nova Scotia and the often under investigated influences of the built environment on injury severity outcomes of pedestrians and cyclists. In addressing these issues, the thesis first describes the patterns and trends of collisions in Nova Scotia and then investigates injury severity levels of cyclists and pedestrians using an econometric modeling approach. Many current injury severity models place their main emphasis on characteristics related to the person, the natural environment, and the factors contributing to the collision itself. It is important, however, that the injury severity model should examine the influences of the built environment. Interpreting the information revealed through the empirical analysis is useful to transportation planners in making recommendations to improve road safety.

1.1 General Objective

The main objective of the thesis is to investigate road safety issues in Nova Scotia using descriptive and econometric analysis methods. The research presented in this thesis attempts to inform the broader issues of road safety while at the same time empirically investigating injury severity of cyclists and pedestrians to understand specific contributing factors to injury severity outcomes.

1.1.1 Specific Objectives

The general objective can be divided into three specific objectives:

1. Investigate and characterize the trends and patterns of collisions at a macro-level, road user level and by each county in Nova Scotia.
2. Examine pedestrian and cyclist injury severity outcomes and the statistical association with of personal, collision, environment, built environment, and land use characteristics using ordered response econometric models and evaluate model fit.
3. Interpret results from descriptive analysis and econometric models and offer recommendations to inform provincial and municipal government, police, and other agencies on what areas to concentrate resources to improve road safety for the public.

1.1.2 Ethical Considerations

Ethical considerations were taken into account and deemed to have no significant implications to the study. The collision records used in this study can be considered secondary use. Under Dalhousie University guidelines. Secondary use refers to the use of information originally collected for a purpose other than the current research purpose. Ethics review is not required for this research as it relies exclusively on secondary use of anonymous information. The process of data linkage or recording or dissemination of results cannot generate identifiable information. The results produced from the study are presented in an aggregate manner. That is, individual persons cannot be identified through their personal information or precise geographic location.

1.3 Thesis Outline

This thesis consists of five main chapters. The **second** chapter presents a descriptive analysis of pedestrian, cyclist, and vehicle collisions. The chapter describes the patterns and trends of collision frequency, characteristics of the road users, injury severity characteristics, temporal characteristics, and spatial distribution. The **third** chapter presents an empirical analysis of cyclist injury severity based on the need to examine the determinants of injury severity of vulnerable road users developed in the previous chapter. Chapter **four** presents an empirical model for pedestrian injury severity. The model focuses on influences of the built environment and other land use characteristics. The final chapter, chapter **five**, summarizes the main findings of the thesis and draws out the overall implications of the research.

Chapter 1	•An introductory chapter that outlines the general theme and objectives (current chapter).
Chapter 2	•A descriptive analysis of pedestrian, cyclist, and auto driver and passenger collisions. •The chapter identifies need to examine the determinants of injury severity for vulnerable road users in the event of collisions.
Chapter 3	•An empirical analysis of cyclist injury severity. •The model focuses on built environment and neighbourhood characteristics. •The chapter identifies need to incorporate variability of built environment in modeling framework.
Chapter 4	•An empirical analysis of pedestrian injury severity. •The model focuses on influence of built environment and land use characteristcs on injury severity. •The modeling framework incorporates built environment and land use variability.
Chapter 5	•Final chapter of conclusions that draws out the overall implications of the research.

Figure 1: Outline of thesis chapters

CHAPTER 2: DESCRIPTIVE ANALYSIS OF COLLISIONS [1]

2.1 Introduction

Increasing trends in road user collisions has made road safety a growing concern in Nova Scotia. Improving safety begins with putting the trends of collisions into context. This chapter presents a comprehensive investigation of collisions involving all road users in Nova Scotia from 2007 to 2011. The key objective of this chapter is straightforward: to describe the patterns and trends of collisions. The analysis represents the first comprehensive analysis of the provincial collision data since 2007.

The analysis uses the Nova Scotia Collision Record Database (NSCRD) data collected from Service Nova Scotia and Municipal Relations (SNSMR). The data includes records of over 74,000 collisions involving about 128,000 road users. The analysis presented in this chapter shows a macro-level and user level analysis of collision frequency, characteristics of the road users involved, injury severity characteristics, temporal characteristics, and spatial distribution of collisions.

The findings of this chapter are expected to be a useful resource for informing policy-makers and decision-makers on what areas to concentrate resources to improve road safety. Furthermore, the analysis described in this report can aid in the design, development, and implementation of road safety programs (e.g. the Share the Road campaign). The contributions of this research are timely given the increased awareness and emphasis on road safety, especially of active transportation users, in Nova Scotia. The county-level analysis will be beneficial to communities throughout Nova Scotia who have expressed the need for collision statistics in making effective decisions and informing planning strategies.

Similar comprehensive descriptive analyses have been conducted in various jurisdictions across North America (and abroad). These studies typically rely on one or a combination of pre-existing databases such as police accident reports or hospital records. The descriptive analysis presented in this chapter utilizes data collected from SNSMR, the department responsible for collecting and maintaining the data for all reported collisions in the province. The collision data classifies collisions based on user type and severity. The dataset includes information on the day and time of the collision, age and gender of the individuals involved, injury severity, location information, safety device use, person position, road and weather conditions, and lighting conditions. Although the dataset is seemingly comprehensive, some variables

[1] This chapter is partially based on the technical paper Forbes J.J. and Habib, M.A. "Nova Scotia Collision Study", November 2013.

were not included in this analysis due to the presence of incomplete and/or inconsistent reporting of some attribute fields.

2.2 Literature Review

Road user safety is one of the primary objectives when designing any transportation system. To reduce the number of collisions that occur, a collision study can be conducted to profile the incidents occurring and for identifying safety countermeasures or policy actions to address collisions. For the purposes of this chapter, a collision study is defined as a descriptive analysis that characterizes patterns of collision by road user type and compares the personal attributes, vehicle, roadway, environmental, and collision characteristics across the study period.

The literature review presented in this chapter is concise, identifying several North American collision studies such as Fredericton, NB (Opus International, 2012), Vancouver, BC (Urban Systems, 2012), New York (NYCDOT, 2010), Chicago, IL (CDOT, 2012), and Boston, MA (Boston Bikes, 2013) to review data collection practices, methodological approaches to safety research, and strategies implemented to address safety issues. More detailed reviews of the literature can be found with the models presented in Chapters 3 and 4. Table 1 presents a summary of collision studies reviewed in an effort to inform the analysis presented in this chapter.

Table 1: Summary of collision studies reviewed

Study	Data source	Analysis framework employed	Road users considered		Key findings
The New York City Pedestrian Safety Study and Action Plan (NYCDOT, 2010)	NYSDOT	Frequency and cross-tabulation analysis	Pedestrian	Yes	• Traffic fatalities are decreasing • Pedestrian experience higher levels of injury severity compared to vehicle occupant • Driver inattention was frequently cited as contributing factor in pedestrian collisions • Males are more frequently involved in collisions
			Cyclist	---	

			Driver/Passenger	Yes	• Collisions occur most frequently between 6PM and 7PM
Capital City Pedestrian Crossing Study, City of Fredericton (Opus International, 2012)	Not stated	Frequency analysis supplemented with stakeholder and public feedback	Pedestrian	Yes	• Downtown core to be the biggest area of concern about pedestrian safety • Survey respondents cited intersections in the downtown core to be "unsafe" • Review of the collision statistics confirmed downtown intersections had the highest number of collisions in the City • Stakeholder and survey respondents identified visibility of crosswalks as an issue
			Cyclist	---	
			Driver/Passenger	---	
City of Chicago Bicycle Crash Analysis (CDOT, 2012)	Illinois Department of Transportation	Frequency analysis	Pedestrian	---	• Total number of cyclist fatalities is decreasing • Largest number of injurious collisions

	National Highway and Traffic Safety Administration American College of Surgeons		Cyclist	Yes	occur between 4 and 7 PM. • The majority of collisions occur during the summer months of June, July, and August • Males are more often involved than females.
			Driver/Passenger	---	
Pedestrian Safety Study (Urban Systems, 2012)	Insurance Corporation of British Columbia (ICBC) Vancouver Police Department (VPD)	Frequency and cross-tabulation analysis	Pedestrian	Yes	• Visibility is a key contributing factor; collisions are most common during the winter • Highest proportion of pedestrian collisions occur during the PM peak period between 5-7 • Persons aged 20-29 ae most likely to be involved in a collision • The majority of collisions occur at intersections • Relatively even distribution of collisions involving males and females
			Cyclist	---	
			Driver/Passenger	---	
Boston Cyclist Safety Report			Pedestrian	Yes	• There has been a minimal increase in
			Cyclist	Yes	

(Boston Bikes, 2013)	Boston Police Department Boston Emergency Medical Services Boston Bikes	Frequency analysis	Driver/Passenger	Yes	total crash incidents between 2010 and 2012 • Young adults, particularly men between 18 and 30 comprise more than half of all injured cyclists • High volume roads have a higher number of collisions • Behavioural factors include cyclists not stopping at red lights or stop signs, cyclists riding into oncoming traffic, drivers not seeing the cyclists and drivers opening doors

From reviewing Table 1, we can see that collision studies utilize information from a number of datasets including insurance agencies, police departments, research centres, and government transportation departments. In all instance of the collision studies reviewed, the data source used for analysis came from either one, or a combination of the specified sources.

These collision studies typically identify patterns and trends of collisions through descriptive statistical analysis (primarily, frequency and cross-tabulation analysis) along with spatial analysis techniques to identify collision hotspots and other areas of high collision density (NYCDOT, 2010; Urban Systems, 2012). Analyzing collisions through injury severity frequency is common, utilizing the ordinal nature of injury severity to compare the outcome with collision conditions. Age and gender profiles are produced to profile the demographics most often involved in collisions. The time that a collision occurs provides valuable links to determine correlations between time of day and day of week that the collisions most frequently occur. Complementing the descriptive and spatial analysis, stakeholder involvement in the study assists in collecting information related to safety perceptions and public priorities (Opus International, 2012).

Most of the studies in Table 1 report a general decrease in collision frequency and severity. The most common trends in collisions include higher proportions of male involvement, decreasing trends in severe injuries, collisions occur most frequently between 4 and 7 PM, and that collision patterns usually follow a temporal trend (either most collisions occurring in the winter or during the summer). The review presented in Table 1 determined that intersections and urban areas are associated with more frequent and more serious collisions. Interaction with other road users and issues related to inattention have been shown to be the primary behavioural factors influencing collision frequency and severity. Collision prevention and reduction strategies arising from the studies reviewed in this chapter have included installing innovative pedestrian crossings, traffic calming devices, and enforcement and education campaigns. Enforcement and education campaigns have focused on distracted driving, impaired driving, safety workshops, social media, and theatrical performances to raise awareness on road safety issues (NYCDOT, 2010; CDOT, 2012; Opus International, 2012; Urban Systems, 2012; Boston Bikes, 2013).

The review indicates that few studies have included road users from all categories (pedestrians, cyclists, and vehicle occupants) in the study and even fewer studies have included a macro-level analysis. All of the previous studies reviewed have focused on one jurisdiction, typically a city. Therefore, this study attempts to investigate the patterns and trends of all collisions, at a macro-level and road user level, for the entire province of Nova Scotia. The current study also provides an analysis for each county in the province.

2.3 Method

2.3.1 Data Description

The analysis presented in this chapter was conducted using records drawn from the Nova Scotia Collision Record Database (NSCRD) retained at SNSMR. SNSMR collects and maintains data for all police reported collisions in Nova Scotia. In Nova Scotia, all collisions involving property damage over $1000 and injuries or fatalities occurring on a public road, as defined by the Motor Vehicle Act, require reporting. The NSCRD consists of data representing collisions in 18 counties in Nova Scotia.

The 2007-2011 NSCRD data includes information on over 74,000 collisions involving about 208,700 individuals. When a collision occurs, the completed collision report forms (MV58A) record a number of accident-related attributes including the date, time, and location of each incident, the age and parties involved, the severity of injuries sustained, as well as other basic information.

The injury severity of each individual involved in the accident is recorded on a five point ordinal scale: (1) not injured, (2) minor – no treatment, (3) moderate – treated and 19 released, (4) major – hospitalized, and (5) fatal. For the purpose of this study, the entire database representing collisions from the years 2007 to 2011 were analyzed. Data preparation involved a great deal of cleaning for validity of reported information and consistency of the data.

2.3.2 Statistical Analysis Process

The statistical analysis process involved a multistep approach. First, a macro analysis of the entire collision dataset, which considers all road users at an aggregate level, was undertaken to identify possible patterns and trends that are common to all road users. Second, an analysis was performed at the road user level. The factors investigated include injury severity, age and gender of involved persons, road and weather conditions, and time of the collisions.

By analyzing the severity of injury of the persons involved, we can identify the extent to which specific road user collisions involve the most risk. Age and gender provides a profile of the age groups most often involved. The time that a collision occurred provides valuable links to determine correlations between time of day, week, and year, and the occurrence of collisions.

The focus of analysis is to compare the characteristics of the different road user types and was facilitated by the use of histograms to compare the distribution of variables among different road user subsets. Figure 2 shows the process that was followed to analyze and categorize the collision data.

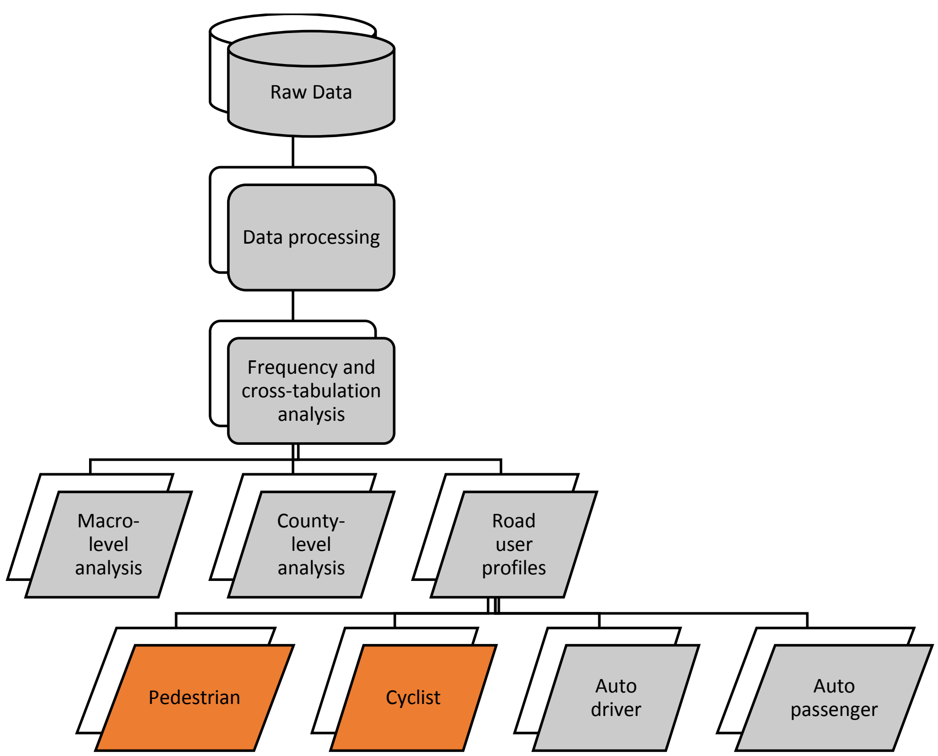


Figure 2: Simplified overview of collision study components

2.3.3 Data Limitation and Reliability

There are a number of limitations associated with the data. Due to the reporting thresholds (i.e. all collisions involving personal injury or exceeding $1000 in damage) in Nova Scotia, minor and less severe collisions are likely underrepresented in the data. There is also evidence of incomplete and inconsistent reporting in the data, which may be attributed to differences in police reporting statements or errors when the data is entered into the database.

The scope of analysis was limited to 2007 to 2011. Data pre-2007 was unavailable due to accessibility issues associated with a software change at SNSMR. The location information in the database is accurate but not precise. While the analysis presented in this chapter can identify the location of and frequency of spatial characteristics, we are limited in our ability to explain the influence of spatial variables.

The collision data was reviewed to check for errors, coded for missing information and additional pertinent information.

2.4 Macro Findings

2.4.1 Collisions Involving All Road Users

This section identifies and describes the factors that are common to all road users. These factors include the severity of injury, age and gender of involved persons, road and weather conditions, and time of collision. The purpose of the macro level analysis is to identify any common factors that may contribute to collisions, regardless of road user type.

Table 2 shows that the number of road user fatalities and injuries has been decreasing within the five-year period. On average, about 14,800 collisions occur in the Province of Nova Scotia every year. From 2007 to 2011, 387 traffic-related fatalities occurred.

Table 2: Road user fatalities and injuries in Nova Scotia (2007-2011)

Year	Fatal	Personal Injury	Total Collisions
2007	99	5100	14183
2008	82	4807	14383
2009	72	4833	15247
2010	70	4841	15016
2011	64	4970	15585
Grand Total	387	24551	74414
Average	77	4910	14883

Figure 3 shows that the total number of collisions is increasing from 2007 to 2011. There was a peak in the general trend as the total number of collisions increased by almost by 1,000 from the previous year but decreased by 300 in 2010. Between 2007 and 2011, there was an increase of almost 1,500 collisions from 14,000 in 2007 and 15,500 in 2011. Consistent with the collision frequency by year, Figure 4 shows the total number of persons involved in collisions increasingly annually.

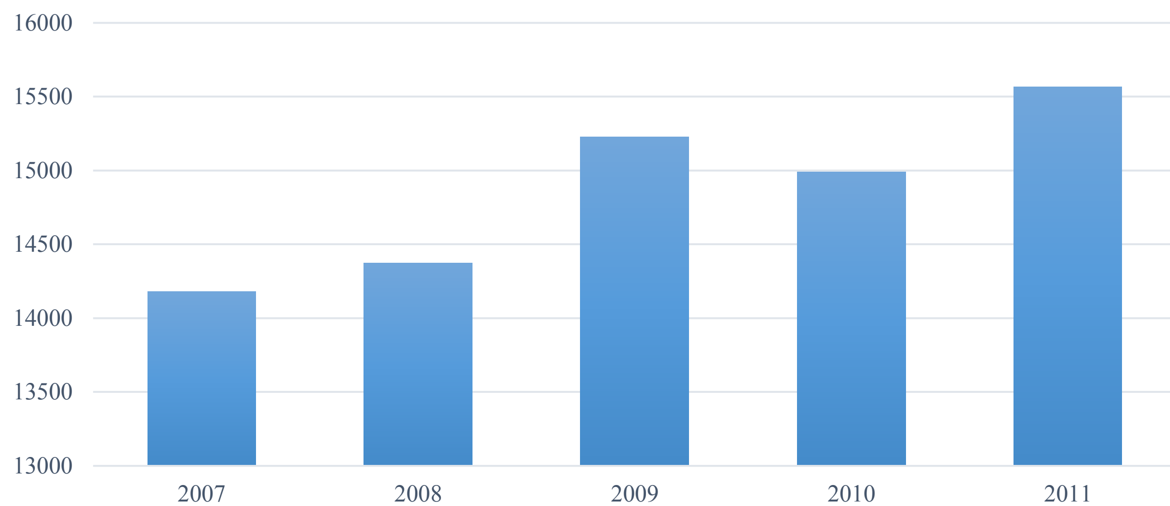


Figure 3: Total collisions by year

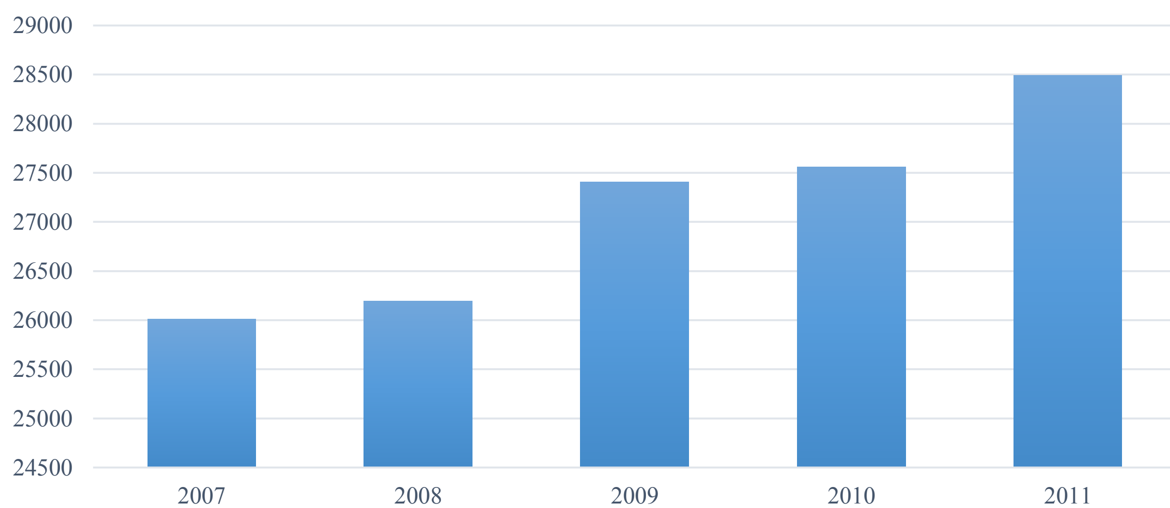


Figure 4: Total persons involved in collisions by year

Figure 5 shows average annual collisions per 1,000 population for each county in Nova Scotia. Halifax County has the most frequent collision per 1,000 population, followed by Colchester and Victoria County.

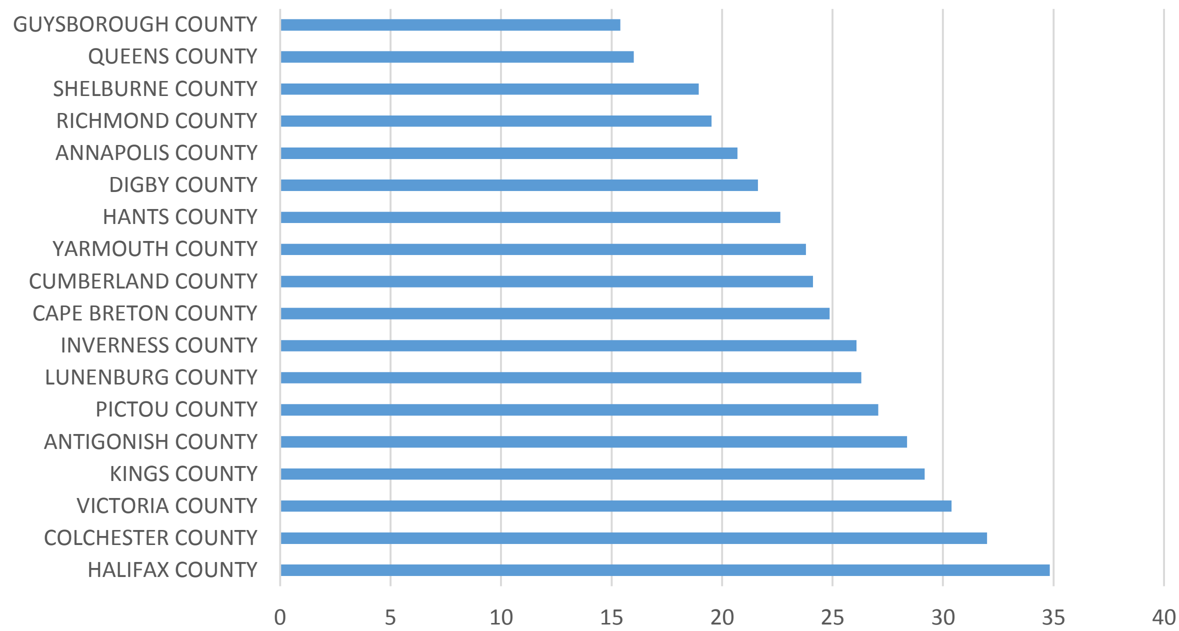


Figure 5: Average annual collisions by county (per 1,000) population)

2.4.2 Injury Severity

The MV58A (collision report form) has an injury field that helps categorize injuries that are sustained in collisions. Table 3 provides a description of injury severity classification. Drivers were most frequently involved in fatal collisions, followed by passengers, pedestrians, and cyclists. There has been a decreasing trend in fatalities from 2007 to 2011 (see Figure 6).

Table 3: Description of injury severity levels

Severity of Injury	**Severity description**
No Injury	No injuries sustained
Minor	This category includes minor abrasions, bruises, and complaint of pain. Minor injuries sustained; did not require medical assistance.
Moderate	Injuries required trip to hospital and treatment in the emergency room. Not admitted to hospital.
Major	Injuries required that person be admitted to hospital. This category includes person admitted for observation.
Fatal	Death occurred as a result of injuries from the collisions

Minor and no injury are the predominant type. The general distribution of injury severity does not change significantly throughout the five year study period (Figure 8). The distribution of injury severity varies significantly across counties in the study area. Figure 6 reveals a decreasing trend in fatalities from 2007 to 2011. Figure 7 shows the spatial distribution of fatal collisions in Nova Scotia; each point represented one collision.

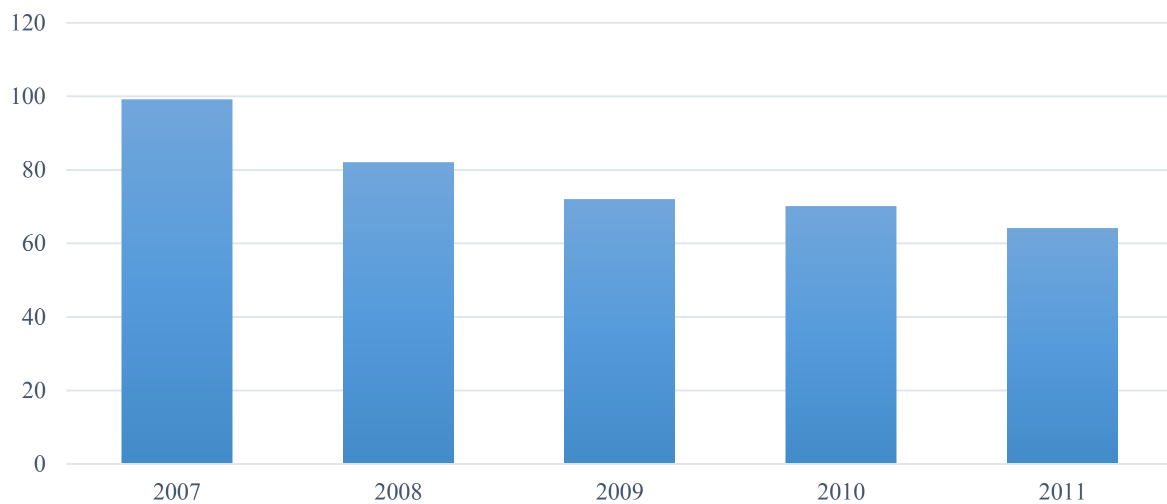


Figure 6: Fatal collisions by year

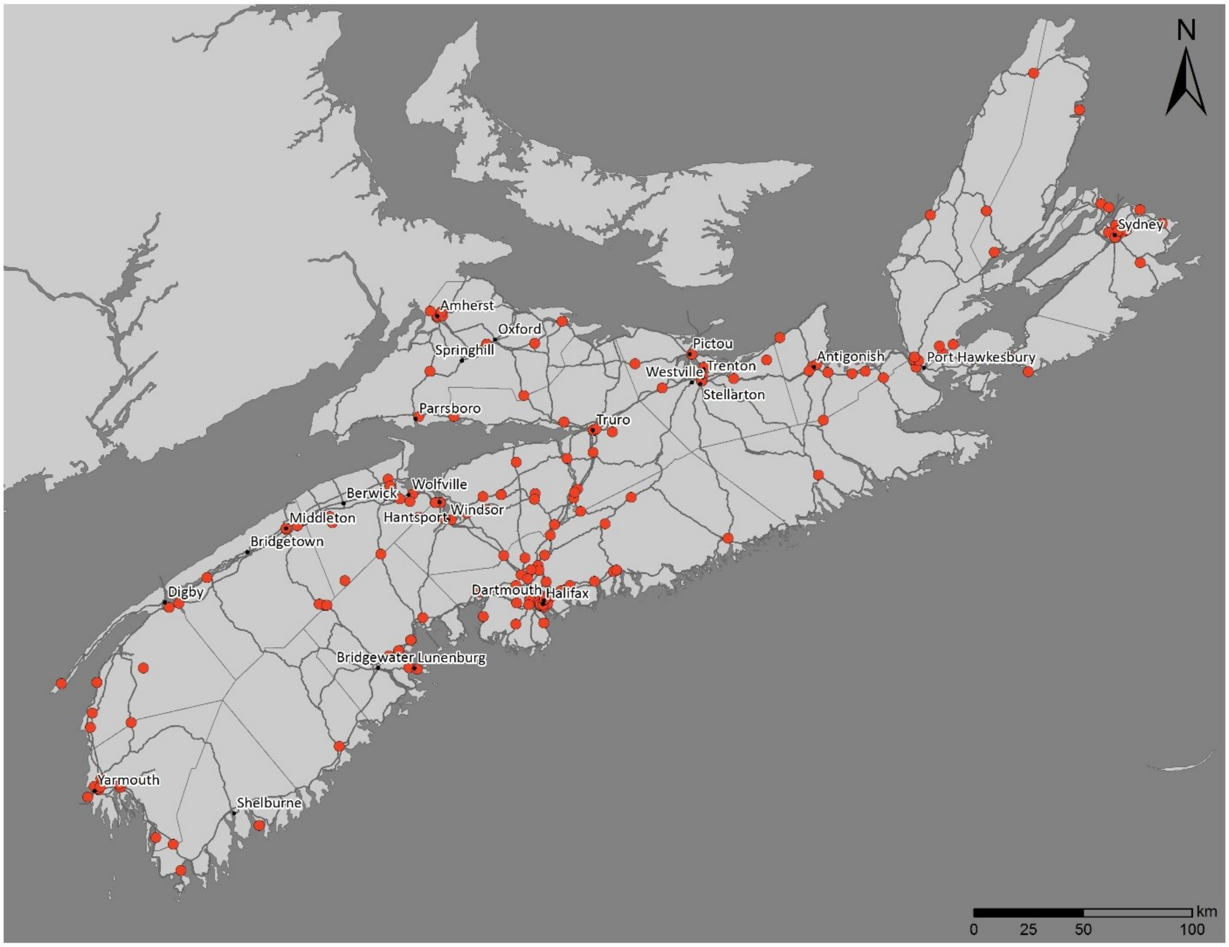


Figure 7: Spatial distribution of fatal collisions

The analysis reveals an increase in non-injurious collisions from 2007 to 2011. Moderate injuries have increased while major and fatal injuries have increased from 2007 to 2011. Figure 8 shows frequencies of injury severity for all road users. The frequency of fatal and major injury severities has decreased from 2007 to 2011 from 84 to 54 and 250 to 239 respectively. There has been a slight increase in moderate levels of injury and an increase in non-injuries and minor injuries.

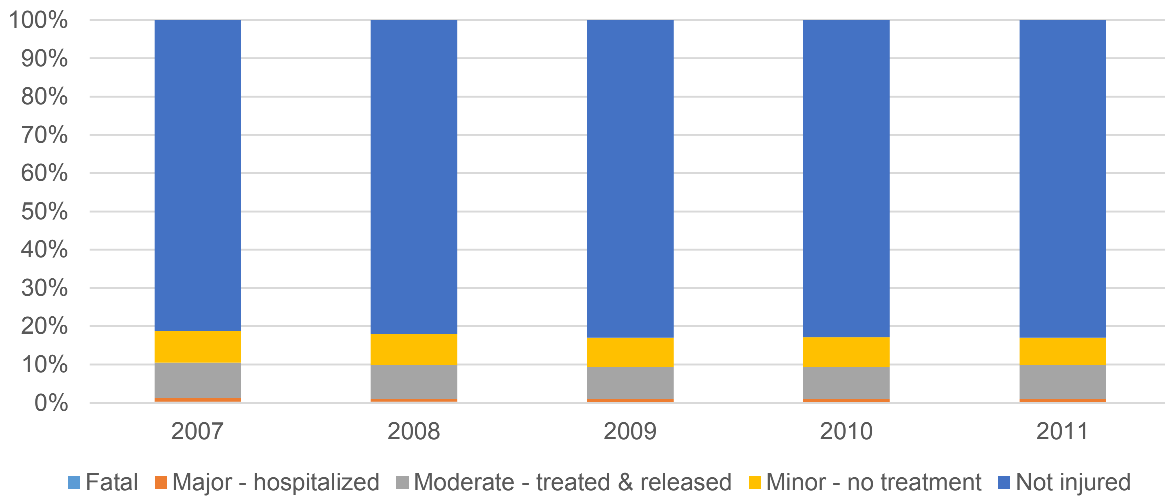


Figure 8: Injury severity of persons involved in collisions

2.4.2 Temporal Variations in Collision Patterns

Figure 9 shows the monthly distribution of all road user collisions. The frequency of collisions is higher during the winter seasons. There is a consistent monthly trend in collisions throughout 2007 to 2011.

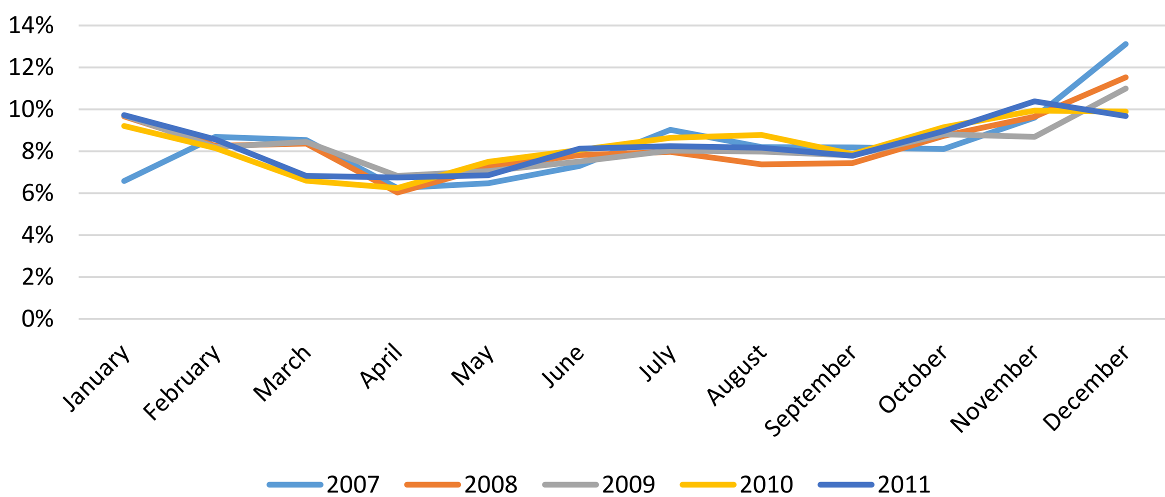


Figure 9: Monthly distribution of collisions

Collisions occur most frequently on Fridays. There is a higher distribution of collisions on weekdays than on weekends. There is little annual variation in the day of week distribution of collisions. Figure 10 shows the day of week distribution of collisions.

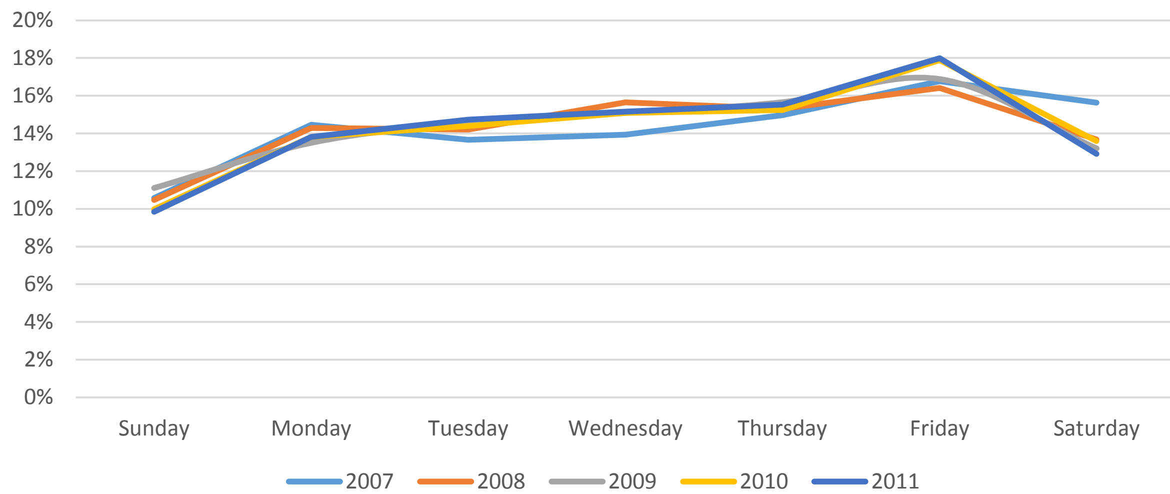


Figure 10: Day of week distribution of collisions

Figure 11 shows the time of day distribution of collisions. Collisions occur most frequently during the evening hours between 4 PM and 6 PM, when traffic volumes are typically higher. There is an increase during the morning peak hour, and one during the lunch hour.

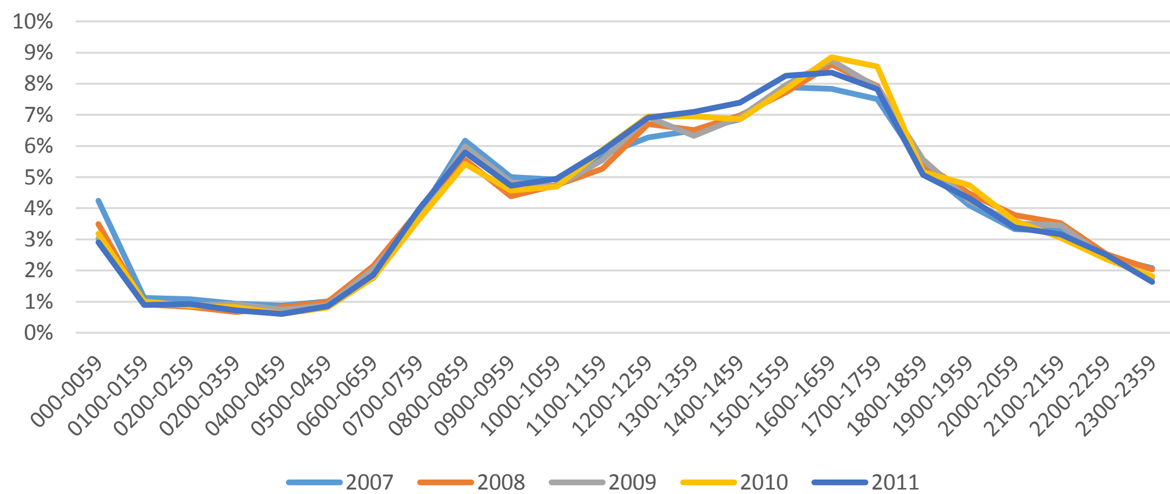


Figure 11: Time of day distribution of collisions

2.4.3 Personal Attributes of Persons Involved in Collisions

The distribution of age and gender of persons involved in collisions is detailed in Figure 12. The figure includes the provincial population distribution for comparing. The age distribution of road users involved in collisions is comparable to the age distribution in the province. The analysis indicates that males are more frequently involved in collisions (56%) than females (44%). This distribution is inconsistent with the gender distribution in the population of Nova Scotia, where males make up 48% of the population and females make up 52%. The age groups of 35-54 were involved in 36% of all collisions and account for 30% of the Nova Scotia population. The trend in age is generally consistent between males and females. Road users within the 45-54 age group are the most often involved in collisions, which is the largest age cohort in Nova Scotia.

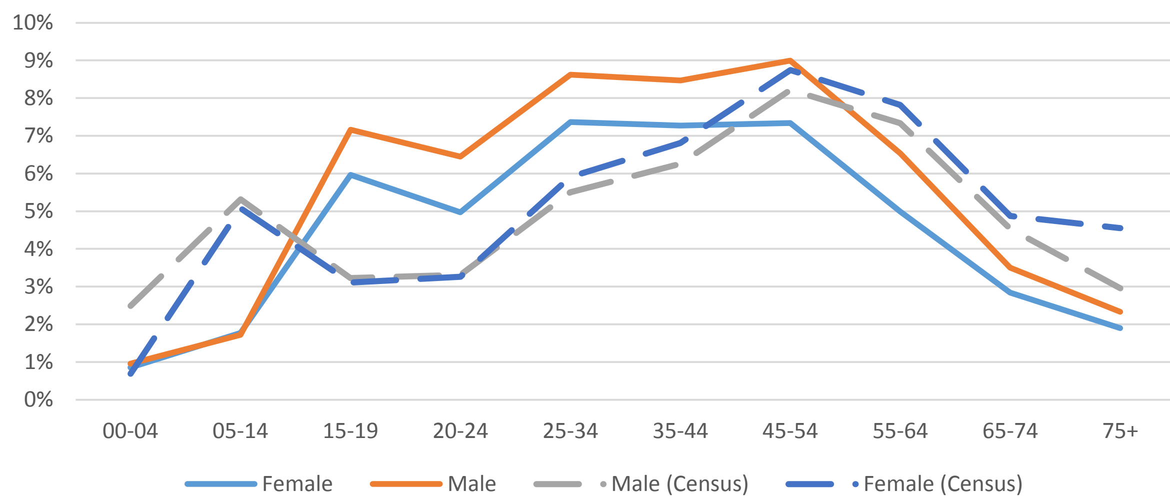


Figure 12: Age and gender distribution of persons involved in collisions

2.4 Collisions Involving Pedestrians

2.4.1 Total Pedestrian Collisions

In total, there were 1567 collisions involving 1751 pedestrians between 2007 and 2011. The total annual number of pedestrians involved in collisions increased from 2007 to 2011. Figure 13 shows the total number of pedestrian related collisions by year.

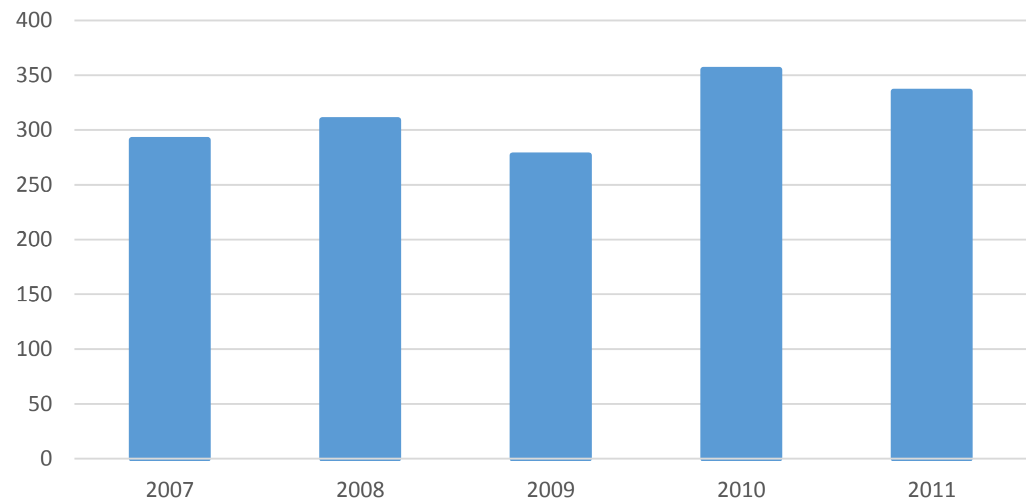


Figure 13: Total pedestrian collisions by year

2.4.2 Injury Severity

Figure 14 shows the injury severity experienced by pedestrians. Many collisions resulted in minor injuries (26%) but a large portion resulted in moderate injuries (50%). Higher proportions of more severe injuries found in the pedestrians is likely attributed to their increased vulnerability relative to other road users.

Figure 14: Injury severity of pedestrians involved in collisions

2.4.3 Temporal Variations in Pedestrian Collisions

Temporal variability (time of day, week, and month) of pedestrian collisions was examined. The distribution of these variables are detailed in the following figures.

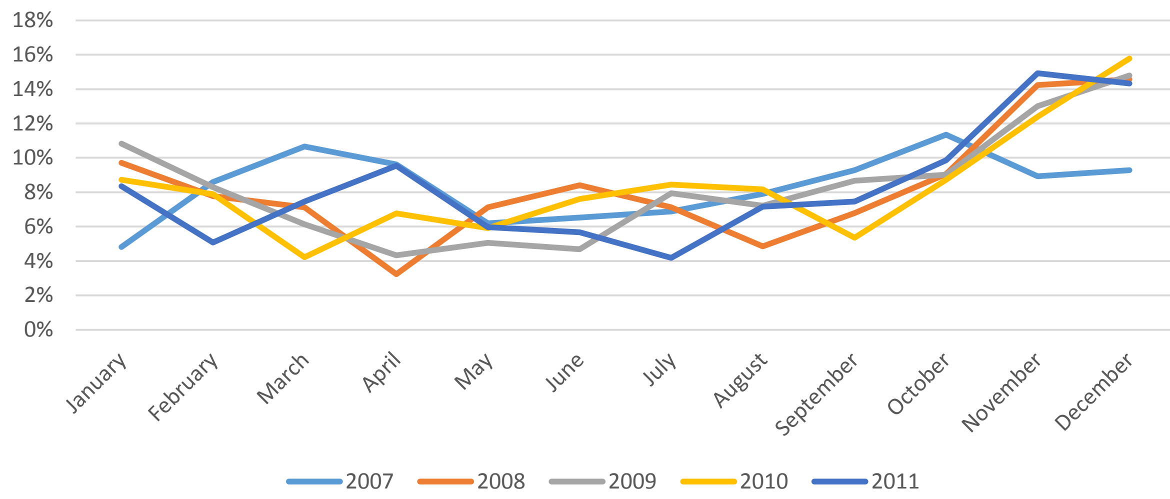


Figure 15: Monthly distribution of pedestrian-related collisions

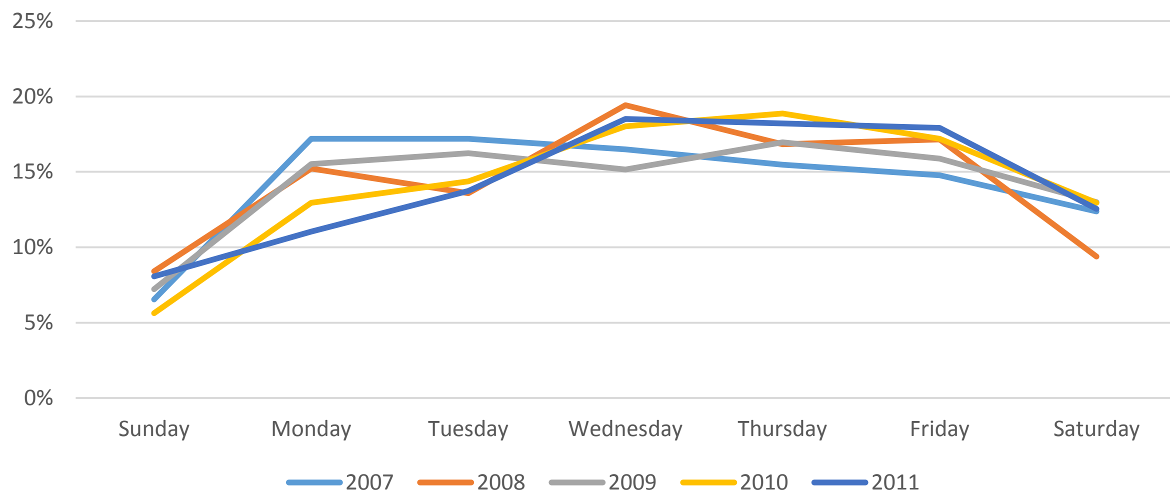


Figure 16: Day of week distribution of pedestrian-related collisions

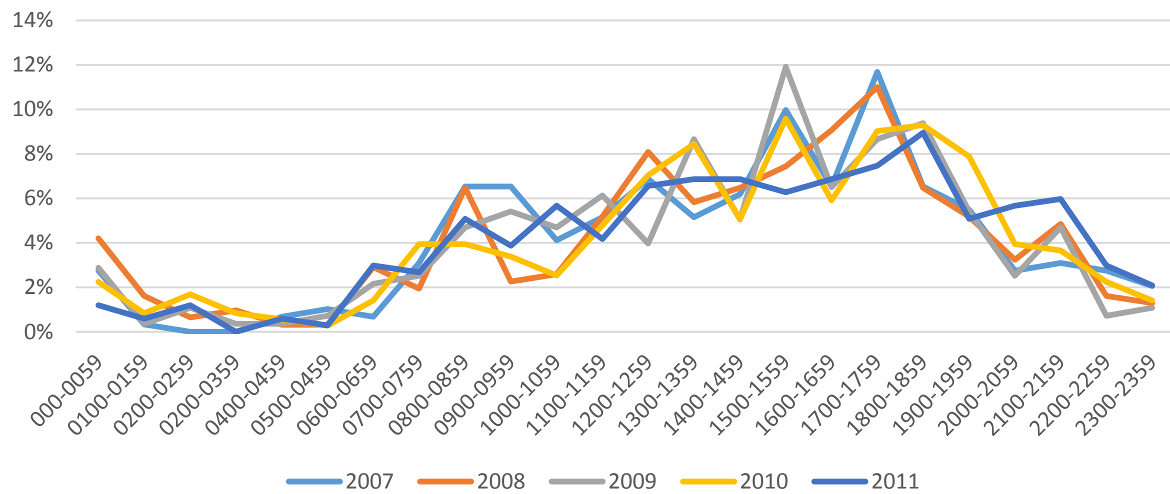


Figure 17: Time of day distribution of pedestrian-related collisions

Pedestrian-related collisions occurred most frequently between 2PM to 3PM and 5PM to 6PM. The apparent peak represented in the 12AM to 1AM time group may be misrepresented. It is believed that the time variable in the raw data defaults to 12AM when no data is entered. Pedestrian-related collisions occur more frequently on weekdays compared to weekend days, which is likely attributed to higher number of pedestrian commuters during the workweek. This trend is consistent with the time of day variable as most collisions occur during the workday hours. The frequency of pedestrian-related collisions is higher in the winter months from November to January. This finding can likely be attributed to road conditions associated with the season, including lack of visibility and poor road conditions.

2.4.4 Personal Characteristics of Pedestrians Involved in Collisions

The distribution of age and gender of pedestrians involved in collisions is detailed in Figure 18. Male and female involvement is relatively equal at 51% and 49% respectively. The 25-34 age group was the most frequently involved, followed by the by 45-54 age group.

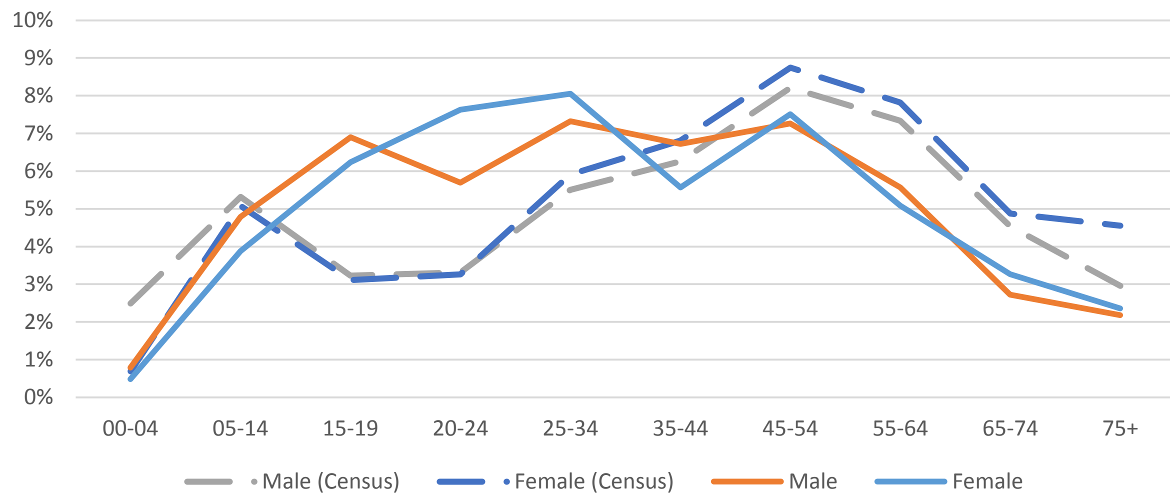


Figure 18: Age and gender distribution of pedestrians involved in collisions

2.4.5 Pedestrian Action and Location at Time of Collision

Forty-four percent of pedestrian-related collisions occurred in marked crosswalks at intersections. A significant portion (23%) of pedestrian-related collisions also occurred in the roadway and not in a crosswalk or intersection.

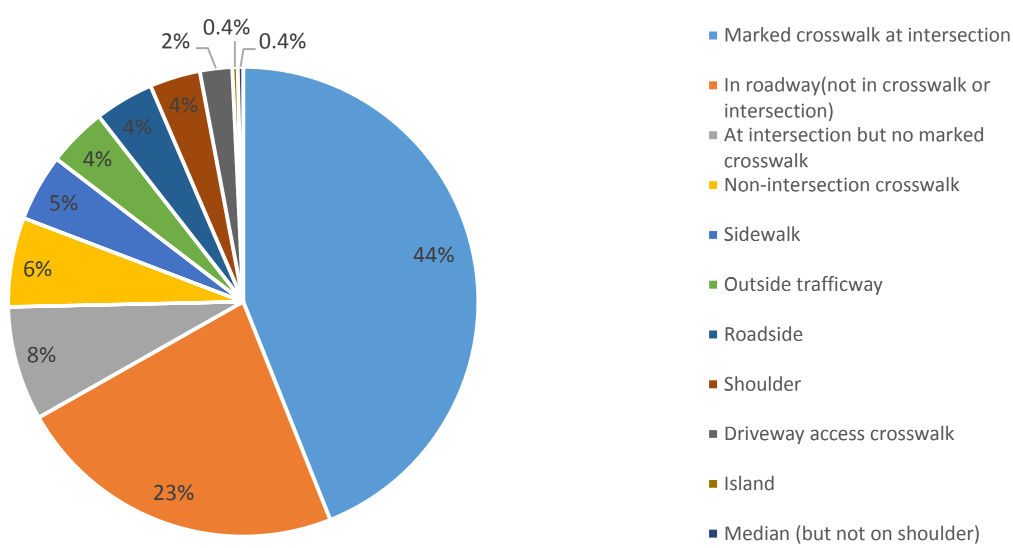


Figure 19: Pedestrian location at time of collision

In 45% of pedestrian-related collisions, there was no pedestrian action as a contributing factor. The most frequently reported pedestrian actions at time of collision include improper crossing (10%), darting into roadway (8%), and not being visible (4%).

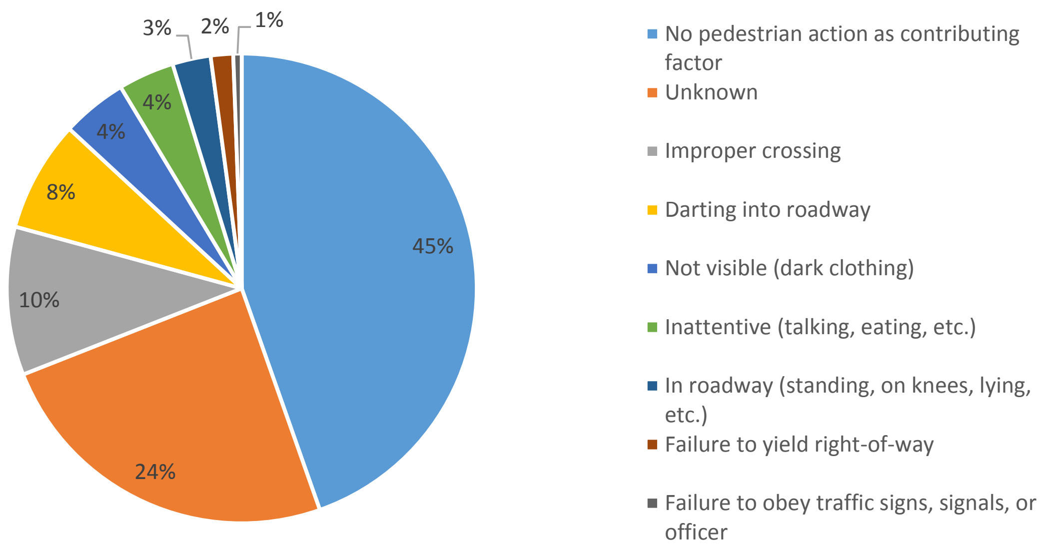


Figure 20: Pedestrian action at time of collision

2.4.6 Spatial Distribution of Pedestrian-Related Collisions

The spatial distribution of pedestrian-related collisions is presented in Figure 21. The majority of pedestrian collisions occurred in the main urban centres of the province including Halifax, Wolfville, Truro, Pictou, Amherst, and Sydney.

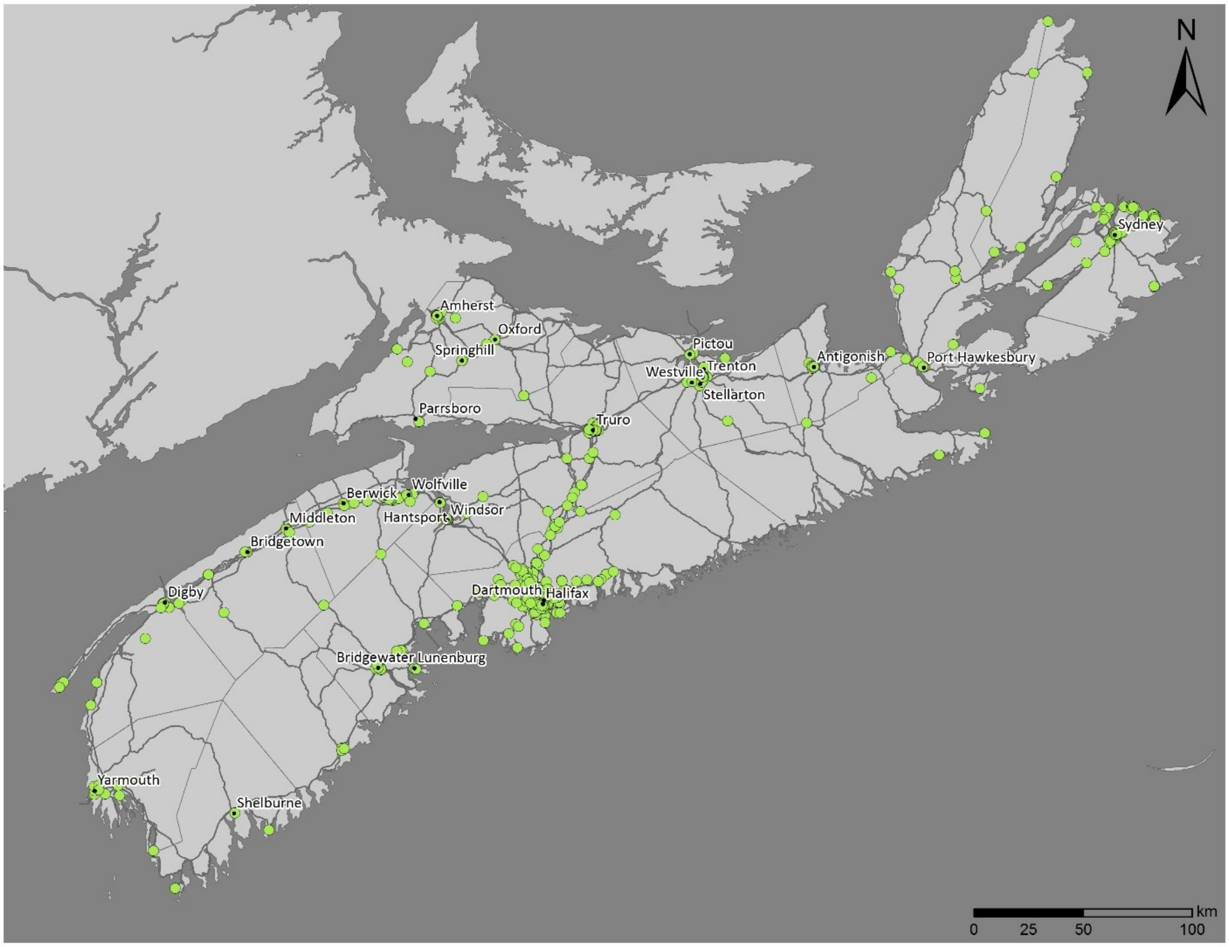


Figure 21: Spatial distribution of pedestrian-related collisions

2.5 Collisions Involving Cyclists

2.5.1 Total Cyclist Collisions

Between 2007 and 2011, there were 473 cyclists involved in collisions, resulting in 3 fatalities. There is no clear trend in annual cyclist-related collisions; the frequency has remained relatively stable throughout the study period with minor annual variations. It is important to note that in Nova Scotia, all collisions involving property damage over $1,000 and/or result in injuries or fatalities on a public road require reporting. It is therefore presumed underreporting is present with respect to the total number of collisions in Nova Scotia. Figure 22 shows the total bicycle-related collisions by year, revealing a consistent pattern in annual collision frequency.

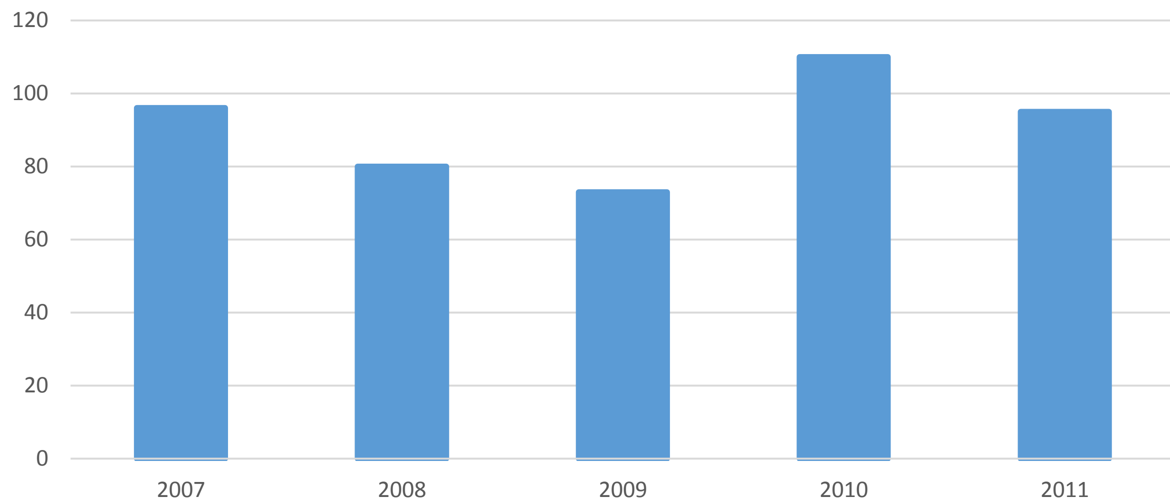


Figure 22: Total cyclist-related collisions by year

2.5.2 Injury Severity

Cyclists sustain more severe injuries compared to pedestrians. A significant proportion of collisions resulted in major or moderate injuries (55%) and minor injuries (26%). There have been three cyclist fatalities in the 5-year period.

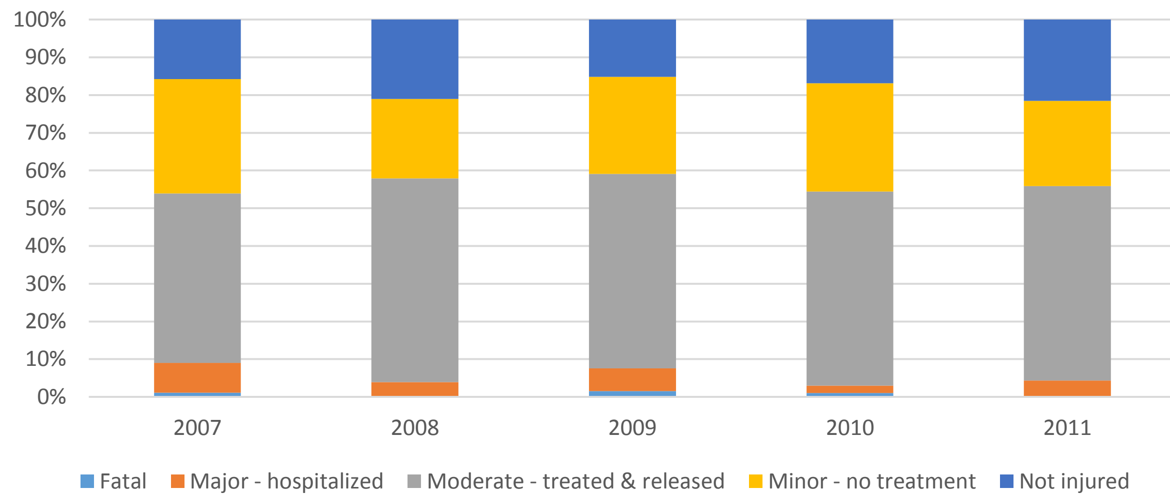


Figure 23: Injury severity of cyclists involved in collisions

2.5.3 Temporal Variations in Collisions Involving Cyclists

The frequency of cyclist-related collisions is higher in the spring and summer months from May to October as shown in the Figure below. This is likely attributed to increased ridership during these months. There is a decrease in collisions during the winter months, which is likely attributed to fewer cyclists on the road.

Cyclist-related collisions occur most frequently on weekdays than during the weekend. These higher collision frequencies may be attributed to the increased volume of road users during the weekdays. During the week, the number of collisions are most frequent on Monday, Wednesday, and Thursday. This trend is consistent with the time of day variable as most collisions occur during the workday hours. Collisions involving cyclists occurred most frequently between 3 and 6 PM.

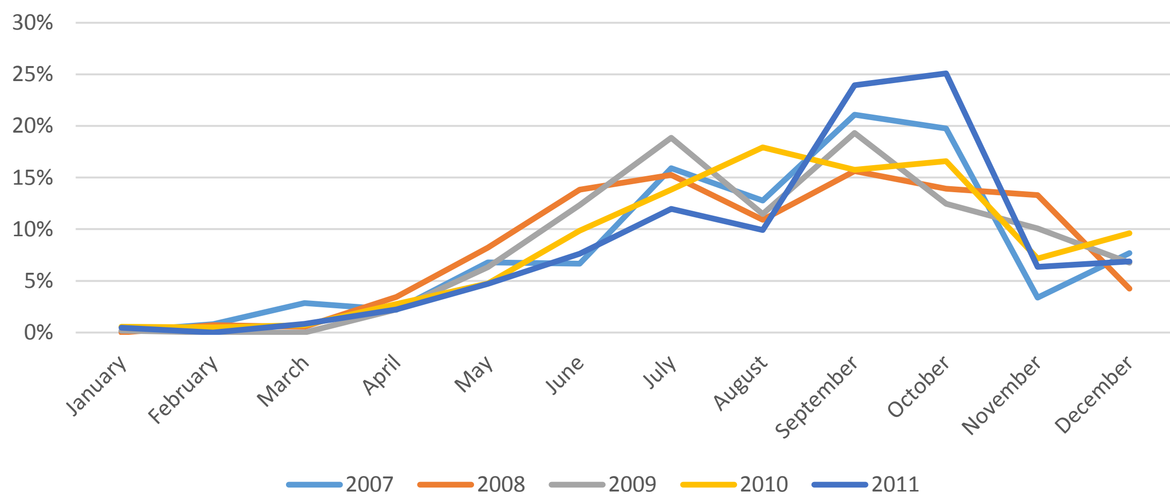


Figure 24: Monthly distribution of cyclist-related collisions

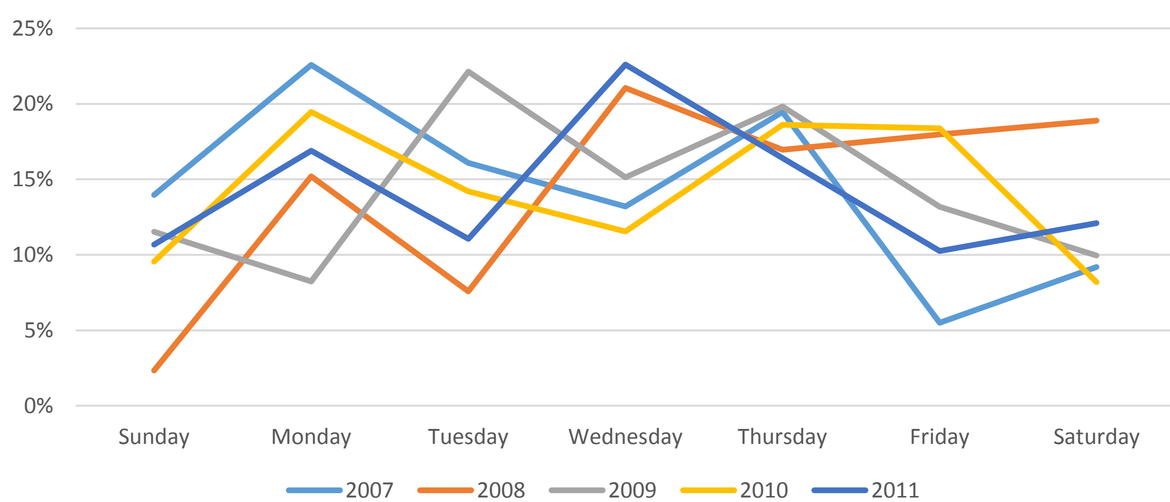


Figure 25: Day of week distribution of cyclist-related collisions

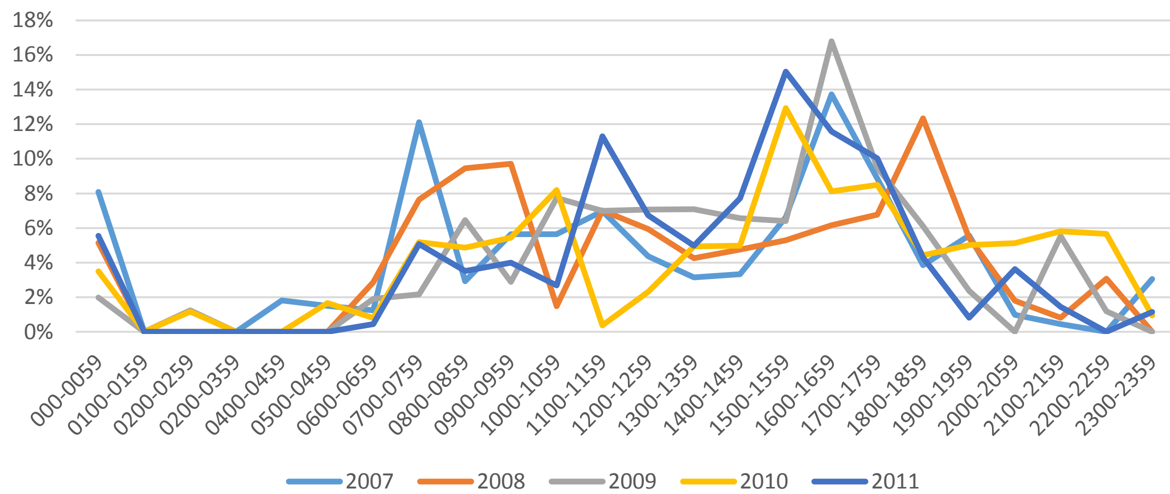


Figure 26: Time of day distribution of cyclist-related collisions

2.5.4 Personal Attributes of Cyclists Involved in Collisions

The distribution of age and gender of cyclists involved in collisions is presented in Figure 27. Gender of involved persons is not equally distributed; males are involved in significantly more collisions compared to females. The findings indicate that males were involved in 77% of collisions while female involvement was at 23%. Male cyclists aged 25-34 were most frequently involved in collisions while the 20-24 age group of females was most frequently involved.

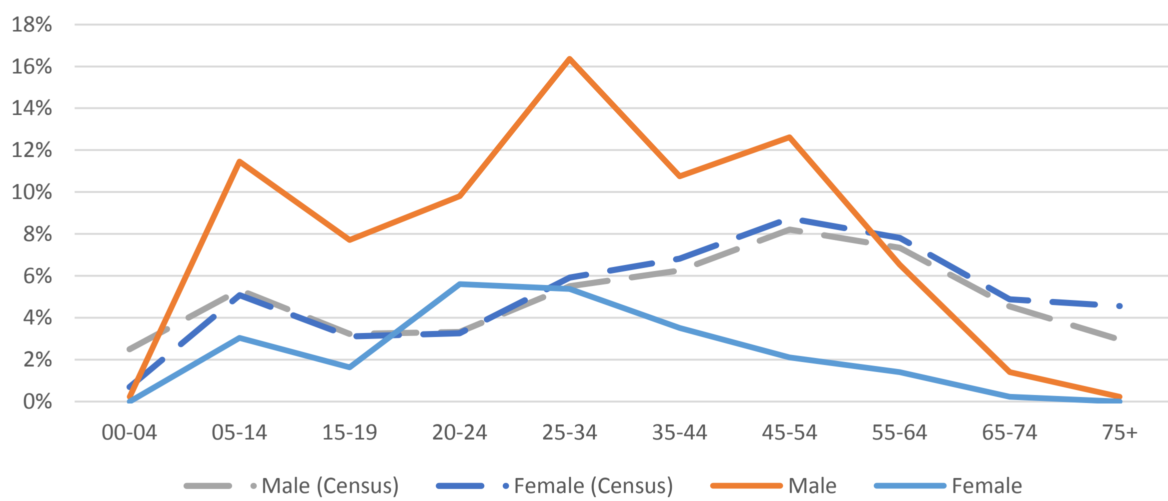


Figure 27: Age and gender of cyclists involved in collisions

2.5.5 Spatial Distribution of Bicycle-Related Collisions

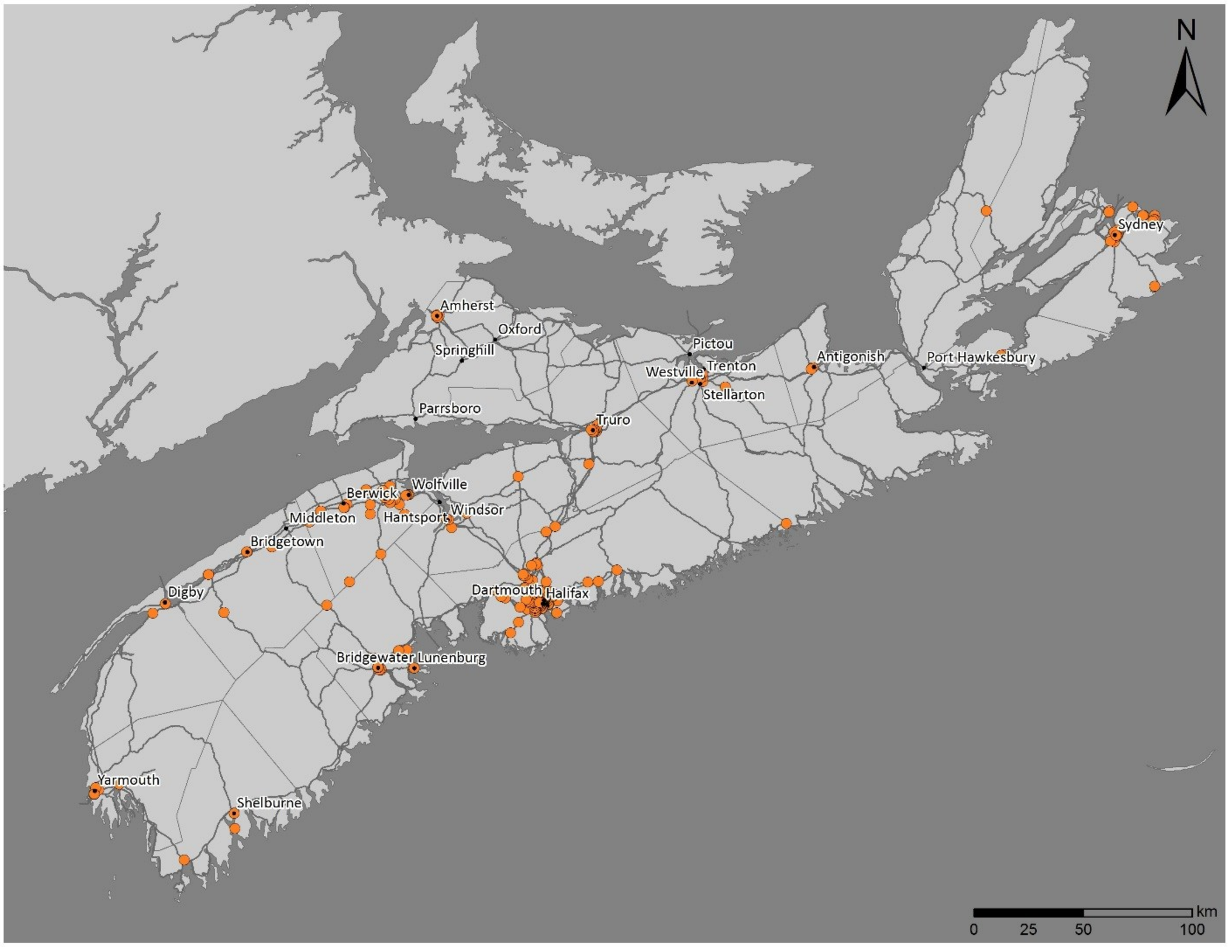


Figure 28: Spatial distribution of bicycle-related collisions

The spatial distribution of bicycle-related collisions, shown in Figure 28, revealed the following: the majority of collisions occurred on urban streets, in intersections, and the main urban centres in the province, which is not surprising considering the practicality of cycling in urban areas.

2.6 Vehicle-Related Collisions

2.6.1 Total Collisions Involving Vehicles

From 2007 to 2011, there were 133,444 auto-drivers and auto-passengers involved in 99,303 auto-related collisions. Auto-related collisions represent a large proportion of total collisions. There has been a steady increase in auto-related collisions since 2007. Figure 29 shows the total vehicle collisions in Nova Scotia by year.

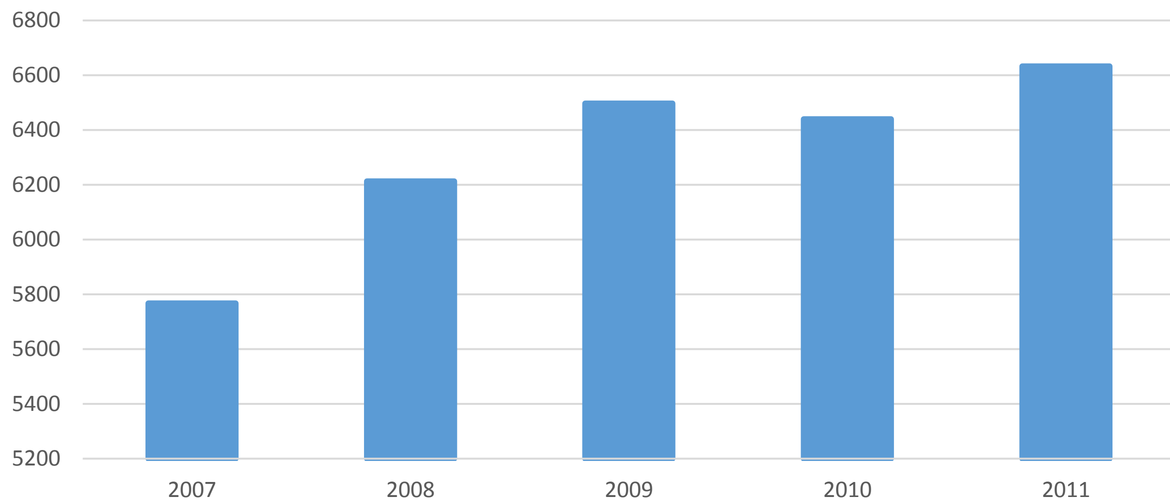


Figure 29: Total vehicle-related collisions by year

2.6.2 Injury Severity

There is an inverse relationship with fatal vehicle-related collisions and collision frequency. Omitting the 2008 outlier, there has been a significant decrease in fatalities from 2007 to 2011. The majority of reported injuries of auto-occupants were non-injured or minor injuries. Major and fatal injuries represent a relatively small proportion (1%) of auto-occupant injuries. Figure 30 shows injury severity of drivers involved in collisions and Figure 21 shows injury severity of passengers.

Figure 30: Injury severity of drivers involved in collisions

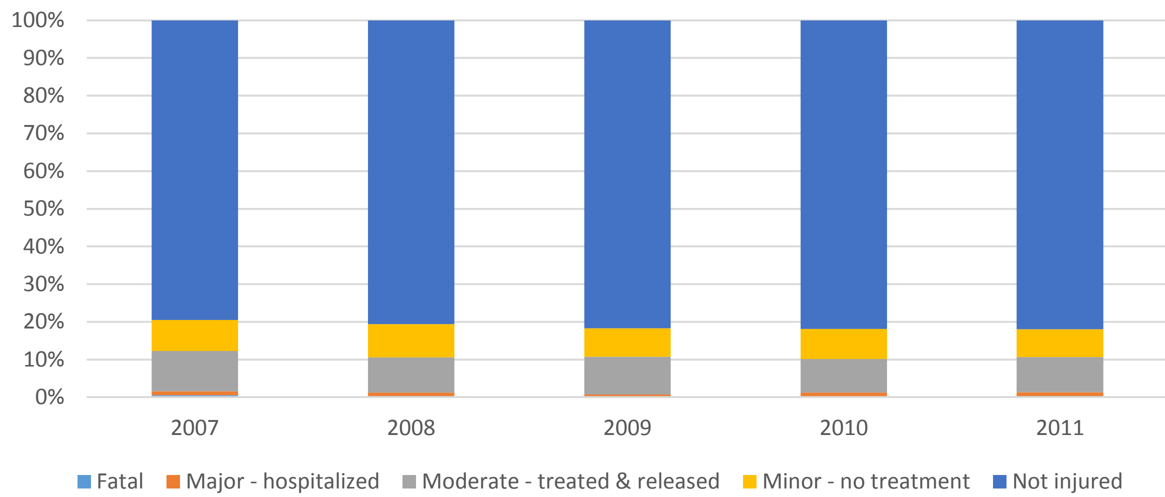


Figure 31: Injury severity of passengers involved in collisions

2.6.3 Temporal Variations in Collisions Involving Vehicles

The frequency of auto-related collisions is higher in the summer and winter seasons from June to August and October to February. There is an annually consistent decrease in collisions during the Spring months. Auto-related collisions occur most frequently during the weekdays. Higher collision frequencies may be attributed to increased volumes of motor vehicles during the weekday. This trend is consistent with the time of day as most collisions occur during the workday commuting time hours. Auto-related collisions occur most frequently starting at 12 PM and continuing steadily until 6 PM. The high auto-related collision frequency corresponds to expected times of higher traffic volumes (lunch break, end of school, end of workday).

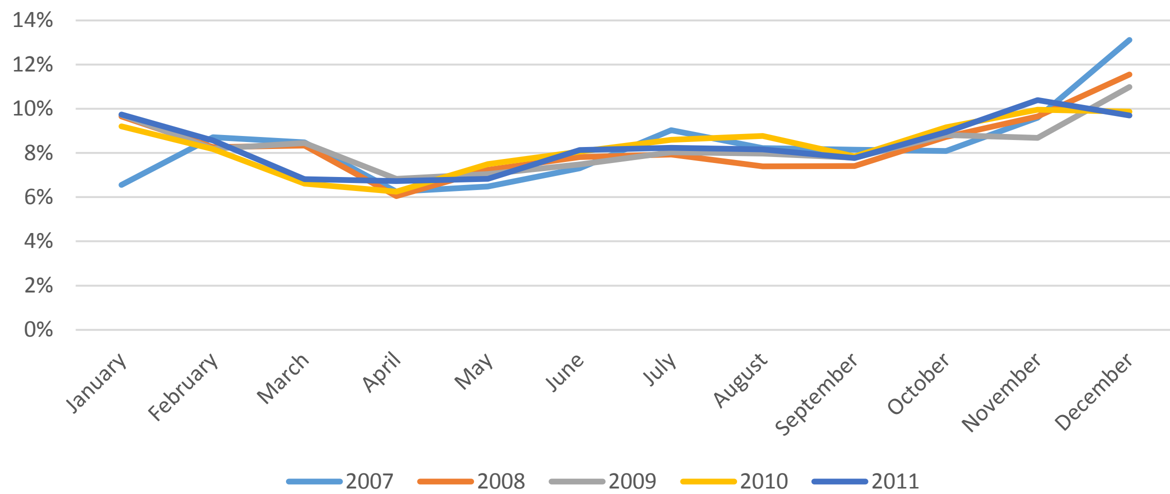


Figure 32: Monthly distribution of vehicle-related collisions

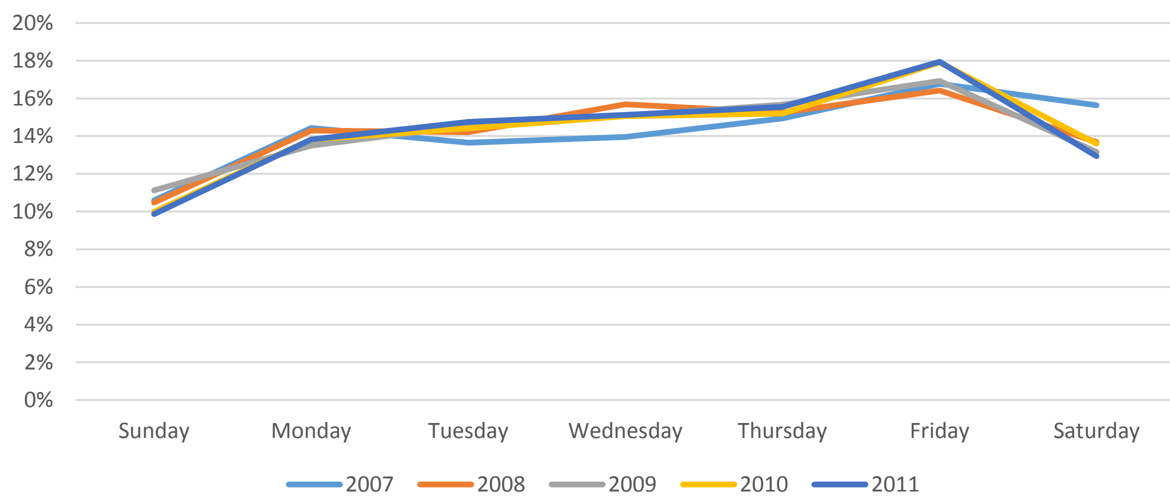


Figure 33: Day of week distribution of vehicle-related collisions

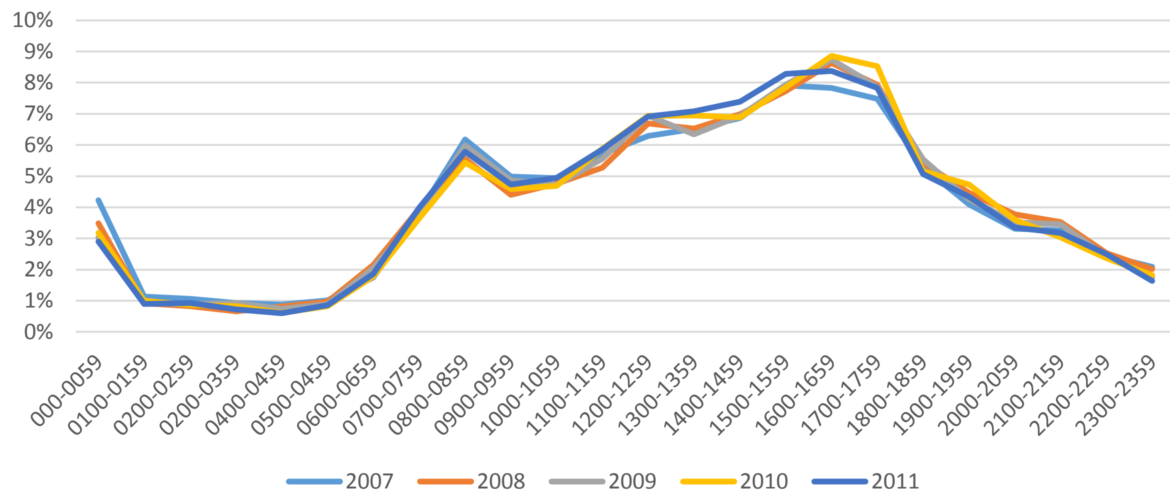


Figure 34: Time of day distribution of vehicle-related collisions

2.6.4 Personal Attributes of Drivers and Passengers

The distribution of age and gender of auto-occupants is detailed in the following section. Male auto-drivers are more frequently involved in collisions than female drivers are. Female auto-passengers are more frequently involved in collisions than male passengers are. The 45-54 age group of auto-drivers is most frequently involved for both genders, and 15-19 age group is most frequently involved as auto-passengers.

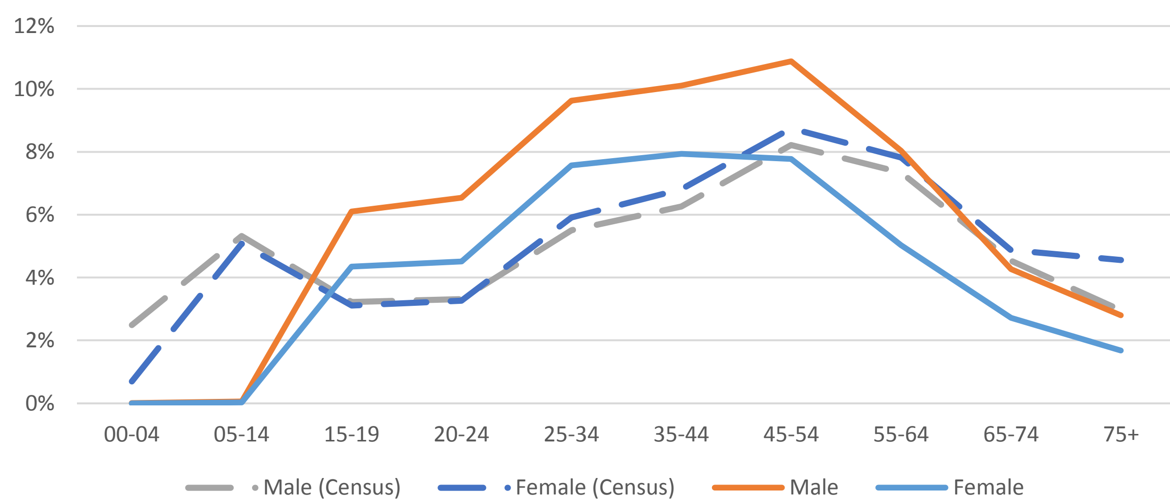


Figure 35: Age and gender of drivers involved in collisions

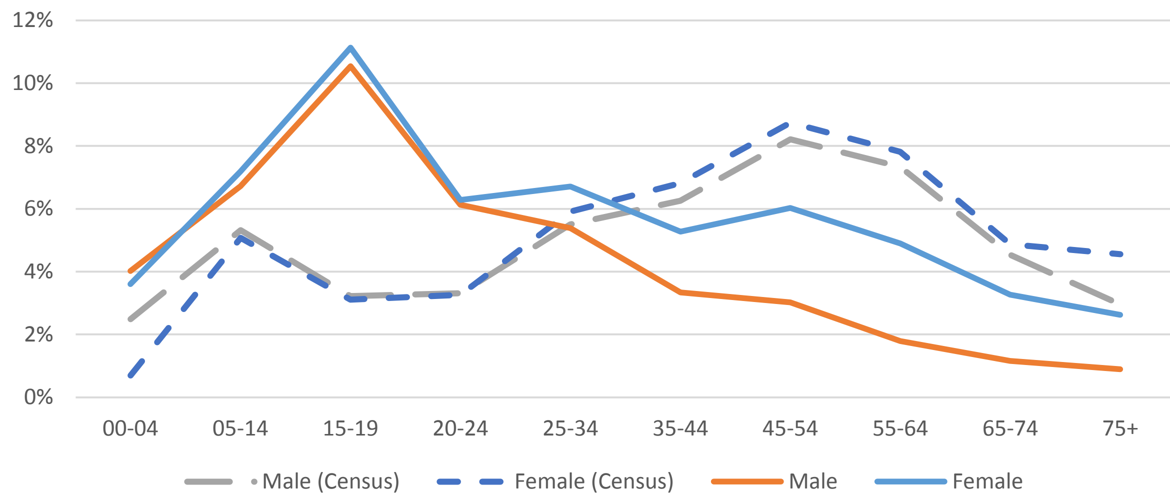


Figure 36: Age and gender of passengers involved in collisions

2.6.5 Spatial Distribution of Vehicle-Related Collisions

The spatial distribution of vehicular collisions, shown in Figure 37, shows that collision are distributed throughout the province, both in urban and rural areas. A higher density of collisions is noted in the main urban centres: Halifax, Truro, Pictou, Amherst, and Sydney.

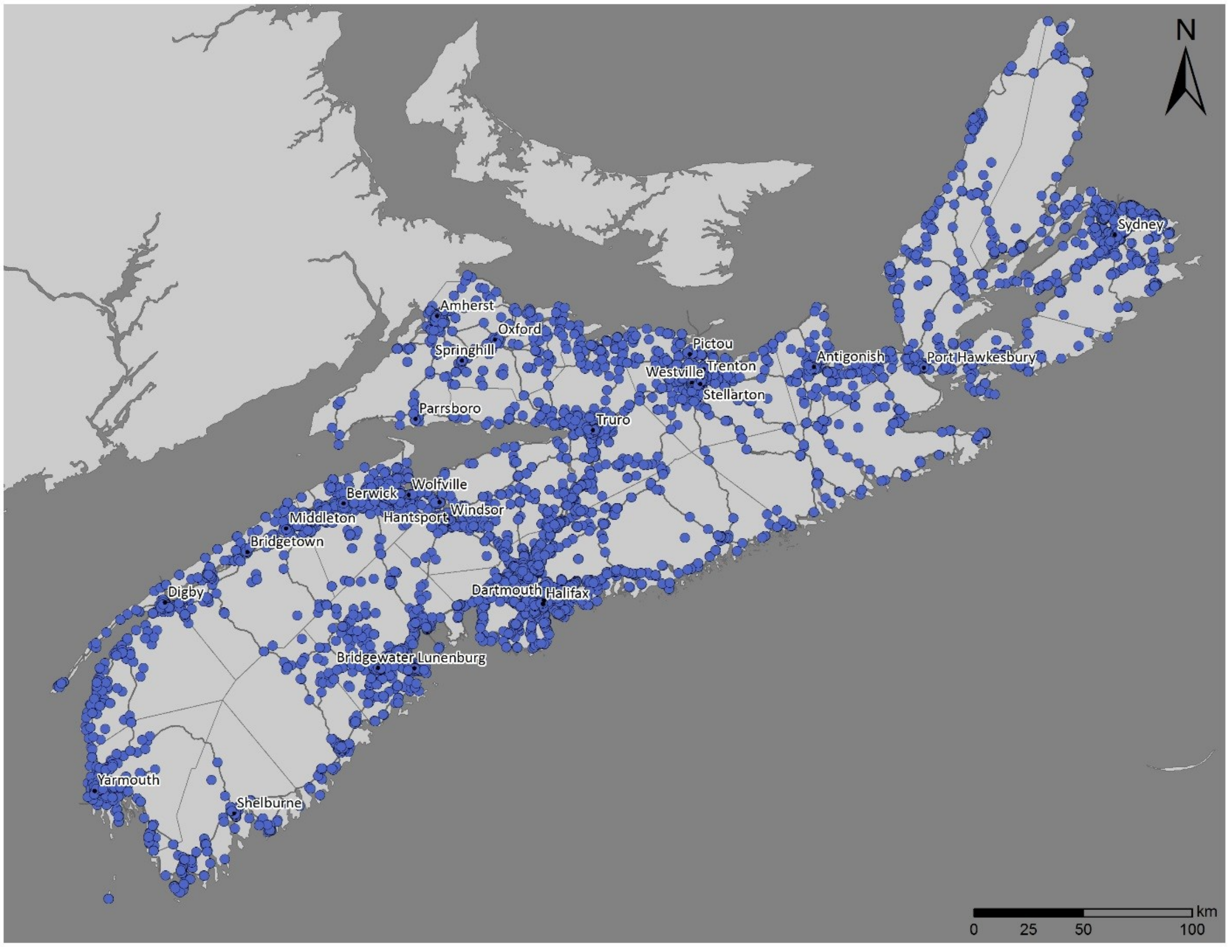
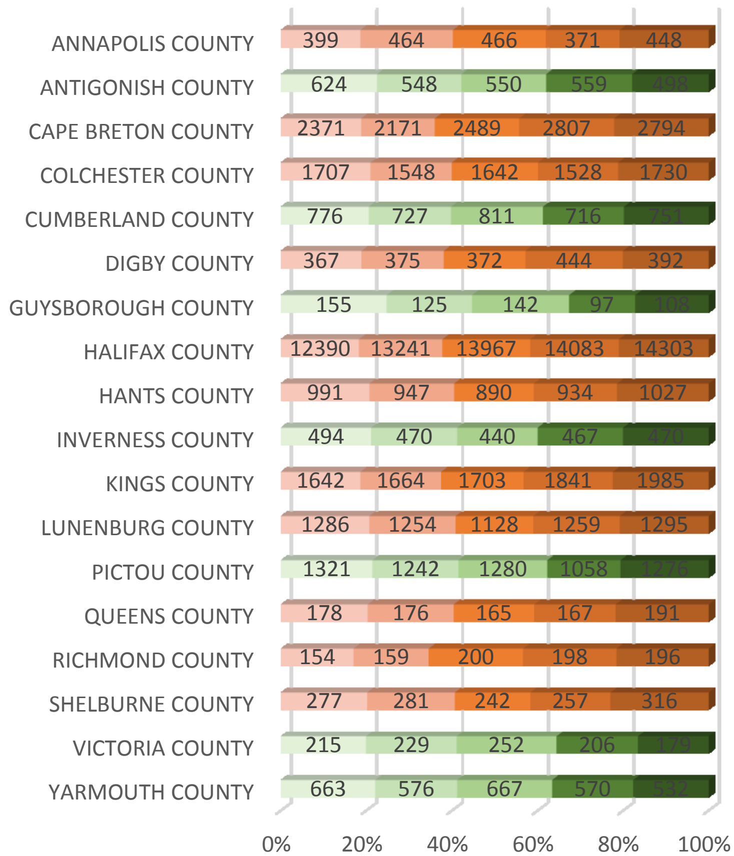


Figure 37: Spatial distribution of vehicle-related collisions

2.7 County-Level Analysis

2.7.1 Total Collisions by County

Figure 38 shows the breakdown of collisions by county. The figure is colored to show increases (red/orange color) and decreases (green color) in collisions from 2007 to 2011. 39% of counties have seen a decrease in collisions over the five year period while 61% of counties have had an increasing trend in collision frequency. The counties experiencing an increase in collisions include Annapolis, Cape Breton Colchester, Digby, Halifax, Hants, Kings, Lunenburg, Queens, Richmond, and Shelburne. Counties that are experiencing a decrease in collisions include Antigonish, Cumberland, Guysborough, Inverness, Pictou, Victoria, and Yarmouth. The differences in trend (i.e. increasing or decreasing frequencies) could be attributed to a variety of factors including population changes, changes in infrastructure (e.g. new road construction), or changing weather conditions.



Note: Each proportion represented in the figure above correspond to the years 2007 to 2011 (read left to right respectively)

Figure 38: Total collisions by year by county

2.7.2 Injury Severity

Table 4 shows the percent change in injury severity levels from 2007 to 2011 by each county. The cells are symbolized from green to red for each injury severity level. The darkest red indicates the county with the greatest growth while the darkest green indicates the county with the greatest decrease in each particular injury severity level. Looking at Table 4, we can see that Richmond County has seen the greatest growth in fatalities. Annapolis County and has generally seen the greatest overall increase in all injury severity levels. Victoria County has seen the great decrease in fatalities and in all other injury severity levels.

Table 4: Percent change in injury severity levels by county, 2007 to 2011

	Fatal	Major - Hospitalized	Moderate - Treated and Released	Minor - No Treatment	Not Injured
Annapolis County	0.17%	1.91%	3.28%	0.90%	4.16%
Antigonish County	-0.26%	-0.47%	1.40%	2.10%	5.15%
Cape Breton County	-0.03%	0.10%	1.49%	1.08%	1.39%
Colchester County	0.12%	0.25%	2.10%	1.87%	0.70%
Cumberland County	0.20%	0.35%	5.05%	2.10%	-0.91%
Digby County	-0.15%	0.19%	2.70%	-1.95%	4.41%
Guysborough County	0.68%	0.34%	-3.22%	1.62%	3.45%
Halifax County	0.09%	0.10%	-0.01%	1.03%	2.92%
Hants County	0.24%	0.51%	-0.30%	1.46%	1.43%
Inverness County	-0.13%	0.60%	-1.13%	2.45%	6.42%
Kings County	0.44%	0.32%	0.54%	0.29%	1.74%
Lunenburg County	0.42%	0.47%	-2.63%	2.25%	6.23%
Pictou County	-0.11%	-0.69%	1.33%	2.08%	2.41%
Queens County	0.00%	1.52%	1.95%	0.03%	-0.25%
Richmond County	1.00%	1.65%	6.88%	3.43%	-0.91%
Shelburne County	-0.22%	-0.04%	2.48%	-0.70%	2.97%
Victoria County	-0.74%	-1.62%	-5.76%	-1.14%	11.78%
Yarmouth County	0.07%	0.68%	0.67%	1.96%	2.75%

2.7.3 Personal Characteristics of Persons Involved in Collisions by County

Table 5 shows the gender distribution of persons involved in collisions by each county. The distribution of gender shows that males are most frequently involved in collisions for every county.

Table 5: Gender distribution of persons involved in collisions by county

	Female	Male
Annapolis County	45%	55%
Antigonish County	44%	56%
Cape Breton County	45%	55%
Colchester County	45%	55%
Cumberland County	42%	58%
Digby County	44%	56%
Guysborough County	37%	63%
Halifax County	44%	56%
Hants County	42%	58%
Inverness County	43%	57%
Kings County	45%	55%
Lunenburg County	44%	56%
Pictou County	45%	55%
Queens County	43%	57%
Richmond County	40%	60%
Shelburne County	45%	55%
Victoria County	40%	60%
Yarmouth County	46%	54%

The age distribution of persons involved in collisions is shown in Table 6. The age groups in the table are colored from green (lowest %) to red (highest %) by each county. The age 45-54 age group is consistently the most frequently involved age group involved in collisions while the 25-34, 35-44, and 55-64 age groups are also frequently involved. This trend is generally consistent among all counties.

Table 6: Age distribution of persons involved in collisions by county

	00-04	05-14	15-19	20-24	25-34	35-44	45-54	55-64	65-74	75+
Annapolis County	2%	4%	13%	8%	12%	15%	18%	13%	9%	6%
Antigonish County	1%	3%	13%	12%	14%	14%	18%	14%	7%	5%
Cape Breton County	1%	3%	14%	10%	13%	14%	19%	13%	7%	5%
Colchester County	2%	3%	12%	10%	14%	16%	19%	13%	7%	5%

Cumberland County	1%	3%	12%	9%	14%	16%	17%	14%	9%	6%
Digby County	1%	3%	12%	9%	14%	16%	18%	12%	8%	6%
Guysborough County	1%	3%	17%	7%	11%	13%	20%	16%	7%	5%
Halifax County	1%	3%	9%	11%	17%	18%	20%	12%	5%	3%
Hants County	1%	3%	15%	10%	15%	16%	18%	12%	6%	4%
Inverness County	1%	3%	12%	9%	13%	15%	18%	16%	9%	4%
Kings County	2%	4%	13%	11%	15%	16%	18%	12%	7%	4%
Lunenburg County	2%	3%	11%	8%	13%	16%	18%	14%	9%	6%
Pictou County	2%	4%	13%	9%	14%	16%	18%	13%	7%	5%
Queens County	1%	6%	12%	8%	12%	16%	16%	15%	7%	7%
Richmond County	2%	3%	11%	11%	12%	12%	16%	17%	12%	5%
Shelburne County	2%	4%	17%	10%	13%	14%	15%	12%	7%	4%
Victoria County	1%	4%	10%	8%	14%	14%	20%	16%	9%	4%
Yarmouth County	1%	3%	12%	9%	14%	16%	18%	13%	7%	6%

2.7.4 Temporal Variations in Collisions by County

Table 7 shows the monthly distribution of collisions by county. Similar to the previous table, Table 7 is colored from green (least %) to red (highest %). The month that collisions occur most frequently is December, while April and May are associated with the fewest collisions. The increase in collisions during the winter months is likely attributed to poor weather conditions.

Table 7: Monthly distribution of collisions by county

	J	F	M	A	M	J	J	A	S	O	N	D
Annapolis County	10%	8%	8%	6%	6%	7%	9%	9%	9%	8%	10%	11%
Antigonish County	8%	6%	7%	5%	7%	9%	9%	11%	9%	9%	9%	11%
Cape Breton County	9%	8%	8%	6%	6%	8%	9%	9%	8%	9%	9%	10%
Colchester County	8%	9%	8%	7%	7%	8%	9%	9%	7%	8%	10%	11%
Cumberland County	9%	8%	8%	8%	7%	7%	10%	8%	8%	8%	9%	11%
Digby County	9%	9%	6%	5%	8%	8%	9%	12%	9%	6%	8%	11%
Guysborough County	7%	6%	10%	6%	8%	7%	10%	11%	8%	7%	11%	8%
Halifax County	8%	9%	8%	7%	8%	8%	8%	8%	8%	9%	9%	11%
Hants County	10%	9%	7%	6%	6%	8%	9%	8%	9%	9%	9%	10%
Inverness County	9%	8%	7%	6%	4%	9%	12%	11%	7%	10%	7%	11%
Kings County	8%	8%	7%	7%	7%	9%	9%	9%	8%	10%	9%	10%
Lunenburg County	8%	8%	7%	5%	7%	8%	10%	9%	9%	9%	9%	11%
Pictou County	9%	8%	8%	6%	6%	8%	10%	9%	8%	9%	10%	10%
Queens County	10%	9%	8%	7%	7%	8%	7%	7%	8%	8%	10%	10%
Richmond County	9%	7%	8%	7%	5%	7%	9%	10%	10%	9%	9%	10%
Shelburne County	7%	8%	5%	6%	9%	7%	8%	9%	9%	10%	11%	11%

Victoria County	7%	5%	5%	4%	5%	8%	14%	19%	9%	11%	6%	8%
Yarmouth County	9%	7%	7%	7%	8%	9%	9%	8%	7%	8%	9%	12%

Table 8 shows the day of week distribution of collisions by county. The table is color coded in a manner similar to previous tables. Friday is consistently the weekday that most collisions occurs while Sunday is generally the day collisions occur the least.

Table 8: Day of week distribution of collisions by county

	Sun.	Mon.	Tues.	Wed.	Thurs.	Fri.	Sat.
Annapolis County	12%	14%	11%	15%	16%	16%	16%
Antigonish County	10%	14%	14%	15%	14%	19%	14%
Cape Breton County	10%	14%	15%	15%	14%	17%	14%
Colchester County	11%	13%	12%	15%	16%	17%	16%
Cumberland County	12%	14%	14%	14%	15%	18%	13%
Digby County	12%	11%	13%	15%	16%	18%	14%
Guysborough County	13%	15%	11%	14%	14%	16%	16%
Halifax County	10%	14%	15%	15%	16%	17%	13%
Hants County	12%	13%	13%	14%	14%	17%	16%
Inverness County	11%	12%	13%	14%	15%	18%	15%
Kings County	10%	14%	13%	14%	15%	18%	15%
Lunenburg County	10%	14%	14%	15%	15%	16%	16%
Pictou County	11%	14%	13%	13%	16%	18%	14%
Queens County	11%	14%	12%	15%	16%	16%	16%
Richmond County	14%	12%	15%	14%	14%	18%	13%
Shelburne County	14%	14%	12%	14%	16%	14%	15%
Victoria County	15%	12%	14%	12%	12%	15%	18%
Yarmouth County	9%	13%	15%	16%	17%	16%	14%

2.7.5 Collision Trends by Mode

Time of day distribution of collisions is presented in Table 9. The trend is generally consistent among each county with collisions occurring most frequently between the times of 4 PM and 6 PM, when traffic volumes are typically heavier relative to other hours of the day.

Table 9: Time of day distribution of collisions by county

	Annapolis County	Antigonish County	Cape Breton County	Colchester County	Cumberland County	Digby County	Guysborough County	Halifax County	Hants County	Inverness County	Kings County	Lunenburg County	Pictou County	Queens County	Richmond County	Shelburne County	Victoria County	Yarmouth County
0000-0099	5%	5%	8%	5%	5%	6%	4%	2%	5%	5%	4%	4%	4%	5%	2%	4%	6%	5%
0100-0199	1%	1%	1%	1%	1%	1%	2%	1%	1%	2%	1%	1%	1%	1%	2%	1%	2%	1%
0200-0299	2%	1%	1%	1%	1%	1%	1%	1%	1%	1%	1%	0%	1%	0%	1%	1%	2%	1%
0300-0399	1%	1%	1%	1%	1%	1%	0%	1%	1%	1%	1%	1%	1%	0%	2%	0%	1%	0%
0400-0499	1%	1%	1%	1%	0%	1%	1%	0%	1%	1%	0%	1%	1%	1%	2%	1%	1%	1%
0500-0599	1%	1%	1%	1%	1%	0%	1%	0%	2%	1%	0%	1%	1%	1%	1%	1%	1%	1%
0600-0699	2%	1%	1%	1%	2%	1%	2%	1%	2%	1%	1%	1%	1%	1%	2%	1%	1%	2%
0700-0799	3%	3%	2%	2%	3%	3%	4%	4%	3%	2%	2%	3%	3%	2%	2%	3%	3%	3%
0800-0899	4%	5%	5%	5%	5%	3%	3%	6%	4%	4%	5%	5%	4%	4%	5%	3%	5%	4%
0900-0999	4%	4%	4%	4%	4%	4%	5%	5%	5%	5%	4%	5%	5%	4%	8%	5%	4%	5%
1000-1099	6%	6%	5%	5%	5%	5%	3%	5%	5%	5%	5%	5%	4%	5%	3%	6%	4%	5%
1100-1199	6%	6%	5%	7%	7%	6%	5%	5%	7%	7%	6%	7%	6%	6%	7%	8%	6%	7%
1200-1299	7%	7%	7%	8%	6%	8%	10%	7%	6%	8%	8%	7%	7%	9%	7%	7%	7%	8%
1300-1399	6%	7%	7%	8%	7%	10%	6%	7%	6%	7%	8%	7%	8%	11%	4%	5%	6%	8%
1400-1499	6%	8%	7%	8%	6%	7%	8%	7%	6%	11%	9%	8%	9%	9%	8%	10%	7%	8%
1500-1599	9%	8%	9%	9%	8%	7%	6%	9%	8%	7%	9%	10%	9%	8%	9%	7%	9%	9%
1600-1699	7%	8%	8%	8%	8%	10%	7%	10%	8%	8%	9%	8%	8%	7%	7%	7%	8%	7%
1700-1799	6%	7%	8%	6%	7%	7%	7%	9%	8%	6%	8%	8%	7%	5%	7%	5%	6%	6%

1800-1899	5%	5%	5%	5%	5%	4%	6%	6%	5%	6%	5%	5%	5%	3%	5%	4%	5%	6%
1900-1999	5%	5%	5%	5%	5%	4%	6%	4%	4%	4%	4%	4%	5%	6%	3%	4%	5%	5%
2000-2099	5%	4%	4%	4%	4%	3%	4%	3%	4%	4%	3%	3%	4%	3%	4%	6%	4%	4%
2100-2199	4%	3%	3%	3%	3%	3%	4%	3%	3%	2%	3%	4%	3%	3%	4%	4%	3%	3%
2200-2299	3%	3%	2%	2%	3%	3%	3%	2%	2%	2%	2%	3%	2%	3%	6%	3%	3%	2%
2300-2399	2%	2%	2%	2%	2%	3%	2%	1%	2%	2%	1%	1%	2%	2%	1%	3%	1%	2%

Table 10 shows the trends of collision frequency by each country. The table follows a color scale; the darkest red indicates the year that had the most collisions while green represents the year that experienced the least. The final column describes whether the trend has been increasing or decreasing from 2007 to 2011. There is no apparent trend in increases/decreases in road user involvement in collisions.

Table 10: Trends in road user involvement in collision by county

	2007	2008	2009	2010	2011	Trend
Annapolis County	**399**	**464**	**466**	**371**	**448**	Increase
Auto Driver	274	309	321	259	322	Increase
Auto Passenger	120	153	142	110	122	Increase
Cyclist	1	1			3	Increase
Pedestrian	4	1	3	2	1	Decrease
Antigonish County	624	548	550	559	498	Decrease
Auto Driver	425	390	398	407	390	Decrease
Auto Passenger	192	151	147	149	103	Decrease
Cyclist	1		1			Decrease
Pedestrian	6	7	4	3	5	Decrease
Cape Breton County	2371	2171	2489	2807	2794	Increase
Auto Driver	1702	1528	1776	2025	2005	Increase
Auto Passenger	623	603	684	733	745	Increase
Cyclist	6	7	3	5	7	Increase
Pedestrian	40	33	26	44	37	Decrease
Colchester County	1707	1548	1642	1528	1730	Increase
Auto Driver	1220	1118	1179	1144	1305	Increase
Auto Passenger	**461**	**404**	**441**	**355**	**407**	Decrease
Cyclist	4	6	4	4	3	Decrease
Pedestrian	22	20	18	25	15	Decrease

Cumberland County	776	727	811	716	751	Decrease
Auto Driver	**527**	**511**	**587**	**527**	**566**	Increase
Auto Passenger	237	204	214	175	175	Decrease
Cyclist	4		1	1	1	Decrease
Pedestrian	8	12	9	13	9	Increase
Digby County	367	375	372	444	392	Increase
Auto Driver	262	273	285	313	305	Increase
Auto Passenger	104	92	81	127	80	Decrease
Cyclist			2			Increase
Pedestrian	1	10	4	4	7	Increase
Guysborough County	**155**	**125**	**142**	**97**	**108**	Decrease
Auto Driver	115	93	106	73	81	Decrease
Auto Passenger	40	32	33	23	26	Decrease
Pedestrian			3	1	1	Decrease
Halifax County	12390	13241	13967	14083	14303	Increase
Auto Driver	9150	9888	10315	10428	10635	Increase
Auto Passenger	2973	3102	3396	3342	3363	Increase
Cyclist	74	55	49	81	64	Decrease
Pedestrian	193	196	207	232	241	Increase
Hants County	991	947	890	934	1027	Increase
Auto Driver	712	692	644	692	757	Increase
Auto Passenger	269	242	243	234	260	Decrease
Cyclist		3	1	1	5	Increase
Pedestrian	10	10	2	7	5	Decrease
Inverness County	494	470	440	467	470	Decrease
Auto Driver	343	342	307	343	334	Decrease
Auto Passenger	146	125	128	121	130	Decrease
Cyclist	**1**			**1**	**1**	Decrease
Pedestrian	4	3	5	2	5	Increase
Kings County	1642	1664	1703	1841	1985	Increase
Auto Driver	1210	1237	1256	1352	1421	Increase
Auto Passenger	412	407	428	462	536	Increase
Cyclist	7	6	6	11	7	Decrease
Pedestrian	13	14	13	16	21	Increase
Lunenburg County	1286	1254	1128	1259	1295	Increase
Auto Driver	943	903	831	913	939	Decrease
Auto Passenger	332	342	286	329	343	Increase
Cyclist	3	2	3	4	2	Decrease
Pedestrian	**8**	**7**	**8**	**13**	**11**	Increase
Pictou County	1321	1242	1280	1058	1276	Decrease
Auto Driver	939	864	934	759	920	Decrease
Auto Passenger	375	356	333	277	345	Decrease

Cyclist	1	2	1	4	1	Decrease
Pedestrian	6	20	12	18	10	Increase
Queens County	178	176	165	167	191	Increase
Auto Driver	128	124	116	129	143	Increase
Auto Passenger	48	52	47	37	46	Decrease
Pedestrian	2		2	1	2	Decrease
Richmond County	154	159	200	198	196	Increase
Auto Driver	102	114	142	133	125	Increase
Auto Passenger	50	45	56	65	69	Increase
Cyclist			2			Increase
Pedestrian	2				2	Decrease
Shelburne County	277	281	242	257	316	Increase
Auto Driver	203	200	188	194	228	Increase
Auto Passenger	**74**	**80**	**52**	**62**	**83**	Increase
Cyclist			1		2	Increase
Pedestrian		1	1	1	3	Increase
Victoria County	215	229	252	206	179	Decrease
Auto Driver	142	140	156	128	123	Decrease
Auto Passenger	70	87	96	76	55	Decrease
Pedestrian	3	2		2	1	Decrease
Yarmouth County	663	576	667	570	532	Decrease
Auto Driver	482	423	491	425	399	Decrease
Auto Passenger	176	149	173	138	129	Decrease
Cyclist	1	1	1	3	1	Decrease
Pedestrian	**4**	**3**	**2**	**4**	**3**	Decrease

2.8 Conclusions

2.8.1 Key Findings

This chapter reviewed the patterns and trends of road users at an aggregate level (i.e. all road user types) and by each road user type. At an aggregate level, the majority of collisions resulted in minor or no injuries while a small proportion results in major or fatal injuries. The trend remains when looking at vehicle collisions but differences can be noted in pedestrian and cyclist collisions. The majority of pedestrian-related collisions and bicycle-related collisions resulted in moderate injuries. When pedestrians and cyclists are involved in a collision, the individual is likely to expect injuries that fall under a higher injury severity category.

The main reoccurring age that was involved in collisions was the 45-54 age group. Among individual road user groups, pedestrians and cyclists aged 25-43 were most frequently involved in collisions. There are notable trends in gender involvement in collisions. Males are more often involved in collisions compared to females, across all road user groups.

The time of day of collision occurrence is consistent annually. Fatal collisions occur most frequently between 12 PM and 6 PM, while motor vehicle collisions between 3 PM and 4PM and 5 PM to 6PM. Pedestrian and cyclist related collisions occur most frequently between 3 PM and 7 PM. The majority of collisions occurred most frequently on weekdays compared to weekends. These higher collision frequencies are likely attributed to the increased volumes of road users during the weekday. Collisions occur most frequently during the summer and winter seasons. Pedestrian-related and vehicle related collisions show similar trends as most of the collisions occur in the summer and winter months between October and February. Bicycle-related collisions occur most frequently during the spring and summer months between May and October. This is not surprising, as there are significantly less cyclists on the road during the winter months. Table 11 offers a summary of key findings.

Table 11: Summary of key findings

Characteristics	**Pattern/Trend**
General	• The number of collisions is increasing from 2007 to 2011. • The number of fatalities is decreasing from 2007 to 2011.
Personal characteristics	• The 45-54 age group was involved in collisions most frequently. • More males than females were involved in collisions.
Temporal characteristics	• From 2007-2011, collisions occurred most frequently on Fridays. • Over the five-year period, the month of December experienced the most collisions. • Most collisions occurred between 4:00 and 5:00 PM; we found between 3:00 and 4:00 PM to be the second highest frequency period. There is also an AM collision peak between 8:00 and 9:00 AM.
Injury severity outcomes	• Less than 1% of all road users experienced fatalities. • Ninety percent of all road users experienced either minor or no injuries. • Less than 1% of all auto-drivers experienced major injuries or fatalities. • One percent of all auto-passengers experienced major injuries or fatalities. • Eight percent of all pedestrians experienced moderate injuries. • Fifty-one perfect of cyclists experienced moderate injuries.

Most collisions occur in the main urban centres of the province, Halifax, Wolfville, Truro, Pictou, Amherst, and Sydney. This is obviously attributed to the increase of actual road users in these areas but also to these areas having environments conductive to pedestrian and cyclist activity. To minimize repetitive reporting of analysis results in this chapter, a more detailed county-level analysis can be found in Appendix A. The analysis presented in Section 2.7 has shown that the patterns and trends of collisions are comparable with those presented in this chapter. The county-level analysis should be a valuable resource for municipalities in Nova Scotia, specifically individuals working in transportation, public works, planning, community development, recreation, and physical activity fields.

When comparing counties in the province, the patterns and trends of collisions is generally consistent. Although the frequencies of collisions are decreasing or increasing depending on the county, the collisions have similar characteristics concerning injury severity, age and gender of persons involved, and the time of day, day of week, and month that collisions are occurring. This may indicate that road safety planning strategies informed by the findings of this chapter could be universally apply to most of the counties in the province, both rural and urban in character.

CHAPTER 3: ANALYSIS OF CYCLIST INJURY SEVERITY [2]

3.2 Introduction

When reviewing collision trend frequencies it is important to consider causality. Causality is the relation between an event (a collision) and a second event (the injury severity outcome) where the second event is understood as a physical consequence of the first. Although the descriptive analysis of collision trends in the previous chapter has identified frequently occurring pattern and collision characteristics, it does not mean that it caused the collision to occur. Moreover, the previous analysis cannot directly tell us how much influence the factor is having on the injury severity outcome of the collision. It is also difficult to explain through the earlier analysis the relationship between collision outcomes and features of the built environment.

This chapter presents the findings of a hierarchical ordered probit model (HOPIT) that examines cyclists' injury severity levels. Bicycling is becoming an increasingly important element of sustainable transport systems; their pollutant and noise emissions, and the accident risks they pose for other road users are very low which contribute to a more attractive urban environment (Rietveld and Daniel, 2004). Bicycling also offers economic benefits, such as reduced household expenditure on transportation, reduced work hours lost in traffic congestion, and reduced healthcare costs resulting from increased physical activity and reduced pollution (Transport Canada, 2008). Furthermore, there is increased recognition of the health and wellness perspective of cycling as an effective way for people to cope with health problems and obesity (Rietveld and Daniel, 2004). Given the benefits of bicycling, improving road safety conditions and reducing injuries to cyclists is an important consideration for encouraging people to cycle more. Effective injury reduction requires an understanding of the factors that affect the likelihood of a collision occurring as well as the characteristics that may mitigate or exacerbate the level of injury sustained (TRIP, 2006). Many studies have applied various modeling frameworks to analyze injury severity, although limited research has focused on bicycle collisions for improving road safety for the cyclists. Relatively little is known about the influence of the built environment and neighborhood attributes on injury severity, especially within the context of bicycling. This chapter attempts to fill the gap, specifically by investigating characteristics of the neighborhoods in which collisions occur. It is to our best knowledge that this analysis may be the first to solely model cyclists' injury severity levels, incorporating neighborhood and built

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[2] This chapter is partially based on the paper Habib, M,A. and Forbes, J.J. "Modeling Bicyclists' Injury Severity Levels in the Province of Nova Scotia, Canada using a Generalized Ordered Probit Structure", reviewed proceeding, 93rd Annual Meeting of the Transportation Research Board, Washington DC, January 2014.

environment characteristics in the model estimation. Furthermore, the results generated in this analysis provide an evidence based foundation for the implementation and evaluation of bicycle-related road safety strategies and campaigns in Nova Scotia.

We apply an ordered probit modeling approach to examine the factors affecting injury severity levels. A HOPIT model structure is utilized to account for heterogeneity across individuals, particularly in relation to the threshold parameters, something previously not attempted in bicycle collision research. The paper uses data drawn from the Nova Scotia Collision Record Database (NSCRD) at Service Nova Scotia and Municipal Relations (SNSMR) for the empirical application of the model.

The rest of the chapter is organized as follows: first, we provide a review of the literature. Following the literature review, we discuss the data used in the empirical application. The next section describes the modeling approach used in the analysis, followed by a discussion of model results. The paper concludes by providing a summary of contributions and future research directions.

3.3 Literature Review

There is a wide body of safety literature examining the occurrence and outcomes of bicycle collisions. Several collision studies found that children and older individuals were the main groups that suffered from bicycle related injuries (Chong et al., 2004; Stone and Broughton, 2003; Rodgers, 2000; Rodgers, 1995; Rodgers, 1997; Eilert-Petersson and Schelp, 1997; Maring and Schagen, 1990). Stone and Broughton (2003) observed a higher incidence of fatalities in adults older than 50 years. About half of fatally injured cyclists are 65 years or older in Sweden (Schieman et al., 2013). A study by Kim et al. (2007) support this finding; cyclists older than 55 were found to be more susceptible to fatalities. An early study by Maring and van Schagen (1990) noted that even though age itself is not a causal factor, childhood and elderly ages are strongly associated with relevant variables such as cognitive development and perception. Although not conclusive, gender has been found to play a role in injury outcomes. Males, in Kim et al.'s study (2007), had a higher percentage distribution in bicycle-related injuries compared to females while Stone and Broughton (2003) found no significant difference for males and females.

Several studies have investigated the relationship between bicycle safety and alcohol consumption. Kim et al. (2007) found that alcohol consumption by both cyclists and motorists increase the likelihood of fatal and incapacitating injuries (injuries that prevent normal functioning) for cyclists. Cyclist fatalities have been found to be significantly correlated with alcohol expenditure per capita (Noland and Quddus, 2004). Comparing intoxicated and sober cyclists, some studies have found a greater risk of head and face injuries in intoxicated cyclists (Andersson and Bunketorp. 2002; Olkkonen and Honkanen, 1990). Alcohol increases the cyclists' risk of injury from falling more than from collisions (Olkkonen and Honkanen, 1990).

The literature is in general agreement that most fatal and serious cyclist injuries are associated with higher speed limits (Stone and Broughton, 2003; Kim et al., 2007; Yan et al., 2011; Abdel-Aty et al., 2007; Garder 1994) and that bicycle safety can be improved by reducing bicycle and vehicle speeds (Koike et al., 2003; Fernandez et al., 1999; Garder et al., 1998). High speeds make drivers pay attention to the most relevant direction and ignore the less relevant direction which modifies the driver's visual scanning pattern (Rasamen and Summala, 2000l Summala et al., 1996). This agrees with research that indicates the most frequent type of bicycle-motor vehicle collisions are related to a driver turning right and a bicycle coming from the driver's right (Rasamen and Summala, 1998; Preusser et al., 1982).

Some research has shown that relative rates for falls and injuries is lower when cycling on-road compared to using an off-road path or sidewalk (Forster, 2001; Aultman-Hall and Adams, 1998; Moritz, 1996; Rodgers, 1997). However, Smith and Walsh (1998) and Pucher (2011) argue that bicycle bikeways and bike lanes make cycling safer. Eluru et al (2008) recommend bicycle facilities be designed to be an off-roadway bicycle lane, physically separated from motorized vehicle traffic by an open space or barrier. Research has shown that accident risk for cyclists varies significantly. There are safe, and unsafe bike paths, just as there will be areas where on-road riding is relatively safe. Rifaat et al. (2011) studied effect of street pattern on the severity of crashes involving vulnerable road users and found loop and lollipop design to be associated with a higher likelihood of non-fatal injury in the event of a collision between a motor vehicle and a cyclist but a lower likelihood of non-fatal injury. In a study by Thom and Clayton (1992), the most frequent contributing factor to bicycle-motorist accident risk for both cyclists and drivers was the failure to yield to right away. Garder (1994), and Kim and Li (1996) observed that cyclists were more likely than drivers to violate traffic laws. Specific crash patterns and risk have been found to play a role in elevating cyclist injury severity, for example: head-on and angle collisions, occurrence of running over cyclists, roads without median/division, and heavy vehicle involvement (2011).

Klop and Khattak (1999) observed that injury severity increased in fog, on roads with both straight and curved grades and with higher speed limits. Klop and Khattak (1999) also found that crashes occurring in higher average traffic result in less severe injuries. Wavnik (2009) found the risk of injury accidents to increase in darkness. Stone and Broughton (2003) studied the influence of lighting on fatalities and found that darkness with street lighting has the lowest fatality rate and found that a higher percentage of fatalities occur between 9 pm and 6 am. Some authors identified main causes of bicycle-traffic accidents and found that the main causes were excessive vehicle speed, lack of proper illumination during the afternoon peak period and at night, and a poor roadway design (Fernandez et al., 1999). Kim et al.'s study (2007) found that collisions occurring during the AM peak (9-10 am) and weekends increase the likelihood of fatality.

Numerous studies of bicycle collisions have focused on head injury and helmet usage. Generally, they found that head injuries were the most common type of bicycle-related injuries (Eilert-Petersson and Schelp, 1997; Karkhaneh et al., 2011; Macpherson et al., 2004; Maki et al., 2003; Welander et al., 1999; Stutts and Hunter, 1999). Helmets are protective against head injury and brain injury (Moore et al., 2011; Lapparent, 2005; Depreitere, 2004; Robinson, 2001; Schieber and Sacks, 2001; Povey et al., 1999). On the other hand, it has been argued that helmeted cyclists ride more recklessly as they feel more protected (Thompson et al., 1996). Although helmets are effective for all cyclists, regardless of age, helmets are not always properly used leaving room to improve helmet design to mitigate improper use (Curnow, 2003; Scuffham and Langley, 1997; Ching et al., 1997). Helmet usage has been linked to behavioral characteristics: for example, helmet usage rate in one study was correlated with time spent riding a bicycle each year (2000). Neighborhood characteristics also have an influence on helmet use. One study found those who wear helmets are more highly educated (1998). Another study found helmet use in rural areas to be lower than in urban areas across all age groups and for both genders (1999). When legislative intervention is introduced to mandate helmet usage, the effectiveness is uncertain as injury and fatality rates may fall simply because the legislation produces a decline in bicycle use (1995).

Socioeconomic factors, such as the percentage of poor households within a neighborhood, have been found to play an important role in the prediction of bicycle accident rates (1995). Pless et al. (1989) reported that higher risk of injury was related to fewer years of parent education, a history of accidents in the family, an environment judged as unsafe, and poor parental supervision. Macpherson et al. (2004) found that children living outside urban centers had an increased risk of hospitalization due to bicycling-related injuries. Kim et al. (2007) has noted a need for future research into the interplay between the built environment and bicycle collisions.

The majority of bicycle safety research concentrates on descriptive analysis of causes, occurrences and outcomes of collisions. Studies that employ multivariate models to pursue analysis of the factors affecting injury severity at the level of individual collisions is limited (Eluru et al., 2008). Even more limited, is the amount of studies that examine the relationship between land use and neighborhood attributes, and bicycle collisions. Therefore, this paper attempts to investigate the factors that affect injury severity levels of cyclists, including neighborhood characteristics using collision records of Nova Scotia, Canada.

3.4 Data Used In the Empirical Application

3.4.1 Nova Scotia Collision Record Database (NRSCRD)

Collision records from 2007-2011 were the data source for model estimation. The collision records were drawn from the NSCRD retained at SNSMR in Halifax, Canada. In Nova Scotia, all collisions involving property damage over $1000 and injuries or fatalities occurring on a public road, as defined by the Motor Vehicle Act, require reporting. The NSCRD consists of data representing collisions in 18 counties in Nova Scotia. The 2007-2011 NSCRD data includes information on over 74,000 collisions involving about 208,700 individuals. Of these, about 470 collisions involved cyclists. When a collision occurs, the completed collision report forms (MV58A) record a number of accident-related attributes including the characteristics of individuals involved, vehicle characteristics, roadway design attributes, environment factors, and crash characteristics. The injury severity of each individual involved in the accident is recorded on a five point ordinal scale: (1) not injured, (2) minor – no treatment, (3) moderate – treated and released, (4) major – hospitalized, and (5) fatal. After cleaning the data for validity, consistency, and uniformity, 425 bicycle collisions were deemed suitable and retained for further analysis.

3.4.2 Data Preparation for Modeling

The data preparation for modeling involved multiple stages. First, a database with all relevant attributes was created. Second, collision locations were geocoded using the online service BatchGeo™. Third, neighborhood characteristics were derived by means of the spatial join function in ArcGIS to combine the collision location with dissemination area (DA) data from the 2006 Canadian Census. Joined data included average household income, average number of rooms, housing stock, and dwelling type counts. Population and dwelling densities were normalized by their respective fields with the DA area. Finally, a land use mix measure for Nova Scotia, originally proposed by Bhat and Gossen (Bhat and Gossen, 2004) and adapted by Habib et al. (2013), was spatially joined to the collision location. The land use mix index ranges from 0 to 1, with 1 indicating perfect land use heterogeneity and 0 indicating perfect homogeneity. Other land use and built environment measures were computed using geospatial Enhanced Point of Interest files obtained from Desktop Mapping Technologies Inc. at a 250-meter (0.155 mile) buffer from each collision to capture the context of the area where the collision occurred.

3.5 Methodology

This analysis utilizes an ordered probit econometric structure in which the ordinal nature of the severity levels of cyclists are recognized at the level of individual collisions. The model assumes that there is a latent continuous injury risk propensity metric underlying the observed ordinal responses. The continuous variable y_i^*, albeit unobservable, can be written as a linear combination of predictors and an error term:

$$y_i^* = \beta X_i + \varepsilon_i \tag{1}$$

Where $y_i^*$is the latent injury risk propensity for cyclists i in a given collision. X_i corresponds to a set of attributes associated with the collision, including personal, collision, and neighborhood characteristics. β is a vector of unknown parameters to be estimated. ε_i is a random error term, which is assumed to follow a normal distribution (i.e., a probit link), resulting in the ordered probit model examined in this paper.

The observed injury severity level, y_i, takes on values 0 through m generating an ordered partitioning of the latent risk propensity into the observed severity categories according to the following scheme:

$$-\propto < \theta_1 < \theta_2 < \ldots .. < \theta_{m-1} < \propto \tag{2}$$

Here, θ represents threshold parameters in which $\theta_0 = -\propto$ and $\theta_m = \propto$. Hence, the observed injury severity levels can be represented as:

$$\begin{aligned} y_i^* &= 0 \text{ if } y_i^* \leq 0 \\ &= 1 \text{ if } 0 < y_i^* \leq \theta_1 \\ &= 2 \text{ if } \theta_1 < y_i^* < \theta_2 \\ &\ldots\ldots\ldots. \\ &= m \text{ if } y_i^* > \theta_{m-1} \end{aligned} \tag{3}$$

The estimation of this ordered probit model is straightforward. This model is an extension of a probit model for a binary outcome. Therefore, the probability of observing a particular ordinal outcome can be represented generically as:

$$Prob(y_i = m) = \phi(\theta_m - \beta X_i) - \phi(\theta_{m-1} - \beta X_i) \tag{4}$$

Assuming an indicator variable ψ_{im}, which equals 1 if the cyclist sustains an injury of level m, and 0 otherwise, the log likelihood can be written as follows:

$$lnL = \sum_{i=1}^{n}\sum_{m=0}^{m}\psi_{im}\ ln[\phi(\theta_m - \beta X_i) - \phi(\theta_{m-1} - \beta X_i)] \quad (5)$$

This traditional ordered probit model, commonly used in accident research, restricts the thresholds θ_m to be the same for every individual. Eluru et al. (17) argues that there will be several variables impacting injury risk propensity and several variables potentially influencing the thresholds in reality. Imposing a restriction of fixed θ_m might lead to inconsistent injury risk propensity; thereby inconsistent effects of variables on the likelihood of severity level categories. Hence, several authors offered a generalized ordered probit model, allowing flexibility of varying thresholds (Pudney and Shields, 2000; Greene and Hensher, 2000. This generalized econometric structure assumes that threshold parameters can vary across collisions of different individuals due to both observed and unobserved factors. It is assumed a specific functional form for the thresholds in order to constraint that all predicted probabilities are greater than zero and guarantee the ordering conditions (i.e., equation 2) for all data vectors. The thresholds can be specified as:

$$\theta_{im} = \exp(\gamma_m + \delta' z_i) \quad (6)$$

Where z_i is a set of exogeneous variables corresponding to the m^{th} threshold, δ' represents parameters to be estimated, and γ_m is a parameter associated with severity levels $m = 1,2,\ldots\ldots.m$. Now, denoting $F(.)$ as the cumulative distribution of the standard logistic distribution, and $\propto_{im}$ as a dummy that exhibits the value 1 if the cyclist i sustains an injury level of m and 0 otherwise, the log-likliehood function can be re-written for the i^{th}individual as:

$$L_i = \int_{\beta}\int_{\xi}\ [F\{(\theta_{im}|\xi) - \beta X_i] - F[\{\theta_{i,m-1}|\ \xi - \beta X_i\}]^{\propto_{im}} \times g(\beta)g(\xi)d\beta d\xi \quad (7)$$

Here, β and ξ are drawn from multivariate normal distributions $g(\beta)$ and $g(\xi)$. The overall log-likelihood function can be written as:

$$L = \sum_i\ lnL_i \quad (8)$$

The parameters of this relaxed ordered probit formulation are estimated by maximizing the log-likelihood function of equation 8, and in relation to the moment parameters of the distributions $g(\beta)$ and $g(\xi)$. Finally, the goodness-of-fit of the models are evaluated in terms of adjusted pseudo R-squared $\left(= 1 - (logL_{constant\ only}\ - Q\right)/logL_{full\ model})$. Where Q is the number of parameters in the model.

3.6 Discussions of Results

In the injury severity modeling literature, *t*-statistic and coefficient are the most commonly reported model statistics. In the models produced in this chapter, the *t*-statistic is used to determine statistical significance with a *t*-statistic value corresponding to the 95% confidence interval and *t*-statistic value corresponding to the 90% confidence interval. In testing the various hypotheses and interpreting the model results, variables which conceptually make sense (i.e. can reasonably explain the injury severity outcome) and meet statistically significant confidence intervals are retained in the model. The r-squared value is used to evaluate the models fit during the modeling process. Due to the small sample size of the data employed in the study, some variables with lower *t*-statistics are also retained (if they add to the explanatory power of the model) because they offer empirically plausible explanations to describe injury severity outcomes. It is assumed that a larger dataset would yield statistically significant results (although the sample consists of 425 observations, the distribution of some injury severity levels, like fatal, is relatively small).

Table 12 shows the summary statistics of the independent variables retained in the final model specification. Three alternative model specifications of cyclists' injury severity were estimated. The first model is a traditional ordered probit model that includes personal and collision characteristic variables only (Model 1). The second model is the HOPIT model described in the earlier section, which allows flexibility in the model assumption to allow for systematic variation in the cut-points, and thus incorporates adjustment for heterogeneity likely present in the data, but not accommodated in traditional ordered probit models (Model 2). Parameter estimates of this model are reported with the same variables that are used in the first model specification for consistent comparisons. The third model, the same HOPIT model, retained all variables from previous specifications but was enhanced by the inclusion of variables reflecting neighborhood and land use characteristics (Model 3). In HOPIT models 2 and 3, the thresholds vary with whether or not the cyclist was using a helmet and if the cyclist was at fault. The model results suggest that the signs and approximate values of the estimated coefficients in the previous models remain stable and generally become larger with each new model specification. Table 13 reports parameter estimation results of the three models outlined above.

Table 12: Summary statistics of explanatory variables used in the HOPIT model for cyclists' injury severity

Variable	**Description**	**Mean / Proportion**	**St. Dev.**	**Min**	**Max**
Personal characteristics					

Age 45-54	Cyclists between age of 45 and 54 (dummy)	11%	-	-	-
Female	Gender - female (dummy)	23%	-	-	-
Cyclist impairment	Cyclist impaired at time of collision (dummy)	2%	-	-	-
Collision characteristics					
Intersection	Collision occurred in intersection with parking lot entrance/exit, private driveway or laneway (dummy)	14%	-	-	-
Road slope	Collision occurred on steep road grade (dummy)	25%	-	-	-
Lane change	Lane change manoeuver by cyclist at time of collision(dummy)	2%	-	-	-
View obstructed	Cyclist view was obstructed at time of collision (dummy)	2%	-	-	-
Cyclist ejected	Cyclist was ejected from bicycle (dummy)	31%	-	-	-
Street light off	Street lights not on at time of collision (dummy)	62%	-	-	-
After dark	Collision occurred after dark (dummy)	19%	-	-	-
Weekend	Collision occurred during the weekend (dummy)	22%	-	-	-
Weather	Collision occurred during inclement weather (dummy)	2%	-	-	-
Neighborhood characteristics					
Schools	At least one school present within the 250 meter buffer (0.155 mile) (dummy)	7%	-	-	-
Shopping Centre	Distance to nearest shopping center (m)	12,531	30,373	36	197,725
Land use mix	An index, ranges from 0 to 1, with 1 indicating perfect land use heterogeneity and 0 indicating perfect homogeneity.	0.24	0.2	0	0.66
Road facility type	Collision occurred on a collector road (dummy)	2%	-	-	-
Speed limit	Collision occurred on road with speed limit >50 km/hour (31.1 miles/hour)	10%	-	-	-
Population density	Population density of the dissemination area where the collision occurred (persons per sq. km)	15.69	14.69	0.001	55.55
Average person per household	Average person per household (log) in the dissemination area where the collision occurred	2.81	0.26	2	4.5
Average gross rent	Average gross rent (log) in the dissemination area where the collision occurred ($)	442.69	321.44	0	1643

Threshold covariates					
Helmet	Cyclist wearing helmet at time of collision (dummy)	44%	-	-	-
Cyclist fault	Cyclist was at fault during time of collision (dummy)	79%	-	-	-

Table 13: Parameter estimation results from HOPIT model for cyclists' injury severity

	Model 1: Traditional Ordered Probit		**Model 2: HOPIT without Neighborhood Characteristics**		**Model 3: HOPIT with Neighborhood Characteristics**	
	coefficient	*t*-stat.	coefficient	*t*-stat.	coefficient	*t*-stat.
Personal characteristics						
Age 45-54	0.36850114	**2.072	0.39367546	**2.09	0.42645517	**2.187
Female	0.10762794	0.826	0.10580487	0.742	0.12250256	0.834
Cyclist impairment	0.6799049	*1.864	0.64417965	1.54	0.67610472	*1.738
Collision characteristics						
Intersection	0.25052195	1.562	0.25815015	*1.647	0.29033094	*1.815
Road slope	0.24521584	1.93	0.23255537	*1.646	0.21940982	1.515
Cyclist manoeuver (lane change)	0.67397524	*1.811	0.67366255	*1.685	0.70229147	*1.775
View obstructed	1.33739608	**3.482	1.3311095	**3.399	1.37818806	**3.417
Cyclist ejected from bicycle	0.44713461	**3.779	0.43204158	**3.232	0.43548242	**3.134
Street light off	0.16827643	1.407	0.16697159	1.297	0.1446745	1.072
After dark	0.4206568	**2.755	0.4177134	**2.704	0.35810964	**2.185
Weekend	0.26242587	*1.958	0.26413158	**1.999	0.28280126	**2.054
Weather	0.6276363	1.287	0.59065724	1.333	0.64468059	1.509
Neighborhood characteristics						
Presence of schools					0.00014964	1.213

Distance to nearest shopping center					0.19936163	1.262
Land use mix					-0.00022238	-1.297
Road facility type (collector road)					0.53980227	1.099
Speed limit >50 km/hour (31.1 miles/hour)					0.29969097	1.358
Population density					0.00005584	*1.906
Average gross rent (log)					-0.0436924	-1.600
Average person per household (log)					0.04402381	1.606
Threshold parameters						
Theta(1)	0.80498049	12.89	-0.27855624	-2.242	-0.28492061	-2.247
Theta(2)	2.77491176	23.692	0.97111263	10.653	0.97265144	10.34
Theta(3)	3.79534857	15.981	1.28331608	9.82	1.28110396	9.728
Threshold covariates						
Helmet			-0.08069972	-0.842	-0.07458946	-0.754
Cyclist fault			0.11989971	0.991	0.15086669	1.196
Constant	0.3851968	3.026	0.39059542	2.863	0.48202896	2.167
Pseudo R-squared	0.0590564		0.0615906		0.0780812	
Number of observations	425		425		425	
**95% confidence interval; *90% confidence interval						

Overall, Model 3 results exhibit stronger relationships between the explanatory variables and levels of injury severity based on estimated coefficients and *t*-statistic values. It also outperforms the previous specifications by demonstrating better model fit, evaluated in terms of adjusted pseudo R-squared. Most importantly, this model includes land use and neighborhood attributes, mostly ignored in previous bicycle collision modeling research. Therefore, Model 3 is selected as the final model in this study.

The parameter estimation results suggest that personal and collision characteristics are strong factors in explaining cyclist injury severity outcomes. Neighborhood characteristics are also found to add to the explained variance in cyclist collisions based on improved model fit, and overall, inclusion of these variables in Model 3 improves the explanatory power of the model. The majority of the independent variables retained in the model are statistically significant at least at the 90% confidence interval. Some variables exhibit a lower *t*-statistic but have been retained in the final model, with the presumption that a larger dataset would result in statistically significant parameters.

The majority of personal characteristics of the cyclists involved in the collision yield statistically significant associations with sustaining an injury. Cyclists aged 45-54 involved in a collision have a positive relationship with the injury severity levels, implying that these groups are more likely to suffer severe injuries compared to other age groups. This result compliments other studies that found older adults to be more positively associated with injury severity (Chong et al., 2010; Stone and Broughton, 2003; Rodgers, 1997). Age itself may not be a causal factor but may be strongly associated with other relevant variables correlated with age. For example, perception and reaction time, physical fragility, and likelihood of existing medical conditions which come with age; all of these might contribute to higher injury risk propensity. Additionally, it is likely that the 45-54 age group represents the oldest age cohort of cyclists. In our model, females are associated with higher levels of injury severity compared to males, which may be attributed to differences in physical vulnerability associated with females. The presence of alcohol or drugs (represented by a dummy of impairment at the time of collision) shows a strong positive relationship with severity, suggesting that persons affected by alcohol, drugs or other substances have a higher likelihood of being injured or dying in a collision.

The collision characteristic variables were also found to be significant factors. Not surprisingly, collisions reported with view obstructions are very strongly associated with a higher likelihood of injury severity, indicating that sightlines have an effect on the probability of serious injury for cyclists. Collisions occurring when a cyclist is making a lane change positively influence the probability of a more severe injury. This is likely attributed to increased interaction with motor vehicles. The configuration of the road has an influence on the cyclists' injury likelihood. Specifically, a collision in an intersection has a higher injury risk. These findings are likely attributed to vehicles underestimating the speed of cyclists or perhaps not expecting bicycles to be on the road. Additionally, cyclists are subjected to maneuvering through conflicting vehicular movements if they need to make a turn at intersections. Road grades, particularly steep roadways, were found to increase the likelihood of a higher injury severity level outcome. It is possible that steeper grades allow riders, especially those who are inexperienced, to build up speeds on steep descents which may create hazardous conditions for stopping or staying in control. The model also suggests that there is a positive, yet relatively weak relationship between street lighting and increased injury severity. As expected, a positive relationship with injury severity is found when cyclists are ejected from their bicycles during a collision. Weekend collisions were found to result in a greater likelihood of increased injury severity. This finding is consistent with the literature, which indicates bicycle use as a leisure activity increases on weekends which perhaps results in higher absolute injury severity. The model found inclement weather conditions (rain or snow) to be a strong predictor of injury severity. The effect of weather on injury severity is likely a result of reductions in visibility and traction. Reduced visibility due to inclement weather can lead to a more severe collision since it can distract or reduce perception of both cyclists and drivers which reduces their ability to respond (e.g. brake or take an evasive manoeuver). A positive and relatively strong relationship is found with collisions occurring after dark. Certainly lighting condition is directly related with visibility which primarily affects the risk of collisions, but also affects severity due to lack of evasive action (e.g. driver did not see cyclist) which leads to greater impact and thus severity. Inclement weather also makes roads and trails more slippery which can lead to more severe injury since braking and steering are suboptimal, leading to greater impact speeds and possible worse impact angles.

The presence of schools within the collision location is associated with an increase in injury severity. This variable may represent environments that are associated with higher levels of cyclist activity. Distance to the nearest shopping center was found to have a strong, positive relationship with injury severity. As distance increases, the likelihood of higher injury severity increases, indicating that collisions near shopping centers are less likely to result in higher levels of severity or perhaps areas outside of shopping centers are less safe for cyclists. Arguably, there are better cycling facilities located near shopping malls compared to outlying areas.

This paper examines a land use mix variable, defined as an index that ranges from 0 to 1, with 1 indicating perfect land use heterogeneity and 0 indicating perfect homogeneity. In general terms, land use heterogeneity is a spatial phenomenon in which a given area contains a high mix of land uses. An area with land use heterogeneity blends residential, commercial, industrial, government, park, and open space land uses. The model results reveal that the land use mix variable has a negative association with injury severity, indicating that severity risk is lower in relatively higher mixed land uses. Land use heterogeneity is touted as a viable planning option as it promotes greater housing variety and density, reduced travel distances, more compact development, and strong neighborhood character. Based on our observations, these environments typically include pedestrian and bicycle supportive design, which may be a reason why the likelihood of serious injury decreases in these locations. As expected, speed limits over 50 km/hour (31.1 miles/hour) are associated with an increase in the probability of injury severity. Collisions in areas with high population densities are associated with greater levels of injury severity. One likely explanation may be that higher populated neighborhoods have larger number of cyclists in the area. The model shows that average gross rent in the neighborhood is associated with a lower likelihood of injury severity. Presumably, affluent neighborhoods typically have better quality street lighting, roadway markings, and traffic calming measures that may contribute to the association of lower injury severity levels in these areas. On the other hand, average persons per household in the neighborhood negatively affect injury severity levels. This finding may be attributed to greater numbers of people cycling in these areas; or may also represent environments that are less supportive of safe cycling.

As discussed earlier, this paper examines several variables for the threshold parameter specification. Two major variables: cyclist wearing helmets at the time of collision (dummy) and cyclist at fault in the collision (dummy) which exhibits 44% and 79% respectively for the sample collision records. These threshold covariates were selected as they are commonly cited contributors to cyclist injury severity outcomes. The helmet variable exhibits a negative sign, indicating a downward shift of the threshold parameters. On the other hand, the cyclist at fault variable shows a positive relationship, an upward shift of the threshold parameters. These results suggest that the probability estimates of collision severity categories could vary with the observed attributes, which is often ignored in the earlier studies. This result can be interpreted in the following way: the personal, collision, and neighbourhood characteristics have a higher probability of increased injury severity levels when a cyclist is at fault. On the other hand, the probably of a lower injury severity outcome is increased when cyclists are wearing a helmet.

Finally, several other variables were tested during model estimation but those hypotheses could not be confirmed due to lack of reasonable statistical significance and unexpected signs. For example, some neighborhood characteristics, such as intersection density, and institutional and commercial land use densities, yielded counter-intuitive results. These counter-intuitive results could be due to high correlations between the other built environment variables.

3.7 Conclusion

This analysis presents the findings of a HOPIT model that examines cyclists' injury severity levels, capturing the ordinal nature of injury severity and allowing adjustment for heterogeneity likely present in the data, but not accommodated in the traditional ordered probit models. Model 3, with the flexible threshold structure, improved the model fit because the threshold covariates added to the explanatory power of the model (evaluated in terms of adjusted pseudo R-squared). The analysis reveals patterns of cyclist injury severity relative to personal, collision, land use, and neighborhood characteristics. The findings generally confirm those from the body of literature but offer some interesting insights to the role of neighborhood and land use attributes in bicycle safety, which the literature presented in Section 3.2 has shown to be limited.

There are many important findings. The results reveal that females, impaired cyclists, and persons aged 45-54 involved in bicycle collisions have an increased likelihood of sustaining more severe injuries. The estimation results show that there are a number of important collision characteristics that increase the probability of more severe injuries: cycling manoeuvers (lane change), road conditions and configurations (at intersections and on steep road grades), and lighting conditions (after dark and when street lights are off) to be significant in explaining cyclist injury severity levels. Characteristics of the neighborhood in which collisions occur, specifically land use characteristics (heterogeneous land use), accessibility measures (presence of schools and distance to nearest shopping center), and household characteristics (average person per household and average gross rent) were found to be important predictors of cyclist's injury severity. Our findings have important implications for engineering (e.g. traffic calming measures and intersection design), enforcement (e.g. police presence), and education safety interventions. For example, older adults need to be educated about safety risks of cycling as they have been found to be more vulnerable to severe injuries when bicycle collisions occur.

This study has certain limitations associated with the data. Collisions which have not been reported due to minor injuries or collisions which had been reported and resulted in no or minor injury are likely to be underrepresented in the results which may skew injury severity levels toward more severe collisions. Furthermore, the study employs a relatively small sample size (425 collisions). Additionally, as the data pooled collisions representing multiple years in Nova Scotia, temporal variability could not be incorporated in the model. Further research is required in this area, particularly in how time-variation indicative variables, such as improvement of certain infrastructure in a given year, would affect injury severity of cyclists. For example, future efforts could utilize collision records from locations that have had a bike lane installed and estimate models for before and after installation to determine the effect on injury severity.

This study contributes in many ways. Previous research mainly focuses on motorists' injury severity. Moreover, studies on injury severity levels that consider characteristics of the neighborhood in which they occur are limited. This study contributes in understanding how land use and neighborhood characteristics influence injury severity levels for cyclists. Additionally, the contributions of this research is timely given the increased awareness and emphasis on the use of alternative (to the automobile) modes of transportation, including bicycling in recent years. The findings can also inform the direction of policy interventions. For example, one consideration is the need to focus on visibility of cyclists (sight lines and lighting) and reduce the need and ability of cyclists to maneuver when traveling. Possible interventions could include bike boxes, shared roadway markings, cycle tracks, and colored bicycle lanes that increase cyclist visibility and maneuverability. The finding of this analysis will be valuable in road safety planning and policy discussions aimed at encouraging bicycle use.

CHAPTER 4: ANALYSIS OF PEDESTRIAN INJURY SEVERITY [3]

4.1 Introduction

The previous chapter presented an analysis of cyclist injury severity. The cyclist injury severity model analyzed collisions representing multiple geographic areas in the province, which made incorporation of built environment and land use variability in the model difficult. This chapter uses the Halifax Regional Municipality (HRM) as a case study to examine the effect of the built environment on injury severity of pedestrians using two ordered response models. Recent increases of collisions involving pedestrians in HRM has prompted investigation of the factors that may mitigate or exacerbate the level of injury sustained to this vulnerable road user group. This impetus, coupled with the availability of better built environment data, provides an opportunity to examine pedestrian safety in the urban context of Nova Scotia.

In the HOPIT model fit in this study, the thresholds vary (i.e. the thresholds are specified as functions variables, not just as constants) with whether or not the collision occurred at an intersection and with the density of commuters who walk in the area. The study puts particular emphasis on understanding built environment contributing factors including street pattern classifications, land use types, transit supply, and demographic characteristics. These variables are examined together with other variables including pedestrian and driver characteristics, collision characteristics, and environmental conditions (such as weather and lighting conditions).

Halifax Regional Municipality has one of the highest proportion of pedestrian commuters of census metropolitan areas in Canada at 8.5%, surpassing Toronto, ON (4.6%), Vancouver, BC (6.3%), and Calgary, AB (4.9%). Active Transportation (AT) is on an upward trend in HRM and the Province of Nova Scotia, which is apparent when considering the development and implementation of municipal and provincial AT plans, policies, and programs, such as the Thrive! Strategy, the Active Transportation components of the Sustainable Transportation Strategy, and the development of the provincial Active Transportation Policy.

From 2007 to 2011, there were 1751 pedestrian collisions in Nova Scotia, 65% occurring in HRM. Of the pedestrian collisions in HRM, 79% resulted in injuries while 7.4% resulted in major injuries or fatalities. These statistics indicate that pedestrian safety is a great concern for HRM. Any effort to reduce the social

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[3] This chapter is partially based on the paper Forbes, J.J., and Habib, M.A., `` Investigation of Pedestrian Collisions and Injury Severity levels in the Halifax Regional Municipality`, presented at the 49th Annual CTRF Conference , June 2014. (Best Paper Prize, Runner-Up).

and economic burden of these collisions and enhance pedestrian safety requires an understanding the factors that contribute to collision likelihood and pedestrian injury severity in the event of a collision. This paper uses HRM as a case study to examine the effect of the built environment on injury severity of pedestrians using ordered response models. In this study, built environment characteristics include land use types, road network connectivity, transit supply, and demographic characteristics. These effects on injury severity are examined together with other variables including pedestrian and driver characteristics, collision characteristics, and environmental conditions. In this study, two models are specified; first, a conventional ordered probit is used; second, a hierarchical ordered probit (HOPIT) is estimated.

When considering the variety of road user groups, pedestrians are often considered the most vulnerable. Evidence-based safety improvements require an understanding of the relevant factors that contribute towards increasing the severity of these collisions. Many studies have focused on injury and fatality risks of pedestrians, examining vehicle characteristics, roadway design characteristics, pedestrian and driver behaviors, types of collisions and environmental conditions. Although the effects of numerous factors have been explored in past studies, minimal research has been done to explore the effect of the built environment on injury severity.

When analyzing injury severity outcomes, the application of an appropriate econometric model is an important consideration. Typically, pedestrian injury severity is reported as an ordered variable resulting in frequent employment of ordered response models for analyzing the factors affecting injury severity levels. The most commonly employed approach to pedestrian injury severity is the ordered logit and probit models which recognize the inherent ordering in the severity variable while appropriating the probability of injury severity to various alternatives based on population specific thresholds. The HOPIT model used in this study, a variation of the conventional ordered probit model, allows the thresholds to vary across observations and thus incorporates adjustments for reporting heterogeneity.

Organization of the rest of the paper is as follows. First, we provide a discussion on previous research on pedestrian injury severity modeling while positioning the current study. Second, we provide details on the econometric model framework used in the analysis. Third, we describe the data source and preparation process. Following this, we present the model estimation results and discussion. The final section concludes the paper with recommendations and directions for future research.

4.2 Literature Review

Many studies have examined pedestrian injury severity to understand the factors affecting pedestrian collision frequency and injury severity. Typically, these studies fall into one of two categories. The first category concerns studies on pedestrian collision frequencies or on the exposure measure of pedestrian collision risk. The second category involves studies that examine the determinants of injury severity in the event of a pedestrian collision. The literature reviewed in this section will describe only studies that fall into the second category. Table 14, adapted from a recent study by Yasmin et al., (2013), provides a summary of earlier research on pedestrian injury severity studies and provides information on the analysis framework used, and the variables considered in the analysis.

Table 14: Summary of existing pedestrian injury severity studies (Adapted from Yasmin et al., 2013)

Study	**Analysis framework employed**	**Pedestrian injury severity representation**	**Characteristics/factors considered**	
Zajac and Ivan, (2003)	Ordered probit	Fatality, Disabling injury, Not disabling injury, Probable injury, No injury	Crash	---
			Vehicle	Yes
			Roadway design and land use	Yes
			Environment	Yes
			Pedestrian	Yes
			Driver	---
Ballesteros et al., (2004)	Logistic regression	Mortality, Non-mortality/Injury severity score <16 and ≥16	Crash	---
			Vehicle	Yes
			Roadway design and land use	Yes
			Environment	---
			Pedestrian	---
			Driver	---
Roudsari et al., (2004)	Multivariate logistic regression	Severe injury, Non-severe injury	Crash	---
			Vehicle	Yes
			Roadway design and land use	Yes
			Environment	---
			Pedestrian	Yes
			Driver	---
Lee and Abdel-Aty, (2005)	Ordered probit	No injury, Possible injury, Non-incapacitating injury, Incapacitating injury, Fatal injury	Crash	---
			Vehicle	Yes
			Roadway design and land use	Yes
			Environment	Yes
			Pedestrian	Yes
			Driver	---
			Crash	Yes

Sze and Wong, (2007)	Binary logistic regression	Killed or severe injury, Slight injury	Vehicle Roadway design and land use Environment Pedestrian Driver	--- Yes Yes Yes ---
Eluru et al., (2008)	Mixed generalized ordered logit, Ordered logit	No injury, Non-incapacitating injury, Incapacitating injury, Fatal injury	Crash Vehicle Roadway design and land use Environment Pedestrian Driver	Yes Yes Yes Yes Yes Yes
Kim et al., (2008)	Heteroskedastic generalized extreme value logit	Fatal, Incapacitating injury, Non-Incapacitating injury, Possible or No Injury	Crash Vehicle Roadway design and land use Environment Pedestrian Driver	Yes Yes Yes Yes Yes Yes
Kim et al., (2008)	Logistic regression	Serious injury, Non-injury	Crash Vehicle Roadway design and land use Environment Pedestrian Driver	--- --- Yes Yes Yes ---
Clifton et al., (2009)	Generalized ordered probit	No injury, Injury, Fatality	Crash Vehicle Roadway design and land use Environment Pedestrian Driver	Yes --- Yes Yes Yes ---
Kim et al., (2010)	Mixed logit model	Fatal injury, Incapacitating injury, Non-incapacitating injury, Possible/no injury	Crash Vehicle Roadway design and land use Environment Pedestrian Driver	--- Yes Yes Yes Yes Yes
Kwigizile et al., (2011)	Ordered probit, Multinomial logit	No/possible injury, Non-incapacitating injury, Incapacitating injury, Fatal injury	Crash Vehicle Roadway design and land use Environment Pedestrian Driver	Yes Yes Yes --- Yes Yes

Moudon et al., (2011)	Binary logistic regression	Severely injured/dying, Suffering minor/no injury	Crash Vehicle Roadway design and land use Environment Pedestrian Driver	--- --- Yes Yes Yes Yes
Rifaat et al., (2011)	Multinomial logit	No injury, Injury, Fatality	Crash Vehicle Roadway design and land use Environment Pedestrian Driver	--- --- Yes Yes --- Yes
Tay et al., (2011)	Multinomial logit	Minor injury, Serious injury, Fatal injury	Crash Vehicle Roadway design and land use Environment Pedestrian Driver	--- Yes Yes Yes Yes Yes
Zahabi et al., (2011)	Ordered logit	No injury, Minor injury, Fatal/Major injury	Crash Vehicle Roadway design and land use Environment Pedestrian Driver	Yes Yes Yes Yes --- ---
Abay, (2013)	Ordered logit, Mixed ordered logit, Multinomial logit, Mixed multinomial logit	Slight/no injury, Serious injury, Fatal injury	Crash Vehicle Roadway design and land use Environment Pedestrian Driver	Yes Yes Yes Yes Yes Yes
Aziz et al., (2013)	Random-parameter multinomial logit	Property damage and	Crash Vehicle Roadway design and land use Environment Pedestrian Driver	Yes Yes Yes Yes Yes ---
Mohamed et al., (2013)	Latent Class Clustering: Ordered probit, K-Means: Multinomial logit	Injury and Fatal injury, No injury, Minor Injury and Fatal injury	Crash Vehicle Roadway design and land use Environment Pedestrian	--- Yes Yes Yes Yes

			Driver	Yes
Tefft, (2013)	Logistic regression	Severe injury, Non-severe injury/Fatal injury, Non-fatal injury	Crash	Yes
			Vehicle	Yes
			Roadway design and land use	Yes
			Environment	---
			Pedestrian	Yes
			Driver	---

Based on the studies reviewed (Table 14), the dependent variable (pedestrian injury severity) typically ranges from two (fatality/severe injury to slight injury/property damage only) to five (fatality, disabling injury, not disabling injury, probable injury to no injury). We can also see that that logistic regression and the ordered probit and logit models are the most prevalent econometric frameworks used to examine pedestrian injury severity. The summary also indicates that limited research has considered variables from all categories (crash, vehicle, roadway design and land use, environment, pedestrian and driver characteristics). Yasmin et al.'s review (2013) determined that the findings of earlier research are usually consistent with one another. The most common factors that increase pedestrian injury severities include older pedestrians, male pedestrians, intoxicated pedestrians and/or drivers, occurrence of crash in darkness (with or without lighting), vehicle speeding, crash location is in a commercial area or on highways, and collisions involving a bus or truck. Factors found to reduce pedestrian injury severities in earlier research include, older drivers, presence of traffic signal control, snowy weather, and collision occurrence during the day. The influence of built environment and land use variables, which includes a variety of street pattern classifications, land use types, transit supply, and demographic characteristics are generally being explored only recently as injury severity determinants. Little effort has been directed at incorporating built environment and land use variability within model estimation. The HOPIT model fit in the current study incorporates built environment and land use variability characteristics as threshold covariates to model estimation.

4.3 Data Used in the Empirical Application

4.3.1 Data Source

Pedestrian collision data for HRM is drawn from the Nova Scotia Collision Record Database (NSCRD) for the years 2007 through 2011. In Nova Scotia, all collisions involving property damage over $1000 and injuries or fatalities occurring on a public road, as defined by the Motor Vehicle Act, require reporting. The NSCRD database consists of over 74,000 collisions involving about 208,700 individuals. After cleaning and processing the data, 963 records were retained for further analysis. A number of collision-related factors are recorded in the database including characteristics of individuals involved, vehicle characteristics, roadway design attributes, environment factors, and crash characteristics. The injury severity of each individual involved in the accident is recorded on a five point ordinal scale: (1) not injured, (2) minor – no treatment, (3) moderate – treated and released, (4) major – hospitalized, and (5) fatal.

4.3.2 Data Preparation

The pedestrian collision records were geocoded using GeoPinpoint. Built environment characteristics are derived by means of the spatial join function in ArcGIS to combine the collision location with dissemination area (DA) data from the 2011 Canadian Census and 2011 National Household Survey data. Joined data includes average household income, average number of rooms, housing stock, and dwelling type counts. Land use and built environment measures are computed using the Halifax Regional Municipality Corporate Dataset, Nova Scotia Topographic Data, and Desktop Mapping Technologies Inc. at a 250-meter buffer from each collision to capture the context of the area where the collision occurred. Finally, adapting a classification scheme from Rifaat et al. (2011), street pattern is classified into six categories: gridiron, fragmented parallel, warped parallel, loops and lollipops, lollipops on a stick, and mixed pattern, and examined with other factors to determine influence on injury severity.

4.4 Methodology

Injury severity is an inherently ordered outcome and therefore, the ordered probit model has become a widely used econometric framework in safety literature for analyzing injury severity outcomes. The ordered probit model can be written as a linear combination of predictors and an error term:

$$Y_i^* = \beta' Z_i + \varepsilon_i \tag{1}$$

Where Y_i^* is the latent and continuous measure of injury severity faced by pedestrian i in a collision, $Z_i$is a vector of explanatory variables describing personal, collision, and built environment characteristics, ε_i is a random error term assumed to be standard normal distribution, and $\beta'$is a vector of parameters to be estimated.

The injury severity outcome, Y_i^*, takes on values 0 through m generating an ordered partitioning of the latent risk propensity into the observed severity categories according to the following scheme:

$$-\propto < \theta_1 < \theta_2 < \ldots.. < \theta_{m-1} < \propto \tag{2}$$

Where θ represents threshold parameters in which $\theta_0 = -\propto$ and $\theta_m = \propto$. The observed injury severity level can therefore be represented as:

$$
\begin{aligned}
y_i^* &= 0 \text{ if } y_i^* \leq 0 \\
&= 1 \text{ if } 0 < y_i^* \leq \theta_1 \\
&= 2 \text{ if } \theta_1 < y_i^* < \theta_2 \\
&\ldots\ldots\ldots\ldots \\
&= m \text{ if } y_i^* > \theta_{m-1} \qquad (3)
\end{aligned}
$$

The estimation of this ordered probit model is straightforward. This model is an extension of a probit model for a binary outcome whereby the probability of observing a particular ordinal outcome can be represented generically as:

$$Prob(y_i = m) = \phi(\theta_m - \beta X_i) - \phi(\theta_{m-1} - \beta X_i) \qquad (4)$$

Assuming an indicator variable ψ_{im}, which equals 1 if the pedestrian sustains an injury of level m, and 0 otherwise, the log likelihood can be written as follows:

$$lnL = \sum_{i=1}^{n} \sum_{m=0}^{m} \psi_{im} \; ln[\phi(\theta_m - \beta X_i) - \phi(\theta_{m-1} - \beta X_i)] \qquad (5)$$

The ordered probit model assumed the thresholds between the injury severity levels to be equal for all individuals. It assumes that response heterogeneity does not exist or that it doesn't vary among the population. In addition to the conventional ordered probit model, we estimate a HOPIT model, which allows the thresholds to vary across observations and thus incorporates adjustment for reporting heterogeneity. The conventional ordered probit model has an inherent identification problem, because in:

$$Prob(y_i = m) = \phi(\theta_m - \beta X_i) - \phi(\theta_{m-1} - \beta X_i) \qquad (6)$$

If x and y have variables in common, then (with a sign change) the same model is produced whether the common variable appears in θ_m or βX_i. The HOPIT model avoids the indeterminacy by using a different functional form. The following form is provided:

$$\mu_j = \exp(\theta_j + \delta_j{}'z) \qquad (7)$$

The functional form of the HOPIT model reverts the unmodified ordered probit model if the single vector δ equals 0. In that case, θ_j will equal the log of the original μ_j in the ordered probit model.

In the final specification of the HOPIT model in this study, the thresholds vary with whether or not the collision occurred at an intersection and with the proportion of commuters who use walk as a mode in the neighbourhood. These threshold covariates were selected as they are commonly used indicators of pedestrian safety. By incorporating this variability directly in model estimation, we can determine the relationship between built environment characteristics and the other threshold parameters. Finally, to facilitate the comparison of effects of the variables across different models, the marginal effects are computed. The marginal effects are calculated as the average percentage change in the probability of an injury severity category when a variable switches (from 0 to 1) for all observations.

4.4 Discussion of Results

In the injury severity modeling literature, *t*-statistic and coefficient are the most commonly reported model statistics. In the models produced in this chapter, the *t*-statistic is used to determine statistical significance with a *t*-statistic value corresponding to the 95% confidence interval and *t*-statistic value corresponding to the 90% confidence interval. In testing the various hypotheses and interpreting the model results, variables which conceptually make sense (i.e. can reasonably explain the injury severity outcome) and meet statistically significant confidence intervals are retained in the model. The r-squared value is used to evaluate the models fit during the modeling process. Due to the small sample size of the data employed in the study, some variables with lower *t*-statistics are also retained (if they add to the explanatory power of the model) because they offer empirically plausible explanations to describe injury severity outcomes. It is assumed that a larger dataset would yield statistically significant results.

Variables related to the pedestrian and driver characteristics, collision characteristics, and environmental conditions were examined in each model. The first model is a conventional ordered probit model and the second is the HOPIT model, a variation of the conventional ordered probit model. For consistent comparisons, parameter estimates for both models are reported with the same variables used in the first specification. The model results suggest that the signs and approximate values of the estimated coefficients remain stable in each model and generally improve when the threshold covariates are introduced in the HOPIT model. This improvement is especially apparent when comparing the signs and estimated coefficients of the built environment characteristics in the HOPIT model. Overall, the HOPIT model exhibits the strongest relationship between the explanatory variables and levels of injury severity.

Evaluating each models adjusted pseudo R-squared values, the HOPIT model demonstrates significantly better model fit than the conventional ordered probit model. The HOPIT model is selected as the final model for this study. Table 15 reports parameter estimation results of the two models outlined above and the marginal effects are reported in Table 16. Some variables included in the final specification exhibit relatively lower *t*-statistics values but have been retained in the model, with the presumption that a larger dataset would result in statistically significant parameters.

Table 15: Parameter estimation results from ordered probit and HOPIT models for pedestrian Injury severity

	Conventional OP		**HOPIT**	
Category	coef.	*t*-stat.	coef.	*t*-stat.
Personal characteristics				
Female pedestrian	.03609634	.506	.05597466	.751
Pedestrian aged 55 or older	.45047810	**4.834	.46348606	**4.822
Male driver	.17898512	**2.510	.18435015	**2.459
Driver aged 55 or older	-.17989512	**-2.136	-.16157634	*-1.929
Collision characteristics				
AM occurrence (7-9AM)	-.17141604	-1.222	-.14370967	-1.134
Dark lighting conditions	.18975512	**2.365	.18591989	**2.187
Weather (clear)	-.15969738	**-2.210	-.15743616	**-2.030
Vehicle traveling straight	.20865935	**2.857	.18897341	**2.568
Left bumper impact	.11049302	1.068	.11207331	1.044
Built environment characteristics				
Sloped road	.17308594	*1.877	.18508539	**2.099
Average dwelling value (log)	-.03099429	*-1.868	-.03206790	*-1.716
Average children per household	.22437276	1.675	.22745421	1.495
Participation rate	-.00602287	*-1.780	-.00709814	**-2.042
Median shelter cost	.00021993	*1.832	.00025418	**2.123
KM of sidewalk	-.00030799	*-1.774	-.00022148	-1.335
KM of bus route	.00037472	**2.240	.00037910	**2.066
Building area (sq. ft.)	-.00051865	*-1.861	-.00050894	*-1.699
Number of transit stops	.01675820	**2.300	.01661417	**2.340
Street pattern (grid)	.16176621	*1.771	.17883604	*1.941
Threshold parameters				
Mu(1)	.90887270	21.823	-.22413403	-3.348
Mu(2)	2.56895430	40.667	.82548847	17.455
Mu(3)	3.49727014	29.109	1.14875484	22.734
Threshold covariates				
Intersection			.10728926	**2.272
Walking commuters in neighbourhood			-.04297268	**-2.406
Constant	1.19562327	3.861	1.24035356	3.459
Pseudo R-squared		.0334959		.0390020

Number of observations	963	963
**95% confidence interval; *90% confidence interval		

The parameter estimation results suggest that the age and gender of pedestrians and drivers are strong factors in explaining pedestrian injury severity outcomes. Pedestrians aged 55 or older involved in a collision are more likely to suffer severe injuries compared to other age groups. The marginal effects show that pedestrians aged 55 or older have positive associations with moderate, major, and fatal collisions (0.0991, 0.0622, and 0.0124). Drivers aged 55 or older also have a positive relationship with injury severity levels of pedestrians. Older individuals are associated with slower perception and reaction times, physical fragility, and existing medical conditions, which may contribute to a higher risk propensity. Therefore, although not a causal factor itself, age may be strongly associated with other relevant variables correlated with age. Female pedestrians and male drivers are associated with higher levels of injury severity for pedestrians.

The collision characteristic variables were also found to be significant predictors of pedestrian injury severity. Collisions occurring during the AM peak (7-9 AM) were found to be associated with lower levels of injury severity although they have a relatively low effect size and statistical significance but are noteworthy nonetheless. A positive and relatively moderate relationship is found with collisions occurring after dark. Certainly lighting conditions are directly correlated with pedestrian visibility, which primarily affects the risk of collisions, but also affects severity due to lack of evasive action by drivers, leading to greater impacts and thus injury severity. Lighting is a key element of crosswalk design. Seeing and being seen are essential conditions for safety of pedestrians. If adequate lighting is not provided, dark lighting conditions make pedestrians less visible to drivers. As expected, a negative relationship with injury severity is found when weather conditions are clear. The marginal effects also showed that clear weather has a positive effect on non-injurious and minor collisions (0.0344 and 0.0272). Collisions occurring when a vehicle is travelling straight positively influences the probability of a more severe injury to the pedestrian. The pedestrians' location of impact with the vehicle has an influence on the pedestrians' injury likelihood. Specifically, a collision where the pedestrian is struck with the vehicles left front bumper is associated with a higher injury risk.

Model estimation also offers some interesting insights into the role of the built environment on pedestrian injury outcomes. A variety of street pattern classifications, land use types, transit supply, and demographic characteristics were examined in the models. The majority of built environment characteristics exhibit lower effect size and statistical significance, which is likely attributed to interaction with the other explanatory variables. Pedestrians involved in collisions within lower income neighbourhoods, represented by the average dwelling value variable, have a higher risk of severe injuries compared to higher income neighbourhoods. This may be attributed to more frequent speeding, increased levels of crime, unpleasant or unsafe walking environments, and riskier behaviour of walkers and drivers associated with lower income neighbourhoods. Neighbourhoods with higher averages of children per household are found to be associated with higher levels of pedestrian injury severity. Although not supported by the personal characteristic age variable (pedestrians aged 55 and older), this may attributed to the disadvantage children have as pedestrians as they have lower overall physical, cognitive, visual, and auditory development. Neighbourhoods with higher shelter costs are associated with lower levels of pedestrian injury severity. Neighbourhoods that are more affluent are associated with better quality street lighting, roadway markings, and traffic calming measures, which provide a safer environment for pedestrians.

Areas with more kilometers of sidewalk, represented by the km of sidewalk within 250m of the collision location variable, are found to be associated with lower levels of injury severity. This finding is intuitive as sidewalks provide a grade separated facility for walking that is generally considered safer for pedestrians. Conversely, areas with more kilometers of bus route are found to be associated with higher levels of pedestrian injury severity. Buses are an apparent point of conflict for pedestrians. It is likely that pedestrian and other road users may interact with buses in the roadway when crossing the street. The significance of the variable representing kilometers of bus route may also be explained by the increased pedestrian activity associated with areas having transit service. This finding is also supported by the number of transit stops variable, which can be explained with similar reasoning. Interestingly, the building density variable (building area sq. ft.) is found to be associated with lower levels of pedestrian injury severity which suggests that denser areas are safer for pedestrians. It is likely that denser areas are associated with good quality pedestrian infrastructure such as sidewalks and curbs. Collision locations surrounded by higher numbers of general merchandise (GM) stores are found to be associated with higher levels of injury severity. These locations are typically associated with higher volumes of pedestrians and vehicles which may lead to increased interaction and therefore collision incidence and severity. Finally, the grid street pattern is found to be a significant predicator of higher pedestrian injury severity levels. The marginal effects (see Table 16) show that the grid pattern has positive effects on major and fatal collisions (0.0212 and 0.0037). The grid street pattern is characterized by many intersections, which may be conflict areas for pedestrians and other road users.

Two major variables: a collision occurring at an intersection and the density of walking commuters in a neighbourhood were used as threshold covariates in the HOPIT model estimation and both were found to be statistically significant in explaining variations in thresholds. The collision at an intersection variable exhibits a positive relationship, indicating an upward shift on the threshold parameters. The number of walking commuters in a neighbourhood produces a negative relationship, indicating a downward shift on the threshold parameters. This result can be interpreted in the following way: the personal, collision, and other built environment characteristics have a higher probability of increased pedestrian injury severity levels at an intersection. On the other hand, the probably of a lower injury severity outcome is increased in neighbourhoods which contain a higher number of pedestrian commuters.

Several other variables were tested during model estimation but those hypotheses could not be confirmed due to lack of reasonable statistical significance. For example, some built environment variables such as residential and commercial density yielded counter-intuitive results that may be due to correlations with other built environment variables.

Table 16: Summary of marginal effects based on HOPIT model

	Not injured	**Minor**	**Moderate**	**Major**	**Fatal**
Female pedestrian	-0.0124	-0.0096	0.0147	0.0062	0.001
Pedestrian aged 55 or older	-0.0865	-0.0872	0.0991	0.0622	0.0124
Male driver	-0.0411	-0.0312	0.0488	0.0203	0.0033
Driver aged 55 or older	0.037	0.0267	-0.0439	-0.0172	-0.0027
AM occurrence (7-9AM)	0.0298	0.0259	-0.0354	-0.0173	-0.003
Dark lighting conditions	-0.0394	-0.0329	0.0468	0.0218	0.0037
Weather (clear)	0.0344	0.0272	-0.0409	-0.0178	-0.0029
Vehicle traveling straight	-0.0407	-0.033	0.0485	0.0217	0.0036
Vehicle traveling straight	-0.0236	-0.02	0.0282	0.0132	0.0022
Sloped road	-0.0382	-0.0334	0.0454	0.0223	0.0039
Average dwelling value (log)	0.0071	0.0055	-0.0084	-0.0036	-0.0006
Average children per household	-0.0501	-0.0391	0.0598	0.0254	0.0041
Participation rate	0.0016	0.0012	-0.0019	-0.0008	-0.0001
Building area (sq. ft.)	0.0001	0.0001	-0.0001	-0.0001	0
Median shelter cost	-0.0001	0	0.0001	0	0

Number of transit stops	-0.0037	-0.0029	0.0044	0.0019	0.0003
Street pattern (grid)	-0.0374	-0.032	0.0445	0.0212	0.0037
KM of bus route	-0.0001	-0.0001	0.0001	0	0
KM of sidewalk	0	0	-0.0001	0	0

The estimated coefficients in Table 15 do not account for the magnitude of the effect of the variables considered in the empirical analysis. Therefore, marginal effects are presented to account for the magnitude of the effect at each injury severity level. Table 16 presents the computation of marginal effects based on the HOPIT model. The marginal effects show the change in probability when the predictor (independent variable) is increased by one unit. The marginal effects allow us to interpret the coefficient estimates in a useful way. For instance, when considering pedestrian aged 55 or older variable, the marginal effect for a major injury is 0.062. This means that persons aged 55 or older have a 6.2% higher probability to experience major injuries than other age groups, assuming no other characteristics vary. As a second example, if the weather is clear, there is a 4% lower probability to experience moderate injuries, again assuming no other characteristics vary.

4.5 Conclusion

Pedestrians are particularly vulnerable road users within the urban environment. Many studies have examined the factors contributing to the frequency and severity of crashes, but limited research has examined the influence of the built environment. Few, if any, studies have attempted to fit a model for injury severity of pedestrians that incorporates built environment and land use variability directly in the model estimation. This paper presents the findings of an ordered probit and HOPIT model that examines pedestrian injury severity levels. The HOPIT model fit in this study accommodates heterogeneity by allowing the thresholds to vary across observations while incorporating built environment and land use variability directly within model estimation as threshold covariates. In this study, built environment influences were explored in combination with other variables including pedestrian and driver characteristics, collision characteristics, and environmental conditions were explored as determinants of injury severity

Several important empirical findings have emerged. Time of day as well as weather conditions were found to be significant in explaining injury severity of pedestrians. The analysis also suggests that vehicle interaction, road design, and pedestrian action and location are important variables influencing pedestrian injury severity. Additionally, we found built environment characteristics including land use type, presence of activity centers, and demographic attributes to influence injury severity outcomes. The threshold covariates incorporated in the HOPIT model have identified intersections to be significant influences to increasing injury severity outcomes while neighbourhoods with greater pedestrian commuters are associated with reducing injury severity levels.

Important limitations are associated with the study due to the characteristics of the data. Due to the collision reporting criteria in Nova Scotia, collisions resulting in no or minor injury are likely to be unrepresented which may result in a higher number of more severe injuries present in the dataset. Compared to earlier studies in other jurisdictions, our study employs a relatively small sample size. Moreover, our study represents data from a five-year period, which means our study could not incorporate temporal variability in the model. In future studies, time-variation indicative variables should be investigated to examine the effect on injury severity. An additional limitation may exist due to the modeling framework chosen for this study. Recent research has identified the conventional ordered response model to impose a restrictive assumption on the impact of exogenous variables by constraining their impact to be the same for all alternatives. Moving forward, pedestrian injury severity will be compared using an unordered response model to allow the impact of exogenous variables to vary across the injury severity levels.

A number of contributions have emerged from this study. Although gaining increasing attention, earlier research has focused in a limited extent on the built environment contributing factors. This study contributes in understanding how street pattern, roadway design, land use, and neighbourhood characteristics influence pedestrian injury severity levels. Our study presents a HOPIT model that incorporates built environment and land use variability directly within the model structure. Moreover, the contributions of our study are timely given the increased awareness and emphasis on the use of active modes of transportation in HRM, the province, and for other jurisdictions. Our study can inform the direction of policy interventions for pedestrian safety. For example, one takeaway is the need to focus on education and awareness programs for older pedestrians and drivers alike. Another may be to increase the time allowed for crossing the street at intersections where there is a concentration of senior pedestrians.

CHAPTER 5: CONCLUSION

5.1 Summary

The safety of road users is an issue that is receiving much attention in HRM, Nova Scotia, and across jurisdictions. This thesis presents a comprehensive analysis of collisions and injury severity levels in the province. The initial descriptive analysis identified the pattern and trends of collisions at a macro-level, road user level, and a county-level. The descriptive analysis was useful in describing the province's collision experience but identified the need to further explore the determinants of injury severity outcomes, particularly for cyclists and pedestrians. Many earlier studies have examined the factors contributing to the injury severity of collisions, but limited research has examined the influence of the built environment and other land use characteristics. The econometric models used in this research were selected to appropriately capture the ordinal nature of injury severity and allow adjustment for heterogeneity likely present in the data, which have not been accommodated in the traditional ordered probit models used in injury severity modeling. The injury severity model for pedestrians accommodated heterogeneity by allowing the thresholds to vary across observations while incorporating built environment and land use variability directly within model estimation as threshold covariates. Injury severity models for cyclists and pedestrians had particular emphasis placed on built environment and land use influences but also included other variables including pedestrian and driver characteristics, collision characteristics, and environmental conditions as determinants of injury severity.

Two major contributions have arisen from the injury severity modeling of pedestrians and cyclists. The HOPIT model structure utilized in the thesis accounts for heterogeneity across individuals, particularly in relation to the threshold parameters. This model structure has not previously been used in the safety literature. The flexible form ordered probit modeling approach is specified using major contributing factors; that is, helmet use in the cyclist model and intersection occurrence in the pedestrian model. Additionally, previous research has focused primarily on motorist injury severity. Studies on injury severity that consider built environment and land use characteristics are limited. The current study investigated a variety of street pattern classifications, land use types, transit supply, and demographic characteristics and found several to be statistically significant in explaining injury severity outcomes.

There are many important empirical findings. The results reveal that females, impaired cyclists, and persons aged 45-54 involved in bicycle collisions have an increased likelihood of sustaining more severe injuries. Surprisingly, while females have an increased likelihood of sustaining more severe injuries, the descriptive analysis has shown males to be more frequently involved in collisions. The estimation results show that there are a number of important collision characteristics that increase the probability of more severe injuries: cycling manoeuvers (lane change), road conditions and configurations (at intersections and on steep road grades), and lighting conditions (after dark and when streetlights are off) to be significant in explaining cyclist injury severity. Characteristics of the neighborhood in which collisions occur, specifically land use characteristics (heterogeneous land use), accessibility measures (presence of schools and distance to nearest shopping center), and household characteristics (average person per household and average gross rent) were found to be important predictors of cyclist's injury severity. The findings have important implications for engineering, enforcement, and education safety interventions. Engineering interventions could include grade-separated facilities for cycling and walking, road geometry, and intersection design. The results could inform enforcement operations such as the time of day, day of week, and month of year to monitor road user activity. For education, one action may be to address older adults need to be educated about safety risks of cycling as they have been found to be more vulnerable to severe injuries when bicycle collisions occur.

Several important empirical findings have emerged specifically for pedestrian safety. Time of day as well as weather conditions were found to be significant in explaining injury severity of pedestrians. The analysis also suggested that vehicle interaction, road design, and pedestrian action and location are important variables influencing pedestrian injury severity. Additionally, built environment characteristics including land use type, presence of activity centers, and demographic attributes were found to influence injury severity outcomes. The threshold covariates incorporated in the HOPIT model have identified intersections to be significant influences to increasing injury severity outcomes while neighbourhoods with greater pedestrian commuters are associated with reducing injury severity levels.

5.2 Recommendations and Future Research

The contributions of this research are timely given the increased awareness and emphasis on the use of active modes of transportation in HRM, the province, and across jurisdictions. The study can inform the direction of policy interventions for cyclist and pedestrian safety. The findings of this research are also valuable in road safety planning and policy discussions aimed at encouraging the use of active transportation in different regions. A number of recommendations have been developed through the research findings, which are described in the following paragraphs.

The most recent collisions statistics published by the province come from 2006. The analysis presented in this thesis is the first comprehensive analysis of the province's collision data since this time. The data analyzed in this this study ranges from 3-8 years old. Greater efforts need to focus on analyzing the collision data on a regular basis, while the information is current. Decision and policy-making on road safety issues need to be based jointly on the most up to date and historical evidence.

There is also an opportunity to incorporate technology into the data collection process to provide an improved database for analysis. Digital forms and GPS technologies are two viable options that could improve the quality and completeness of collision data collection and also reduce data entry times. The analysis was limited in its ability to investigate the relationship between injury severity and geometric design of roads, which would be particularly useful to transportation engineers. The collision report form (MV58a) should be revised to remove data fields that are unnecessary or irrelevant and include fields that can be useful for analysis and modeling, such as geometric design of the road and characteristics of the built environment at the collision location.

The findings of this thesis research can be used for several practical applications. For example, the findings can inform future development of education and awareness campaigns and enforcement strategies. The results from the descriptive analysis have identified frequently involved gender and groups. These groups can targeted for education or awareness campaigns. Time of day, day of week, and month of year have been investigated and several notable trends have been explained. This temporal variability of collision occurrence can be used to form strategies such as increasing police enforcement at times and locations with high accident rates. The patterns and trends identified in the descriptive analysis have other practical uses. For example, the Dalhousie Transportation Collaboratory (DalTRAC) used the information it to identify which groups to advertise in social media (Facebook) and for the Share the Road Program (Habib and Siabanis, 2014). The results of the injury severity models produced for cyclists and pedestrians, particularly the probability values, can be used to help generate estimates of future collisions of concern, which will be useful for road safety planning and policy formulation.

The model results have implications for policy development. For example, one takeaway is the need to focus on education and awareness programs for older pedestrians and drivers alike. One recommendation is to increase the time allowed for crossing the street at intersections where there is a concentration of senior pedestrians. Model results show that areas with more kilometers of sidewalk are found to be associated with lower levels of injury severity levels. One recommendation may be to provide pedestrians with sidewalks and walkways that are grade separated from vehicles. Encouraging the installment of sidewalks in newly developed areas and retrofitting areas where sidewalks do not exist should be considered. Areas with higher numbers of GM stores are found to be associated with higher levels of injury severity. On the other hand, areas with a high mix of land uses and areas with high building density have been found to be associated with lower levels of injury severity. It is likely that policy aimed at promoting a variety of land use mixes and increasing density could create an environment that provides safety benefits to pedestrians and cyclists.

When considering the descriptive analysis that was performed for each county in Nova Scotia, some limitations related to normalization of the data should be noted. The results either were presented as annual frequencies or were normalized by total collisions per year. Alternative normalizing techniques could produce varied results. For example, if the collision counts were normalized by population size, land area of the county, or by number of road users, different trends or patterns may be present. It is recommended that future work explore alternative normalizing methods and produce rankings of each counties collision experience based on the determined best technique.

One critical limitation of the models developed in this thesis is the lack of temporal interactions explicitly within the model. Although temporal variability is incorporated in terms of parameters representing time and seasonality, the models do not address time variation of the five-year study period. The lack of ability to address this limitation is primarily due to the lack of data and small sample size of cyclists and pedestrians in the data. If a larger dataset was available, it could be possible to develop a cross sectional database and identify and estimate a panel data model. An additional limitation may exist due to the modeling framework chosen for this study. Recent research has identified the conventional ordered response model to impose a restrictive assumption on the impact of exogenous variables by constraining their impact to be the same for all alternatives. Moving forward, injury severity could be compared using an unordered response model to allow the impact of exogenous variables to vary across the injury severity levels. The current sample size used in this study may be a limiting factor in employing the unordered models as the existing proportions of the highest injury severity levels are significantly lower than those used in the extant literature. Another important issue needing further investigation is the certainty of the model output. Future work should explore sensitivity analysis to analyze the effects of variations and uncertainty in inputs on model outputs.

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APPENDIX A: COUNTY LEVEL ANALYSIS

A1 Annapolis County

A1.1 Total Collisions

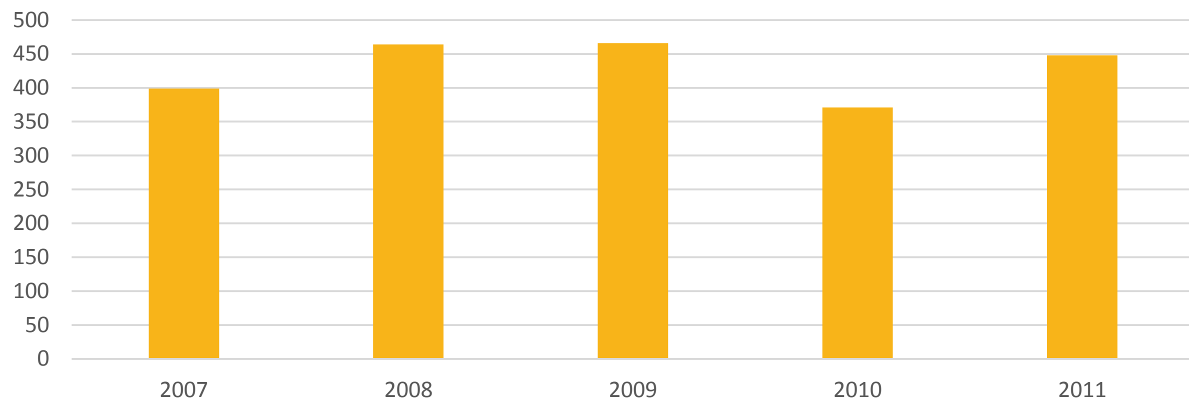


Figure 39: Total collisions by year

A1.2 Injury Severity

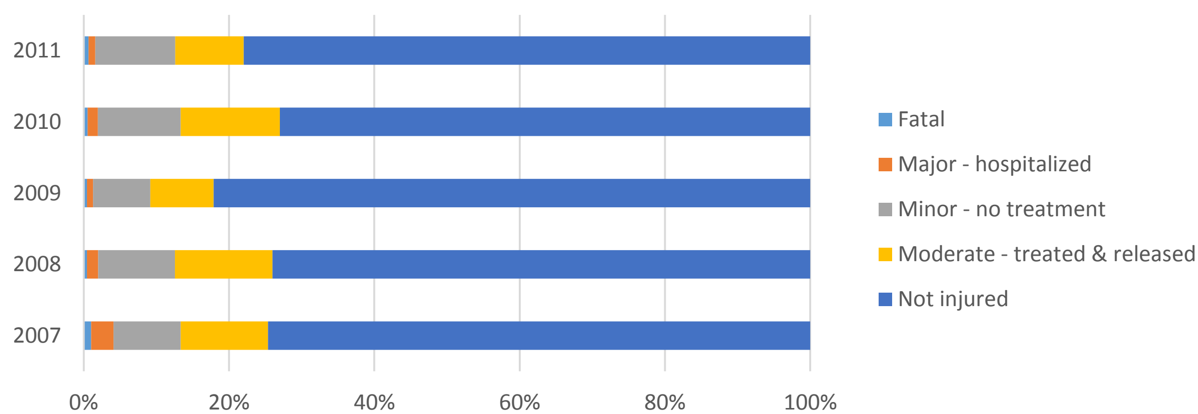


Figure 40: Injury severity of persons involved in collisions

A1.3 Personal Characteristics

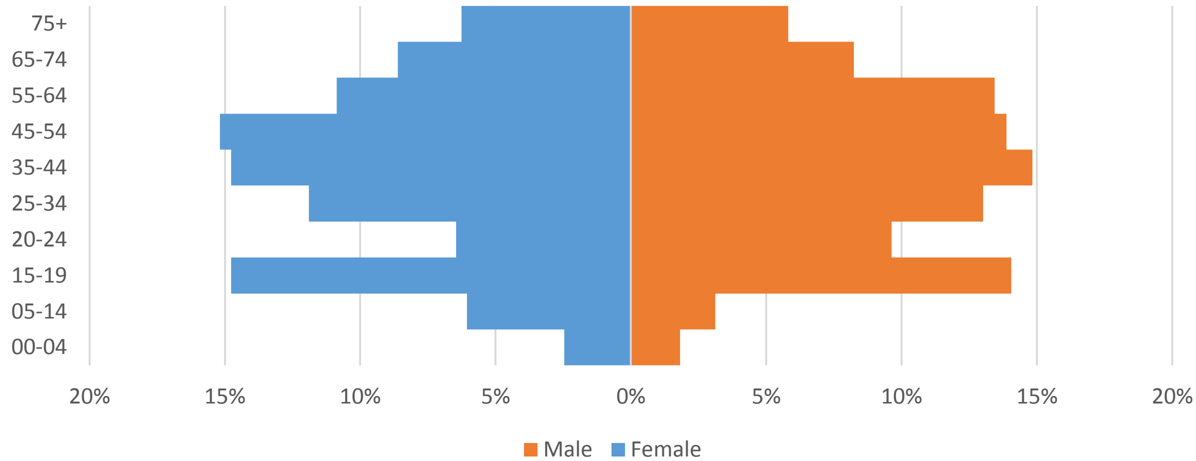


Figure 41: Age and gender distribution of persons involved in collisions

A1.4 Temporal Characteristics

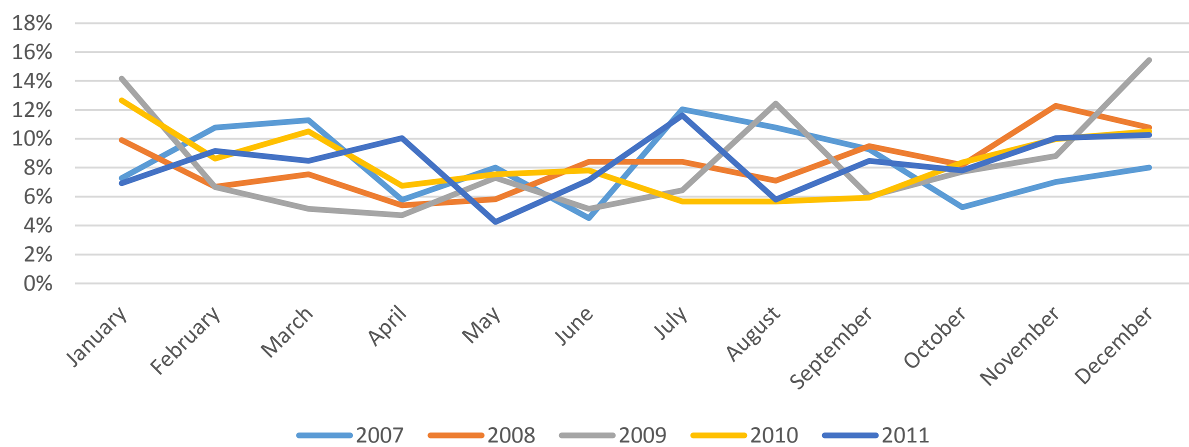


Figure 42: Monthly distribution of collisions

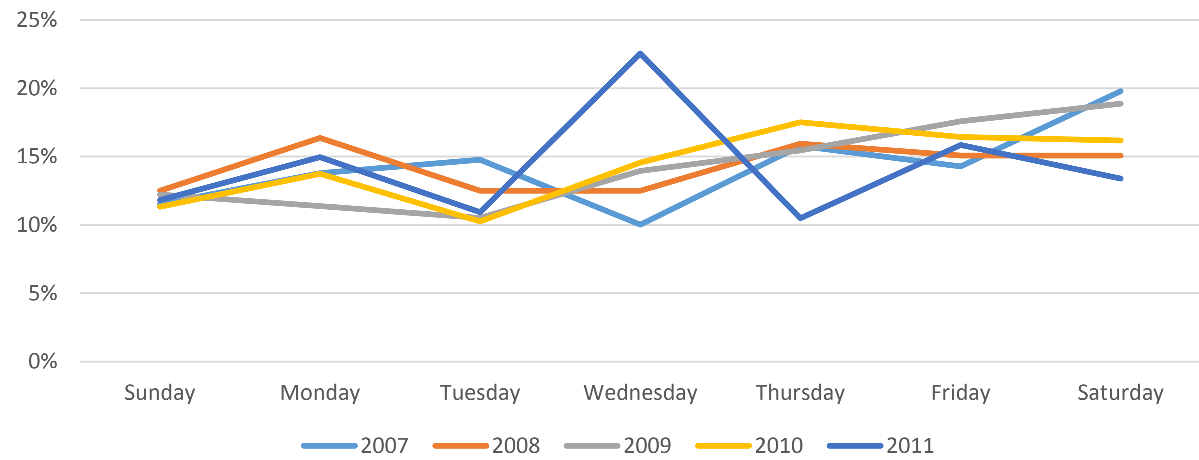


Figure 43: Day of week distribution of collisions

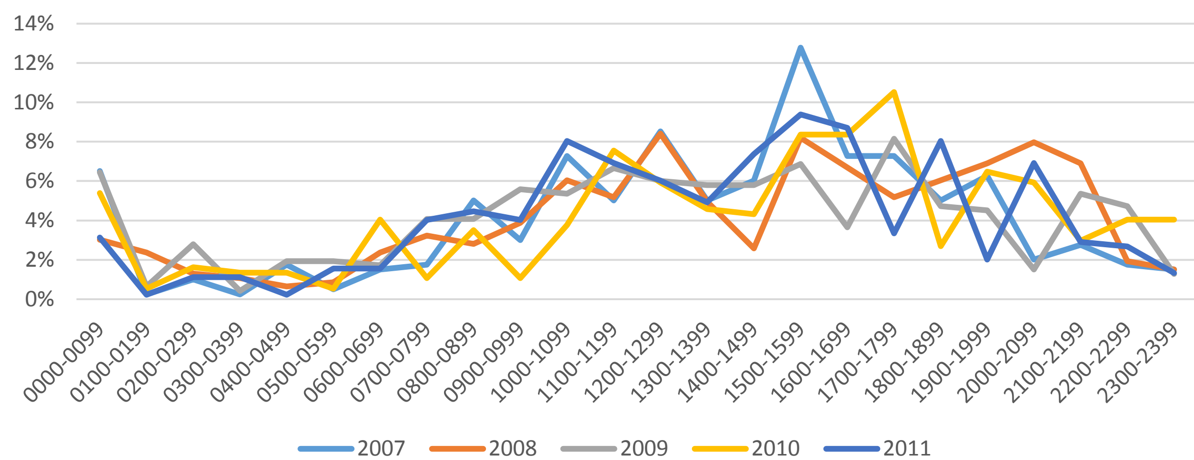


Figure 44: Time of day distribution of collisions

A1.5 Collision Frequency by Mode

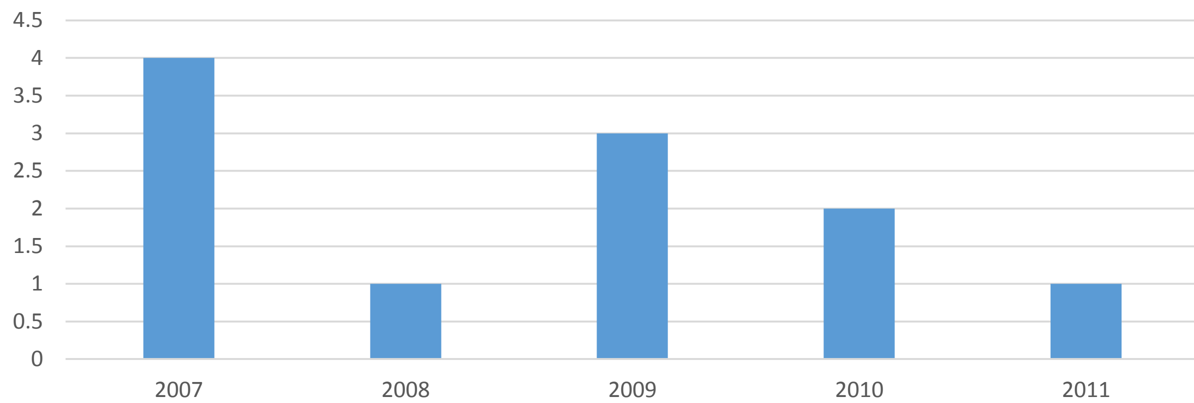


Figure 45: Number of pedestrians involved in collisions

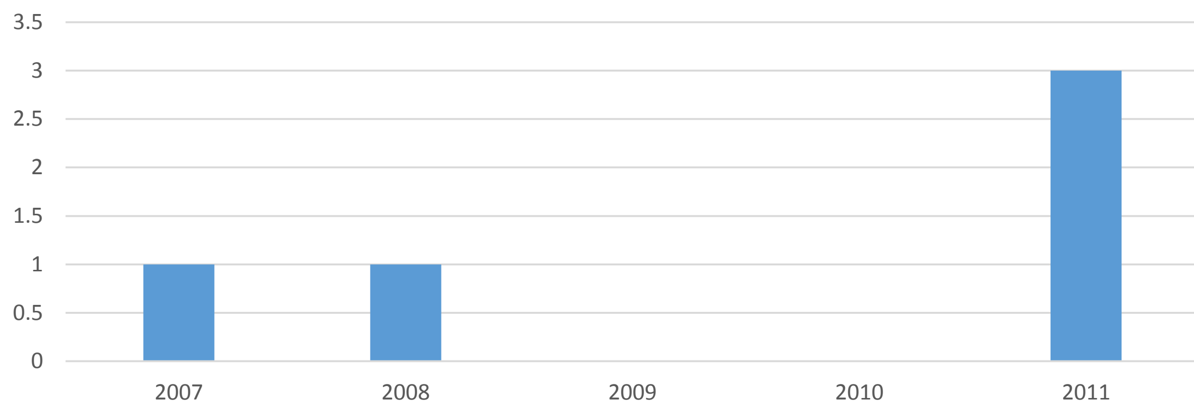


Figure 46: Number of cyclists involved in collisions

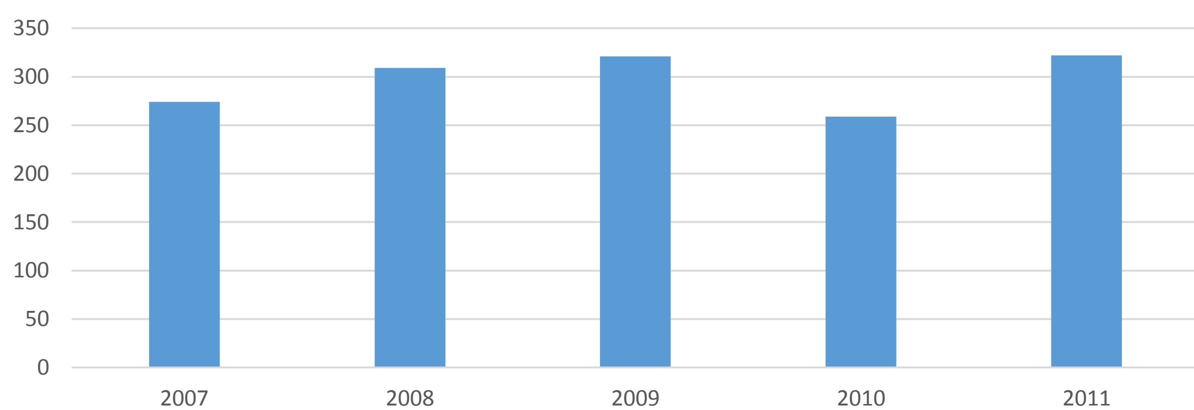


Figure 47: Number of drivers involved in collisions

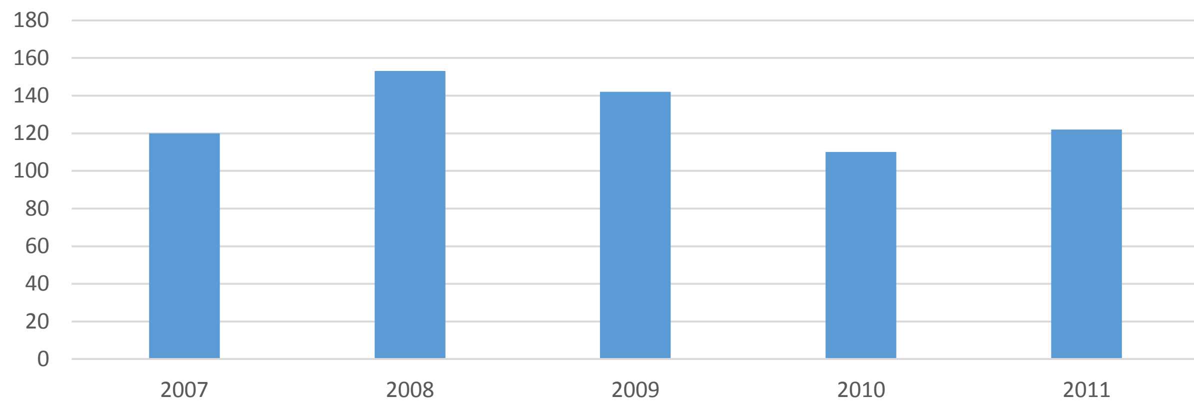


Figure 48: Number of passengers involved in collisions

A2 Antigonish County

A2.1 Total Number of Collisions by Year

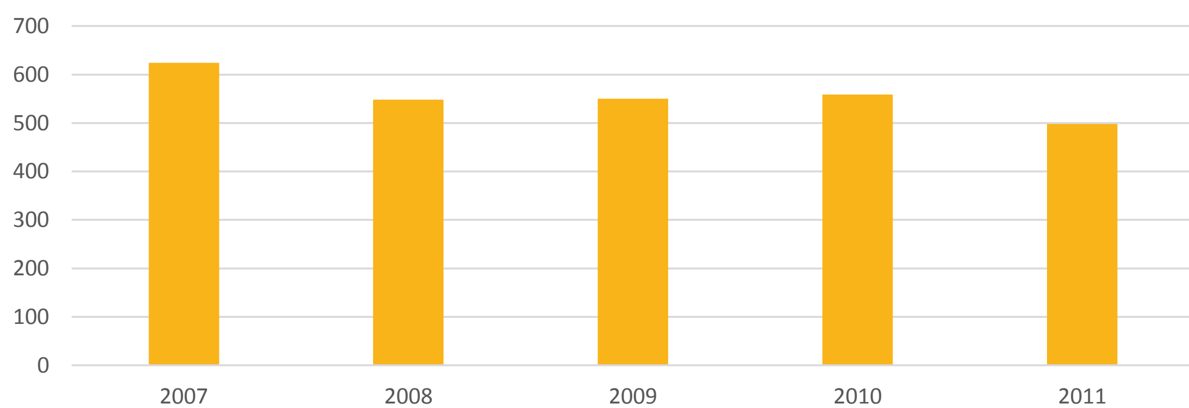


Figure 49: Total collisions by year

A2.2 Injury Severity

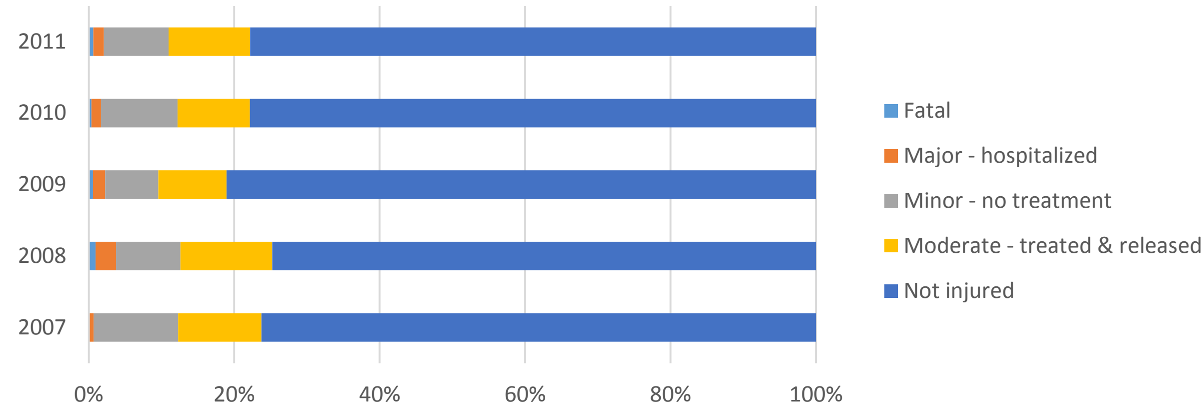


Figure 50: Injury severity of persons involved in collisions.

A2.3 Age and Gender

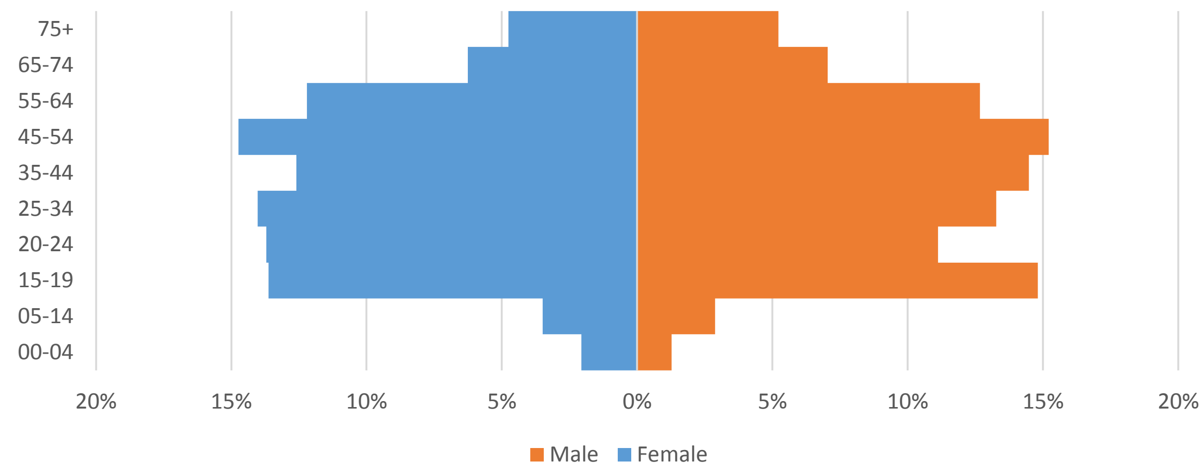


Figure 51: Age and gender distribution of persons involved in collisions

A2.4 Temporal Characteristics

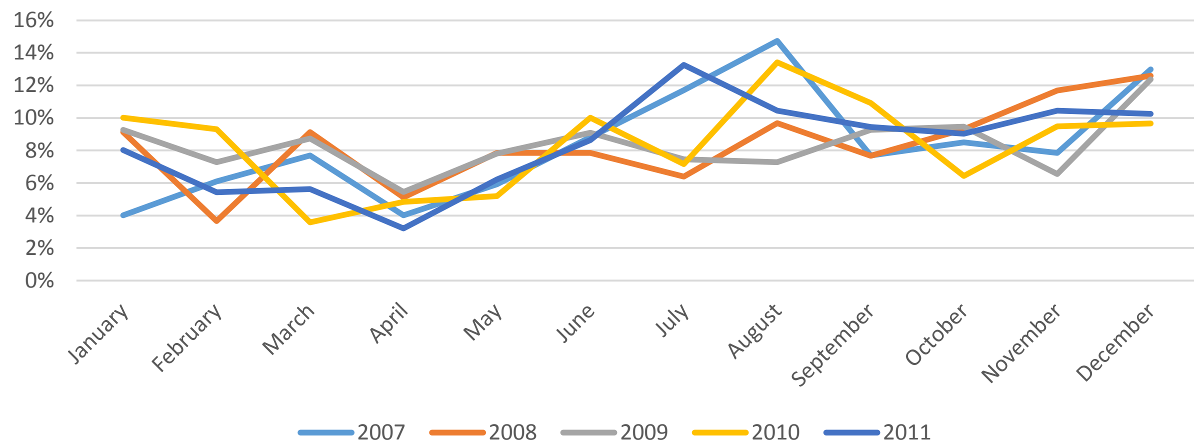


Figure 52: Monthly distribution of collisions

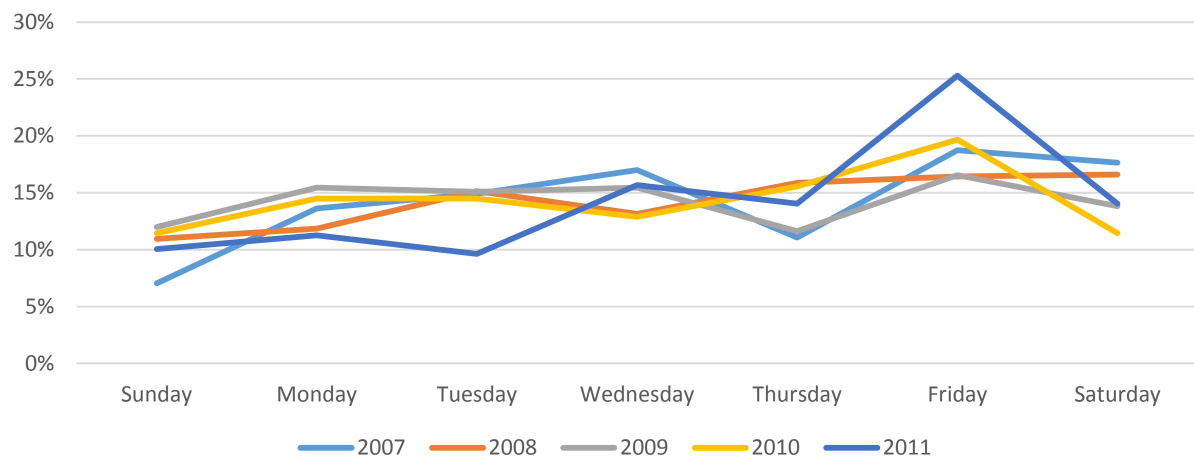


Figure 53: Day of week distribution of collisions

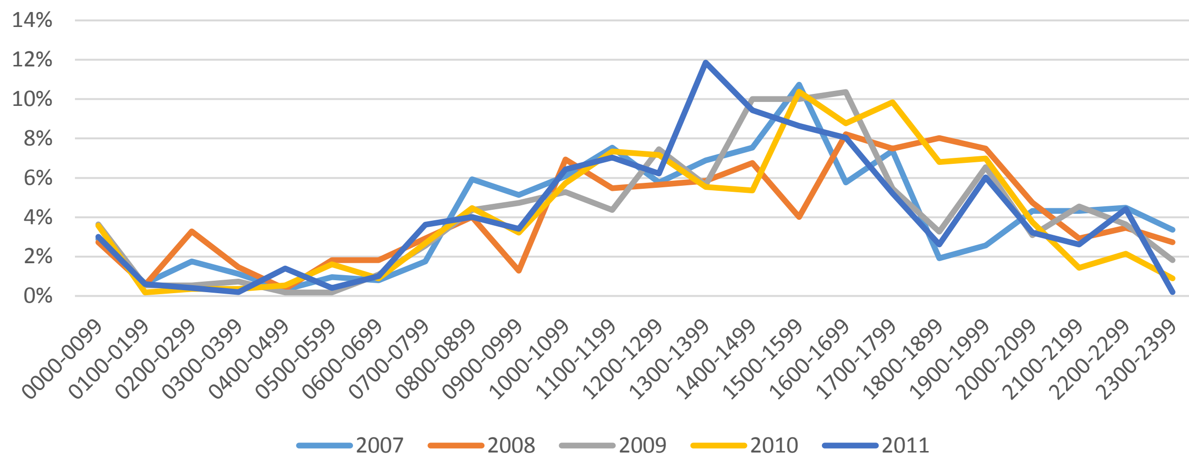


Figure 54: Time of day distribution of collisions

A2.5 Collision Frequency by Mode

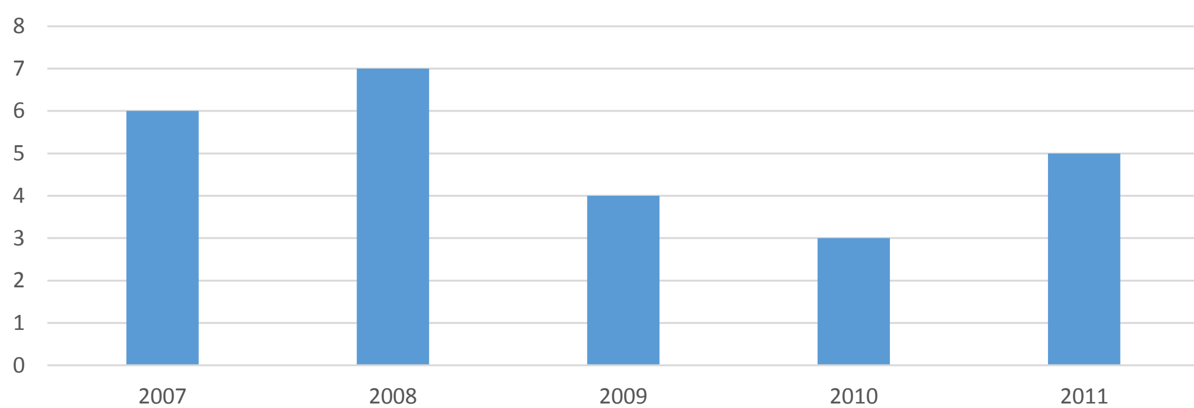


Figure 55: Number of pedestrians involved in collisions

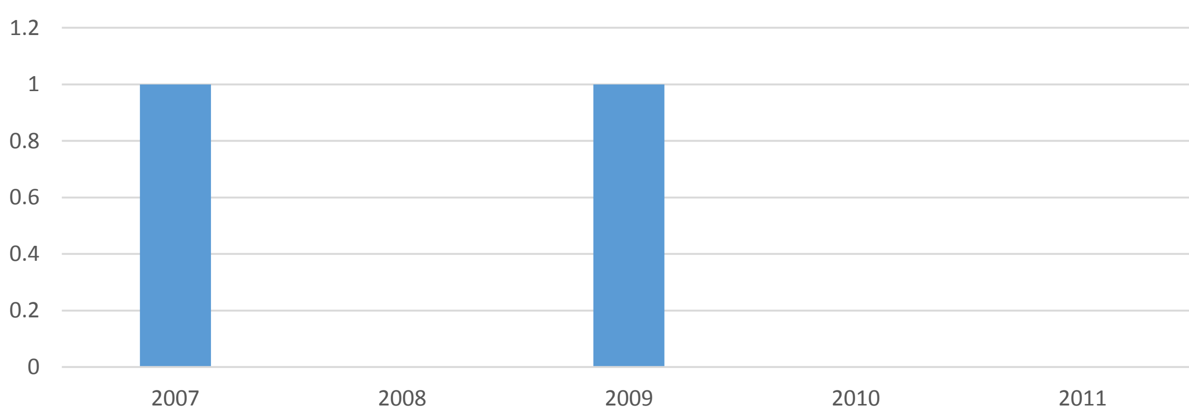


Figure 56: Number of cyclists involved in collisions

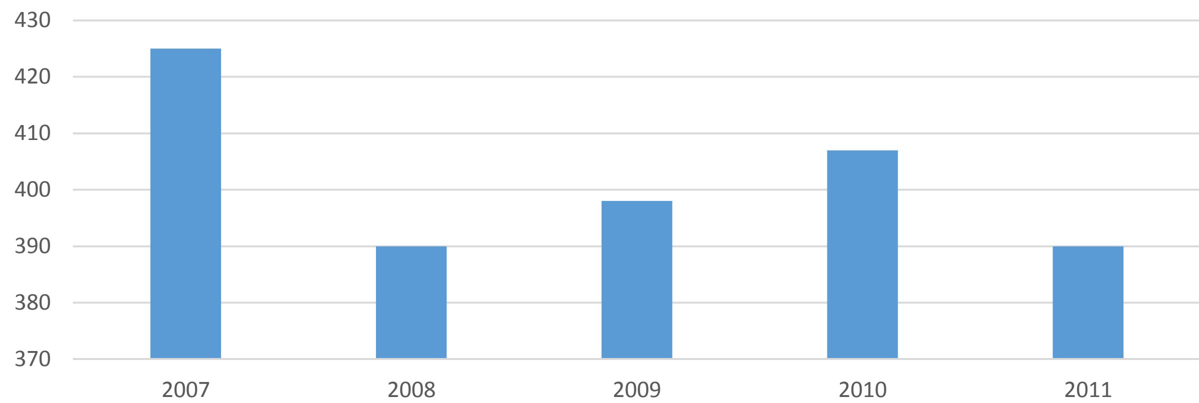


Figure 57: Number of drivers involved in collisions

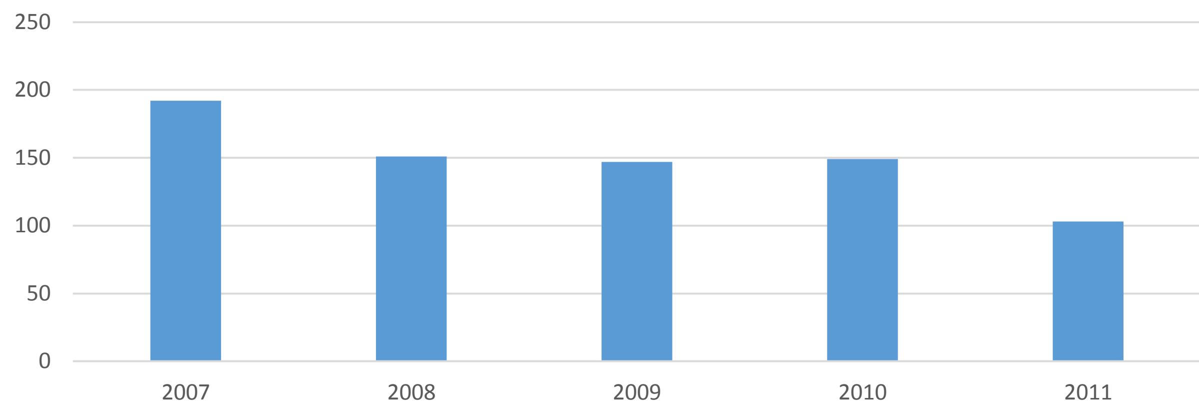


Figure 58: Number of passengers involved in collisions

A3 Cape Breton County

A3.1 Total Number of Collisions by Year

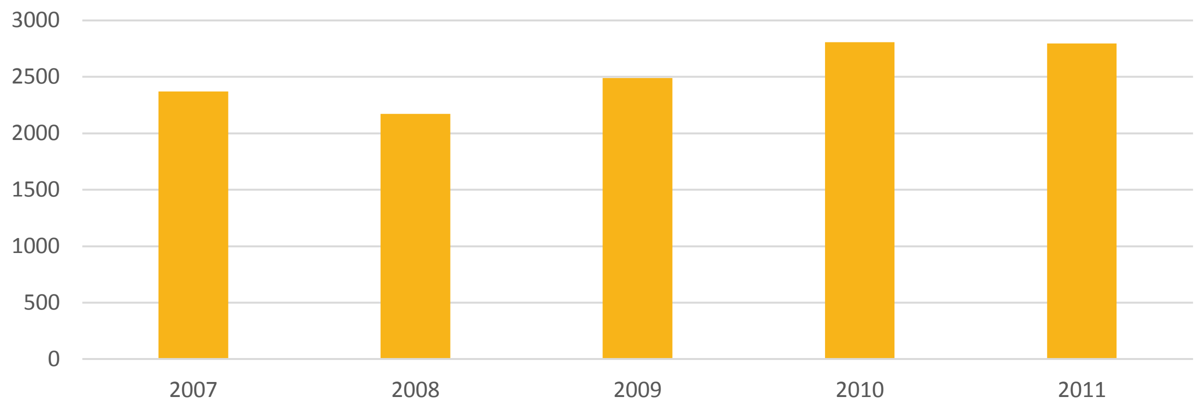


Figure 59: Total collisions by year

A3.2 Injury Severity

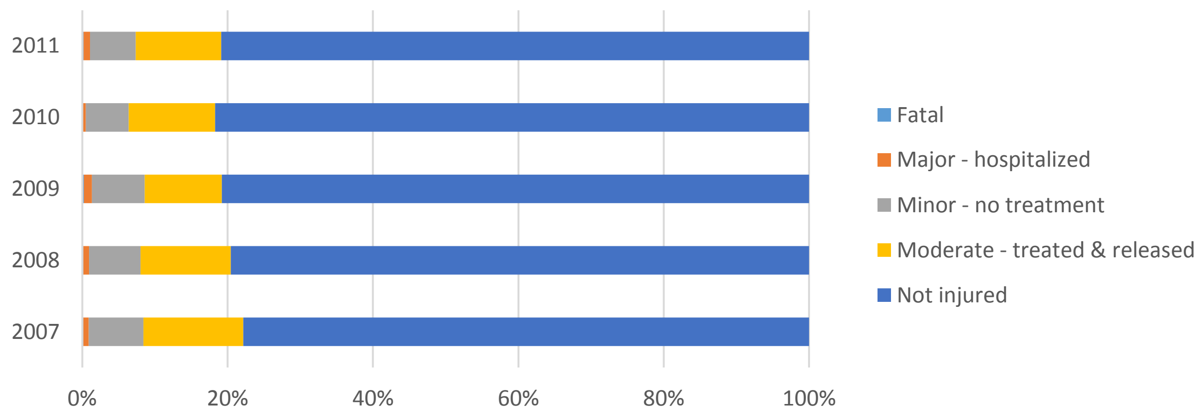


Figure 60: Injury severity of persons involved in collisions

A 3.3 Age and Gender

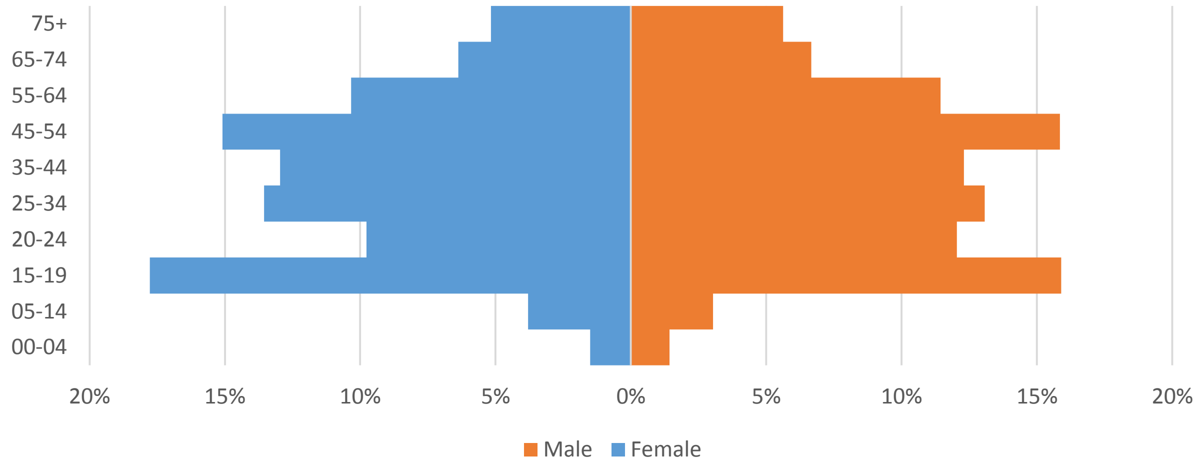


Figure 61: Age and gender distribution of persons involved in collisions

A3.3 Temporal Characteristics

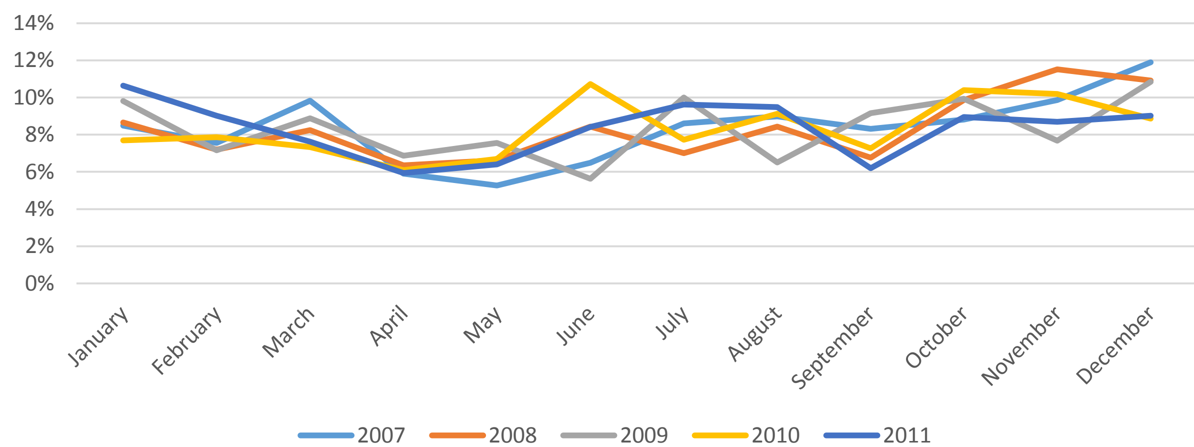


Figure 62: Monthly distribution of collisions

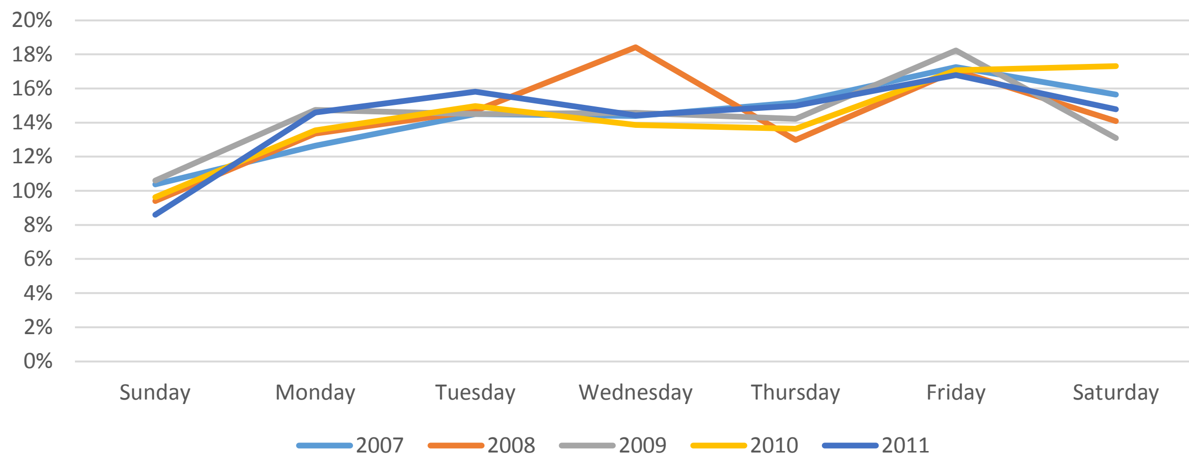


Figure 63: Day of week distribution of collisions

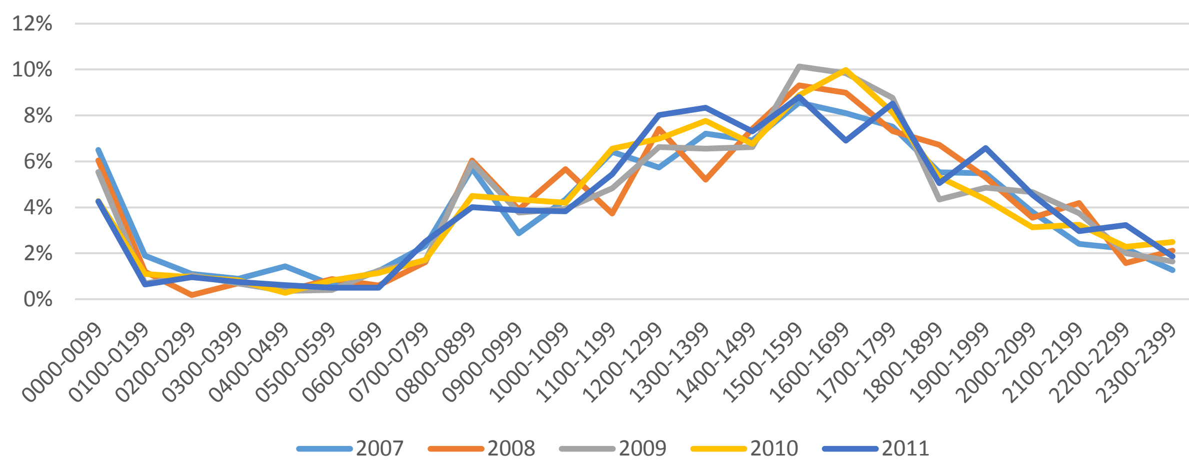


Figure 64: Time of day distribution of collisions

A3.5 Collision Frequency by Mode

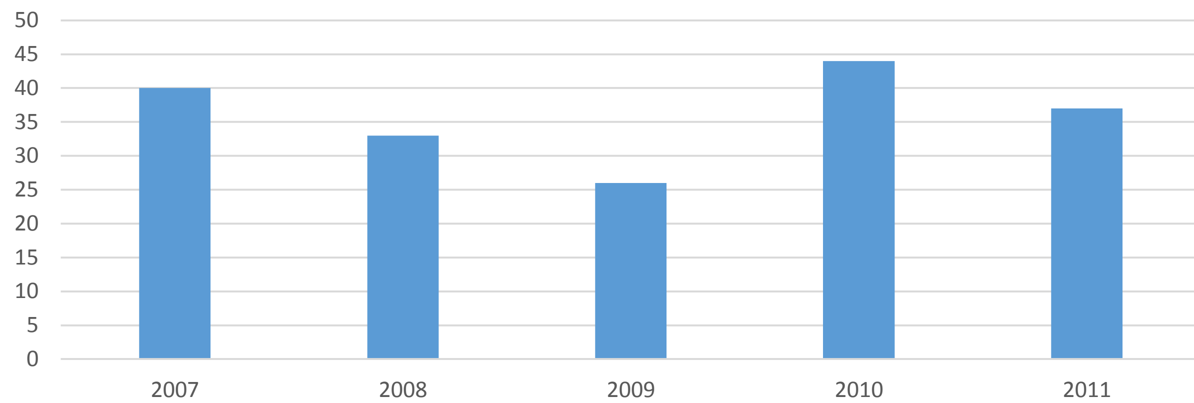


Figure 65: Number of pedestrians involved in collisions

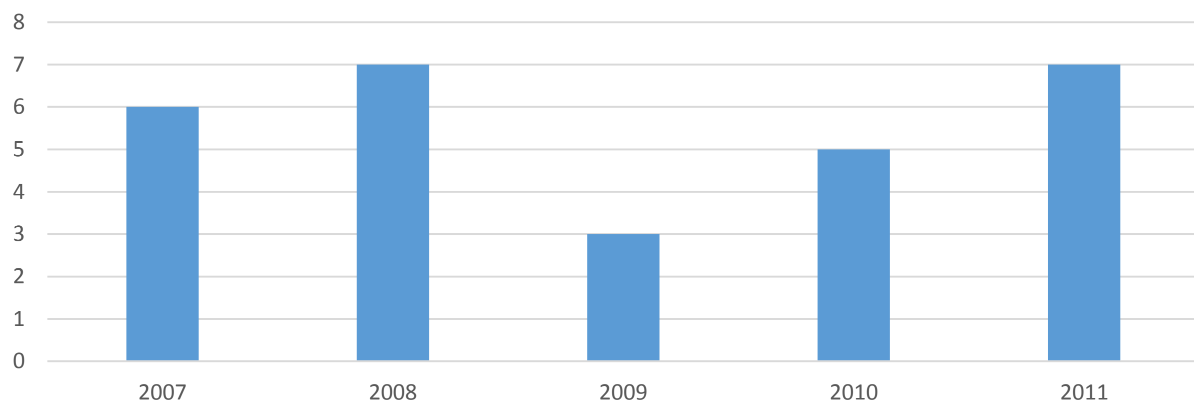


Figure 66: Number of cyclists involved in collisions

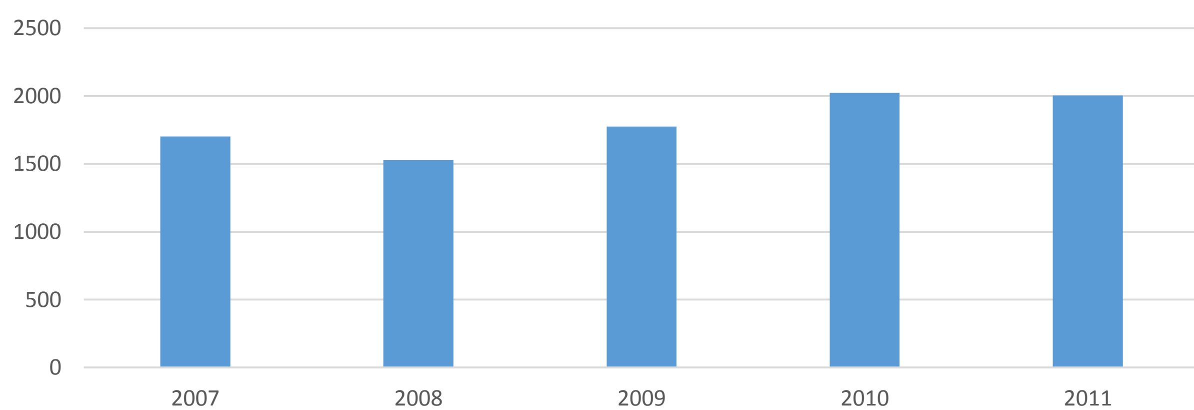


Figure 67: Number of drivers involved in collisions

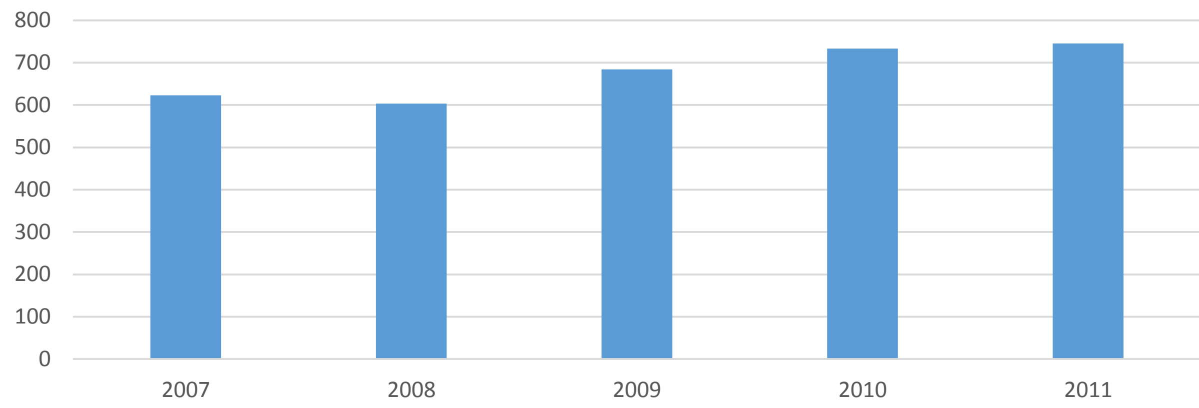
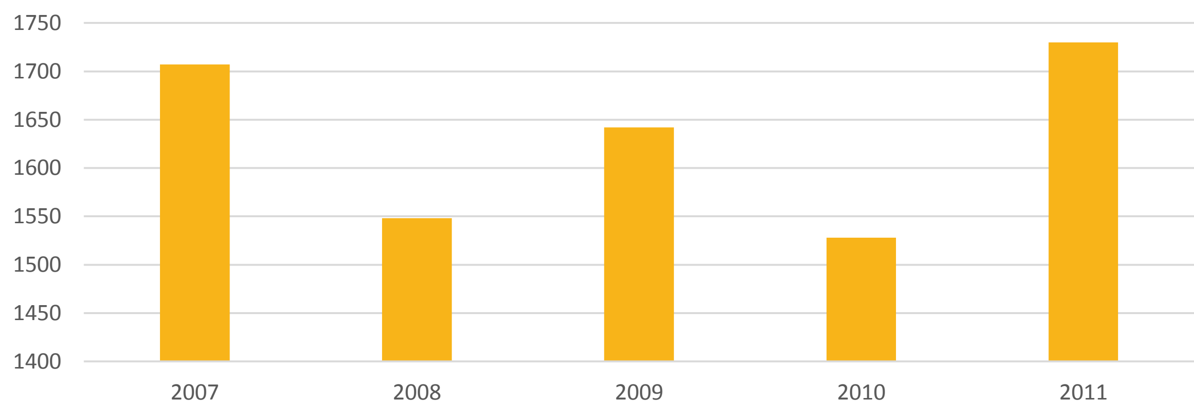


Figure 68: Number of passengers involved in collisions

A4 Colchester County

A4.1 Total Number of Collisions by Year



A4.2 Injury Severity

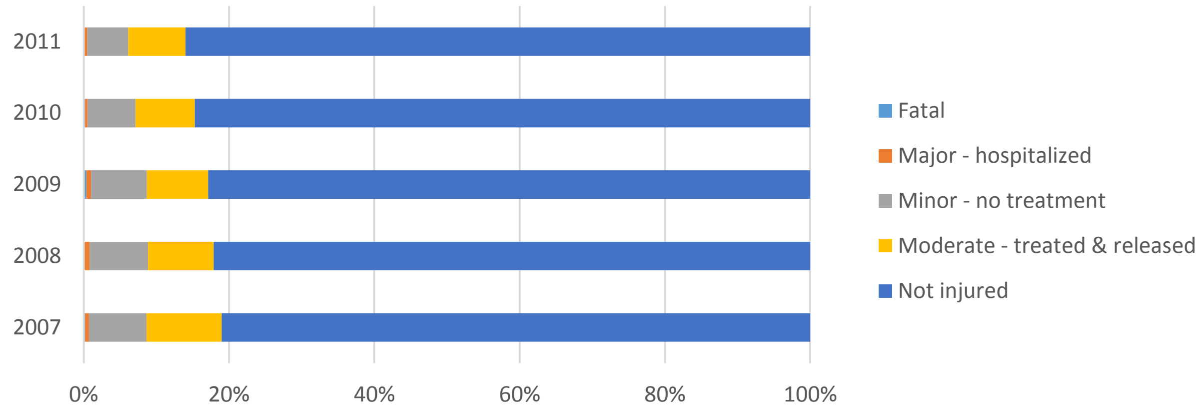


Figure 69: Injury severity of persons involved in collisions

A4.3 Age and Gender

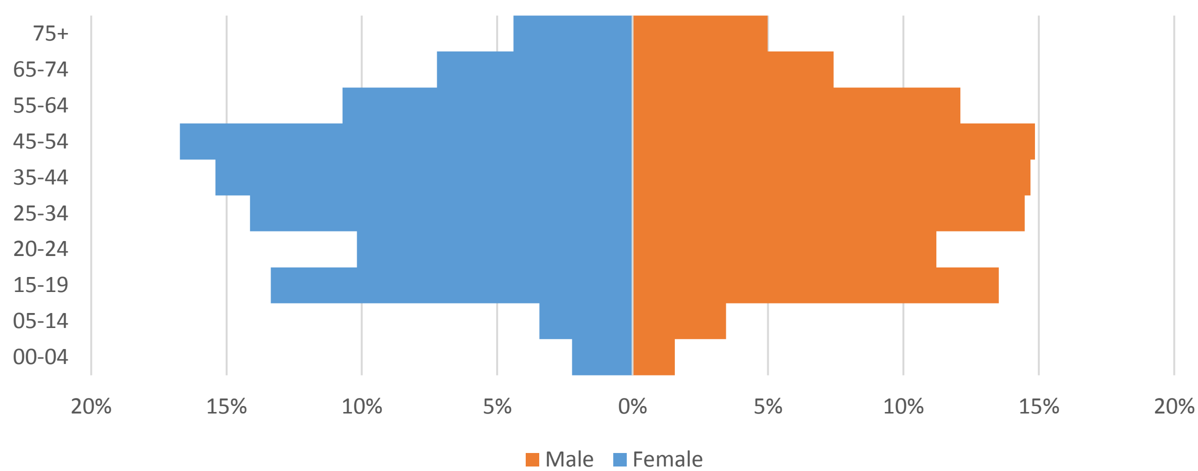


Figure 70: Age and gender distribution of persons involved in collisions

A4.4 Temporal Characteristics

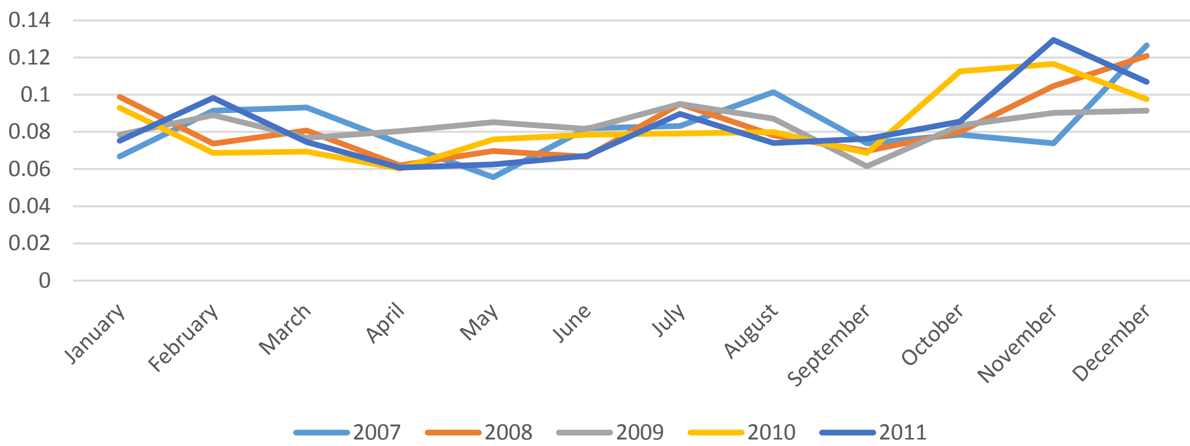


Figure 71: Monthly distribution of collisions

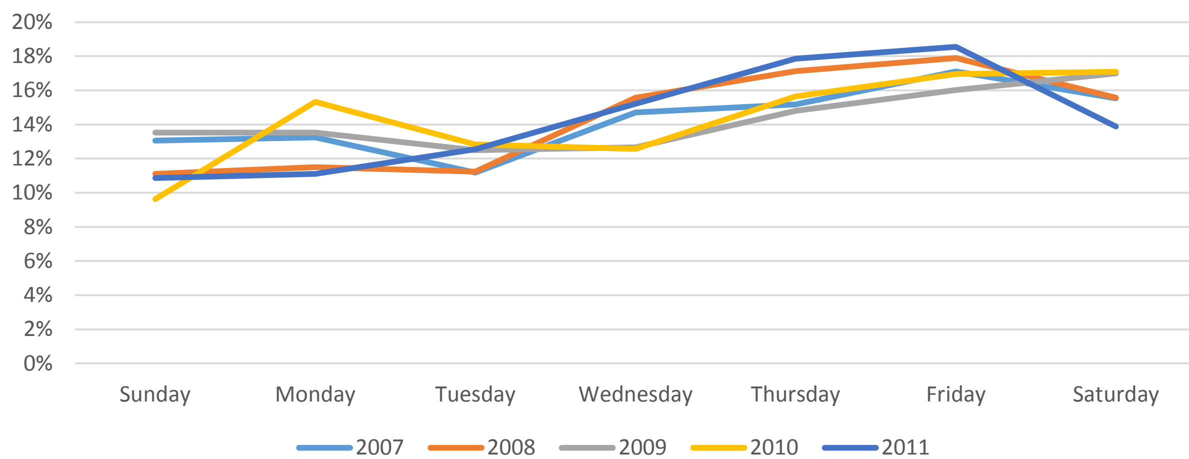


Figure 72: Day of week distribution of collisions

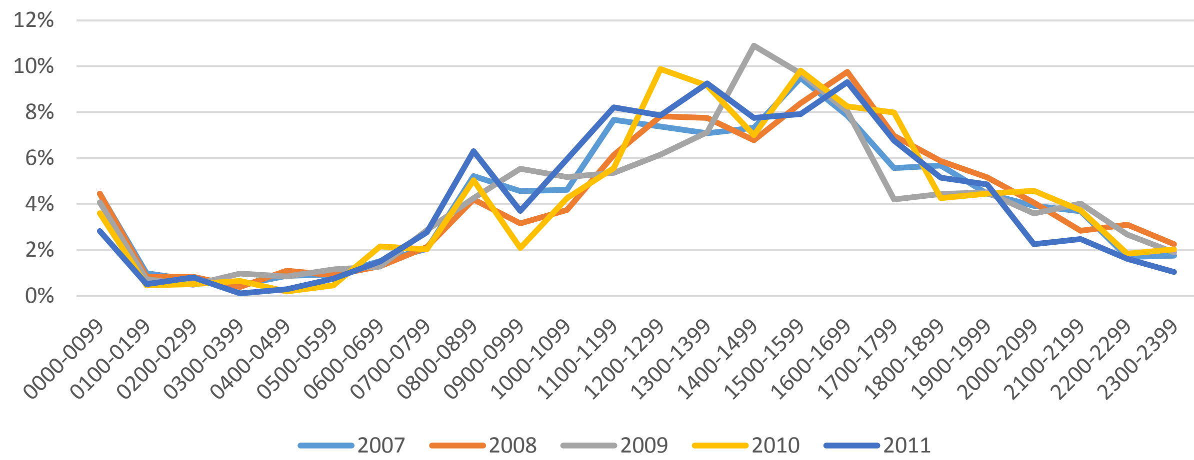


Figure 73: Time of day distribution of collisions

A4.5 Collision Frequency by Mode

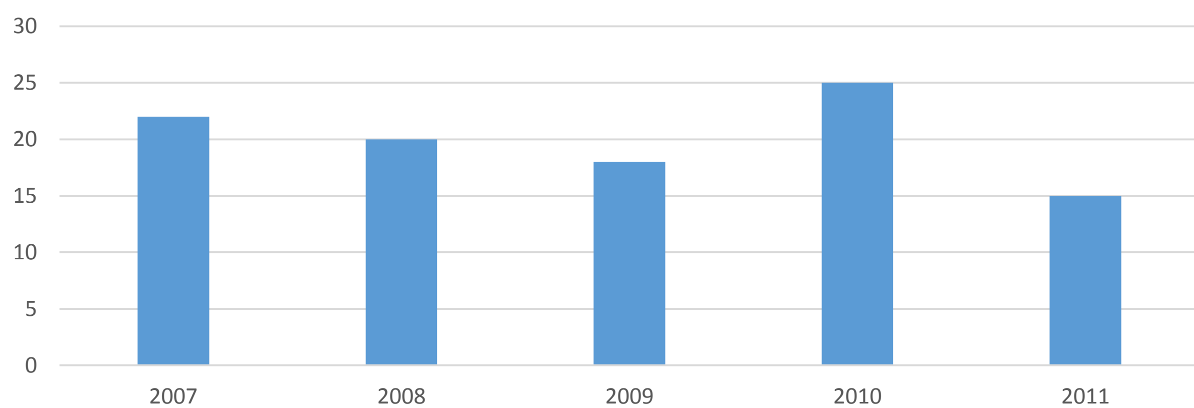


Figure 74: Number of pedestrians involved in collisions

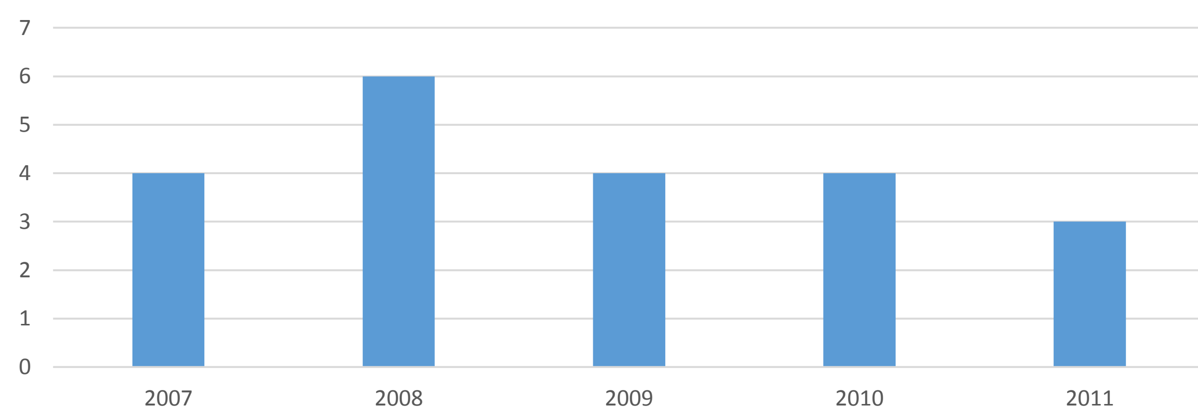


Figure 75: Number of cyclists involved in collisions

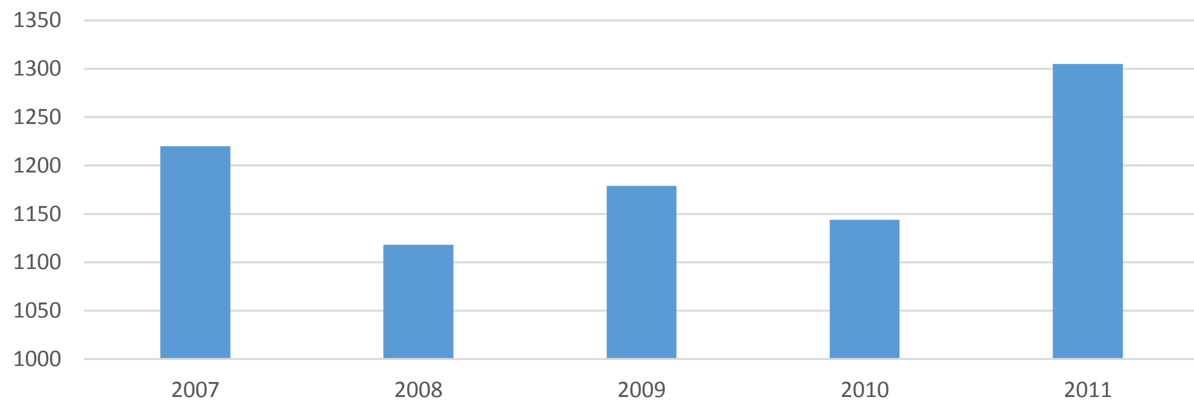


Figure 76: Number of drivers involved in collisions

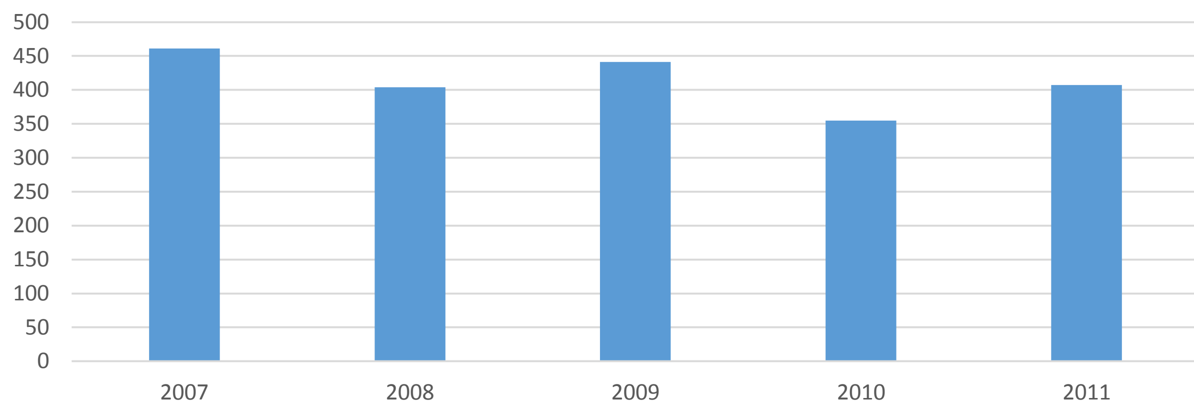


Figure 77: Number of passengers involved in collisions

A5 Cumberland County

A5.1 Total Number of Collisions by Year

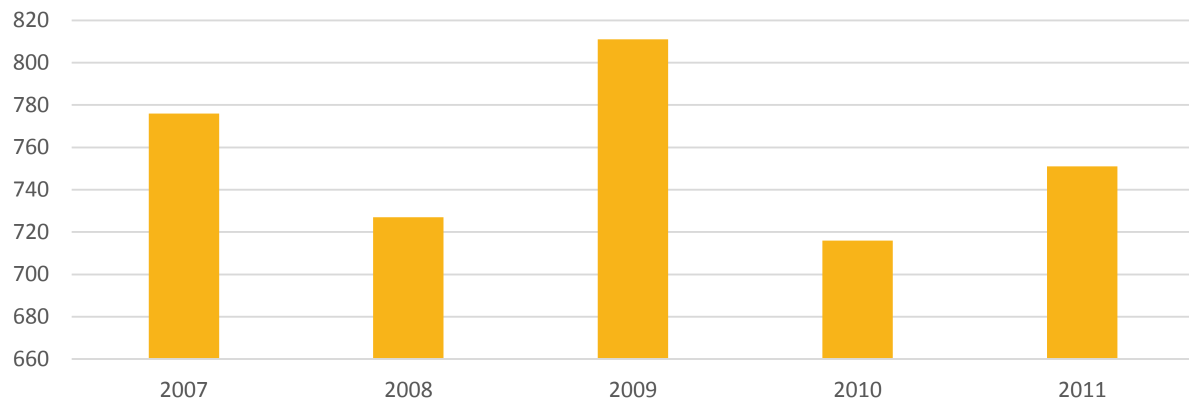


Figure 78: Total number of collisions

A5.2 Injury Severity

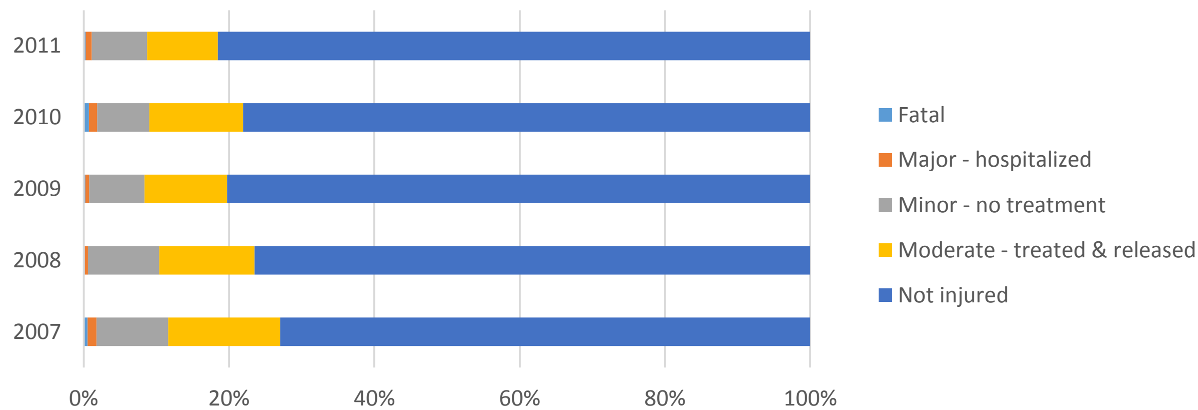


Figure 79: Injury severity of persons involved in collisions

A5.3 Age and Gender

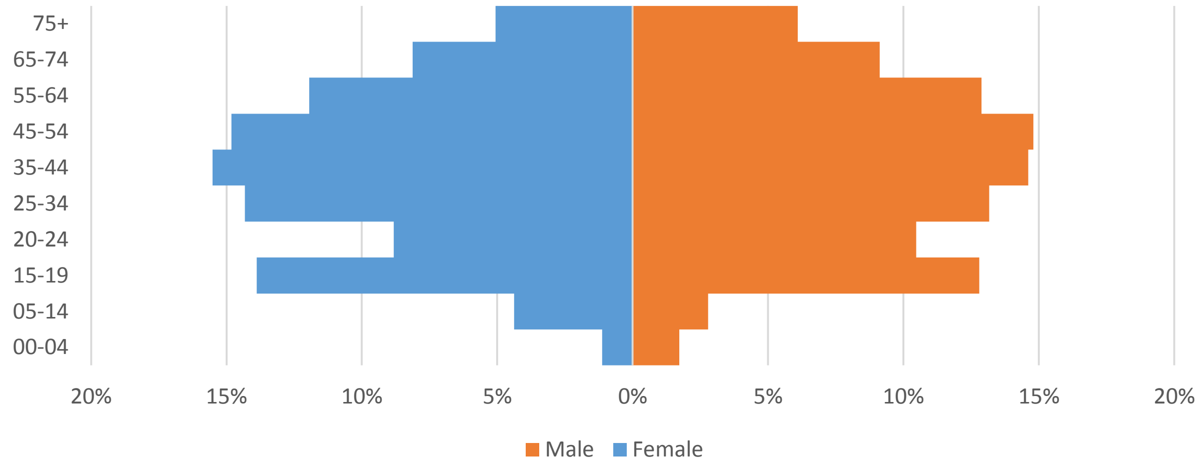


Figure 80: Age and gender distribution of persons involved in collisions

A5.4 Temporal Characteristics

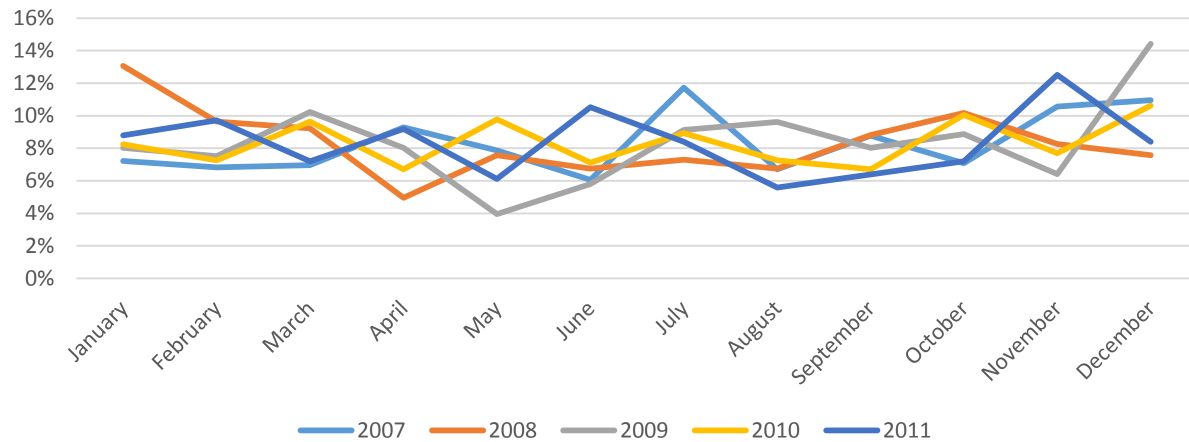


Figure 81: Monthly distribution of collisions

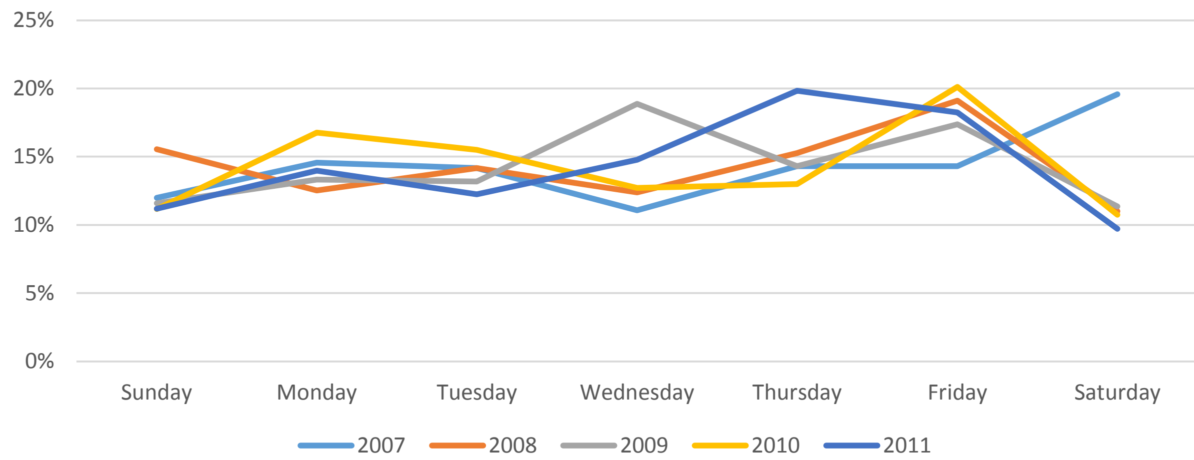


Figure 82: Day of week distribution of collisions

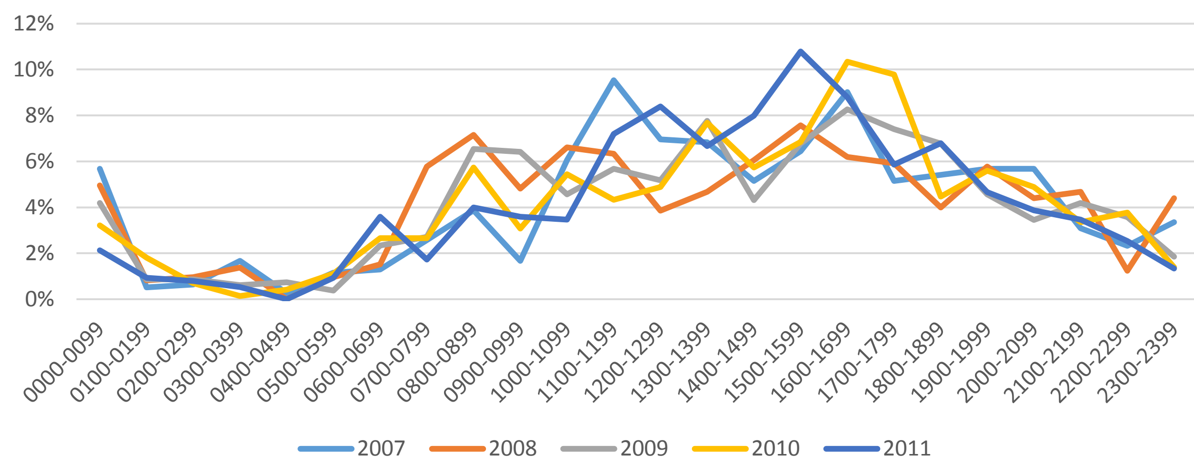


Figure 83: Time of day distribution of collisions

A5.5 Collision Frequency by Mode

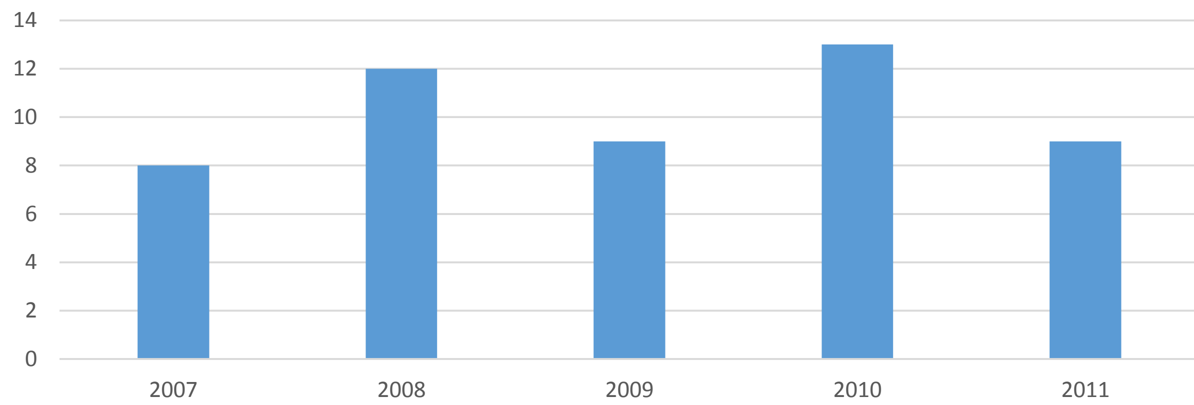


Figure 84: Number of pedestrians involved in collisions

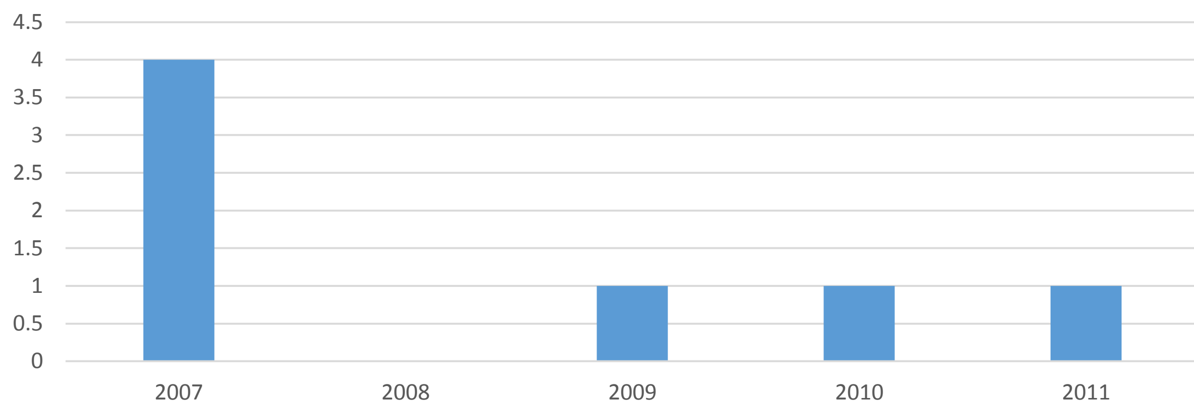


Figure 85: Number of cyclists involved in collisions

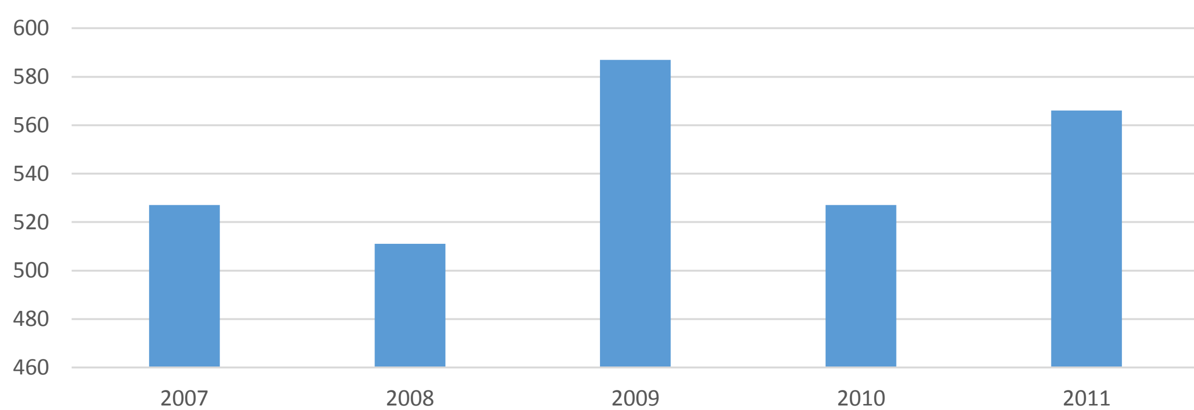


Figure 86: Number of drivers involved in collisions

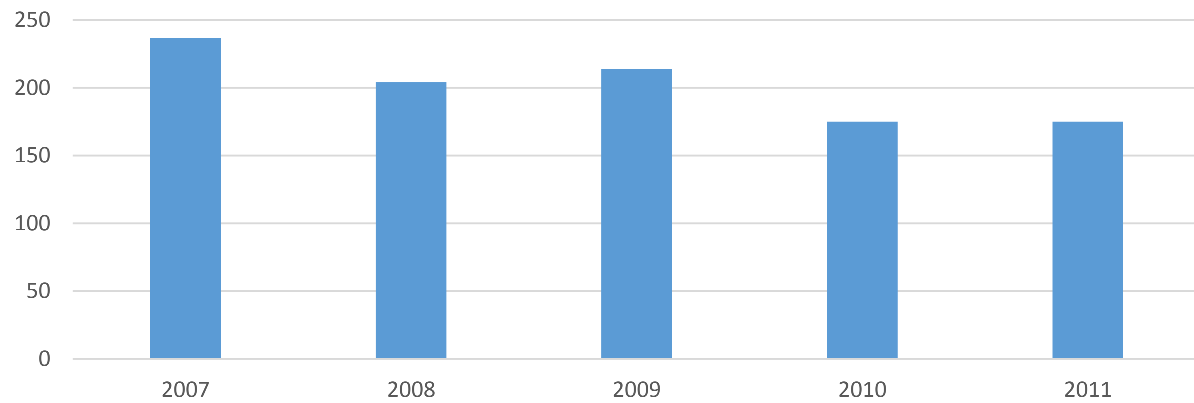


Figure 87: Number of passengers involved in collisions

A6 Digby County

A6.1 Total Number of Collisions by Year

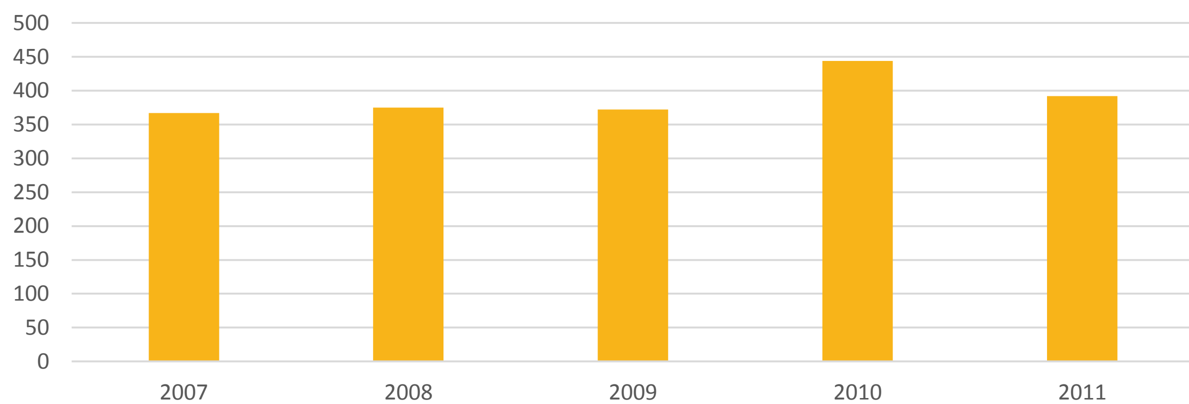


Figure 88: Total collisions by year

A6.2 Injury Severity

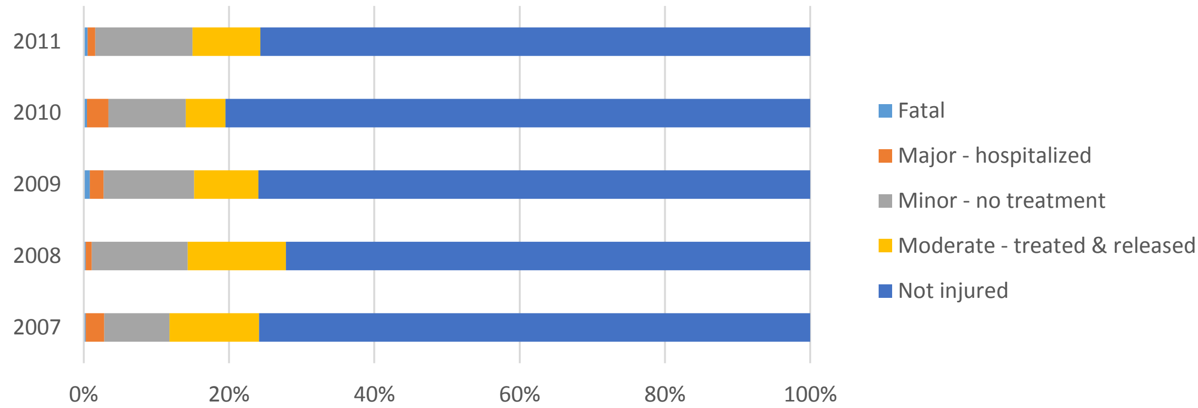


Figure 89: Injury severity of persons involved in collisions

A6.3 Age and Gender

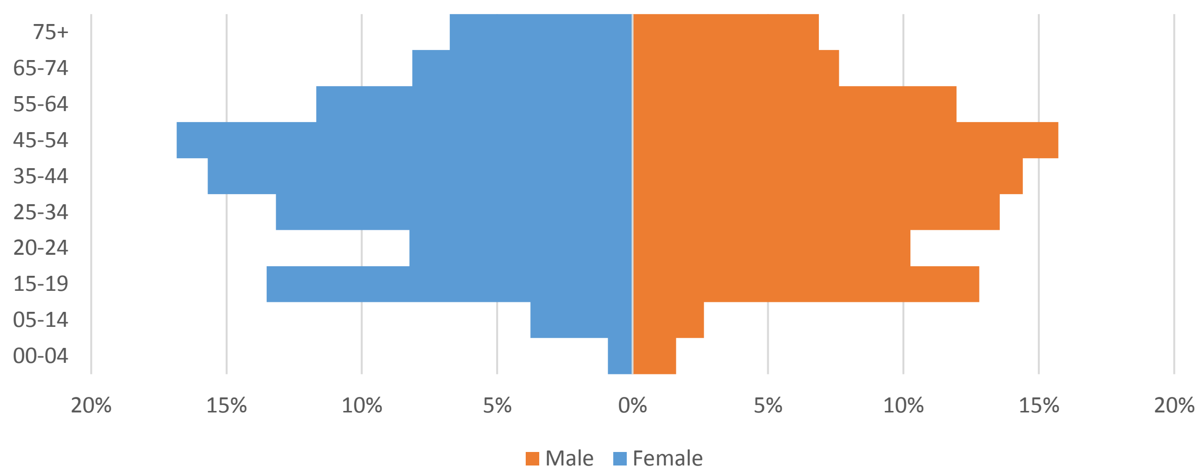


Figure 90: Age and gender distribution of persons involved in collisions

A6.4 Temporal Characteristics

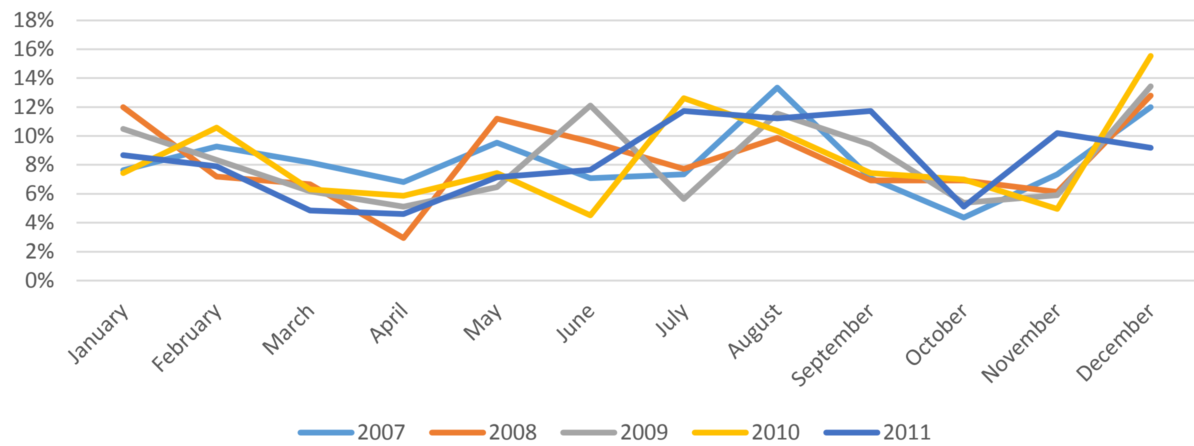


Figure 91: Monthly distribution of collisions

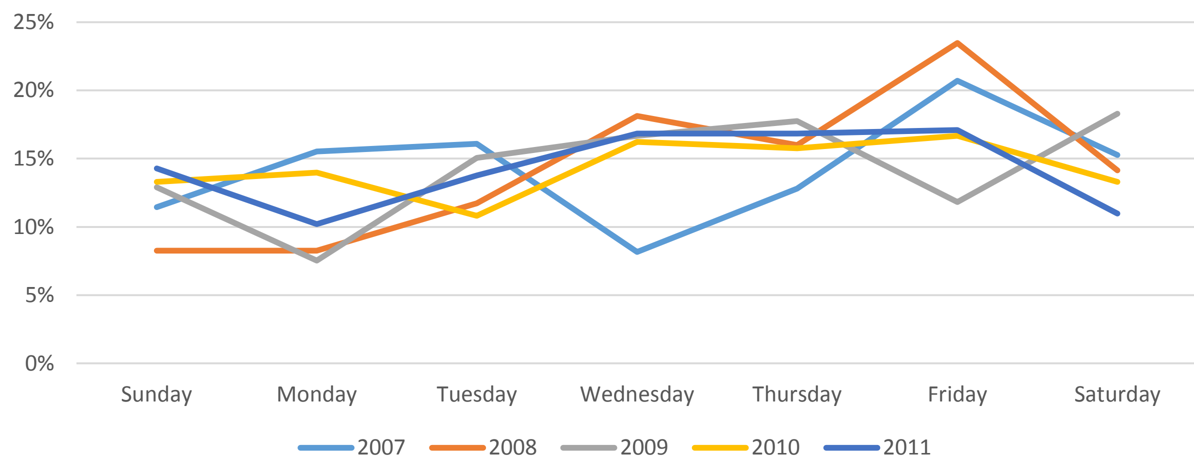


Figure 92: Day of week distribution of collisions

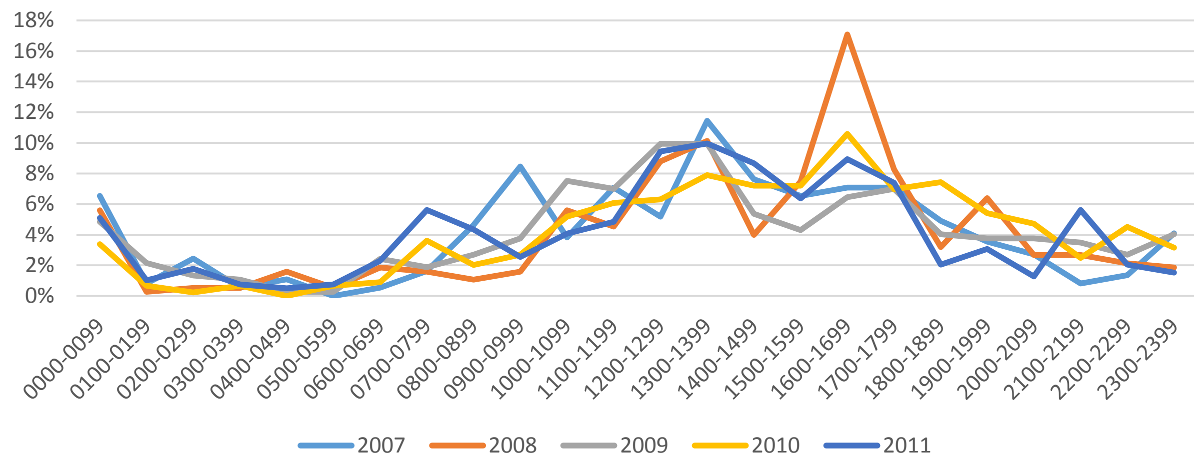


Figure 93: Time of day distribution of collisions

A6.5 Collision Frequency by Mode

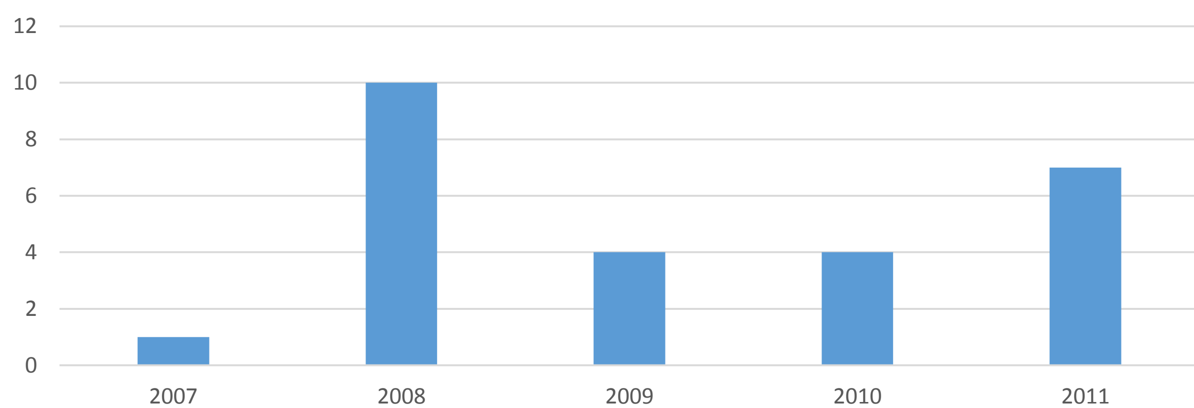


Figure 94: Number of pedestrians involved in collisions

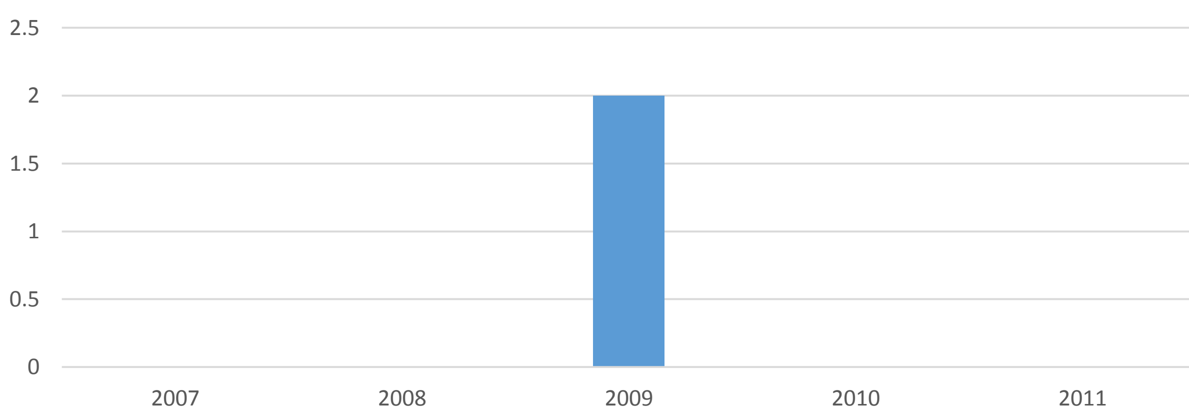


Figure 95: Number of cyclists involved in collisions

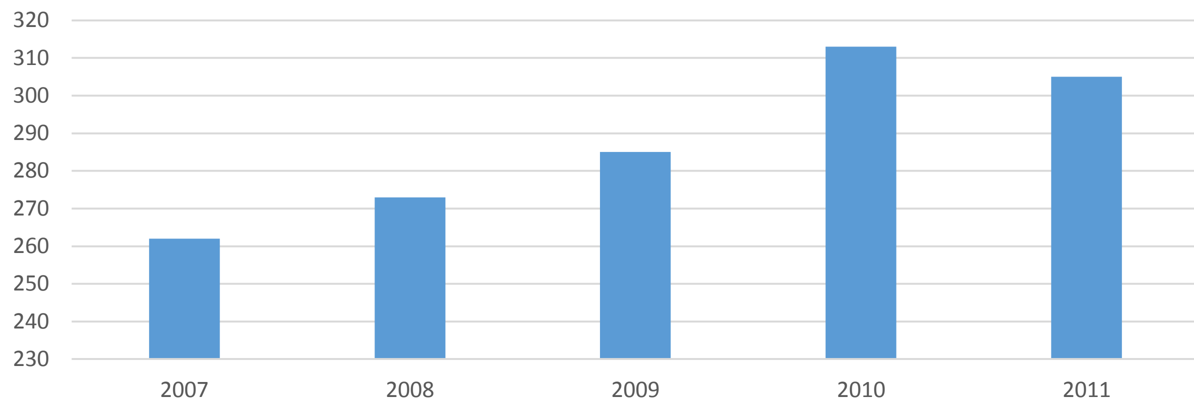


Figure 96: Number of drivers involved in collisions

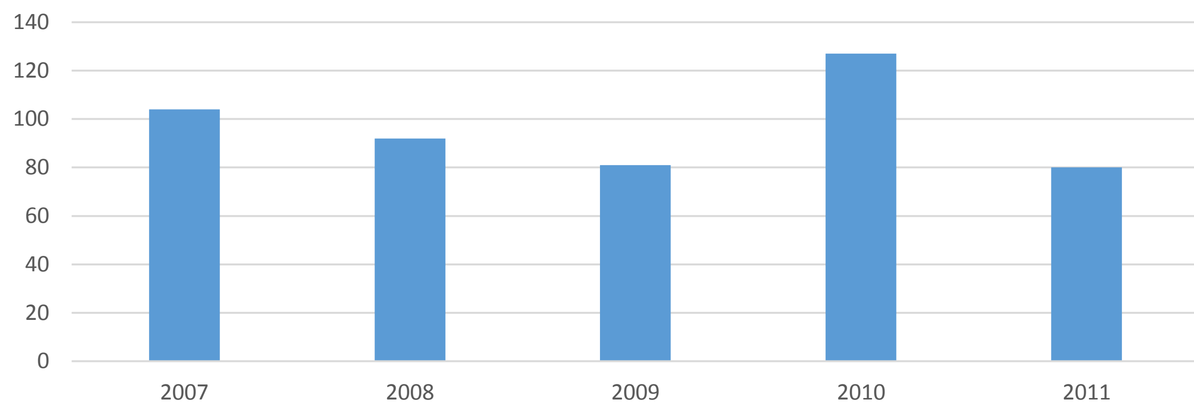


Figure 97: Number of passengers involved in collisions

A7 Guysborough County

A7.1 Total Number of Collisions by Year

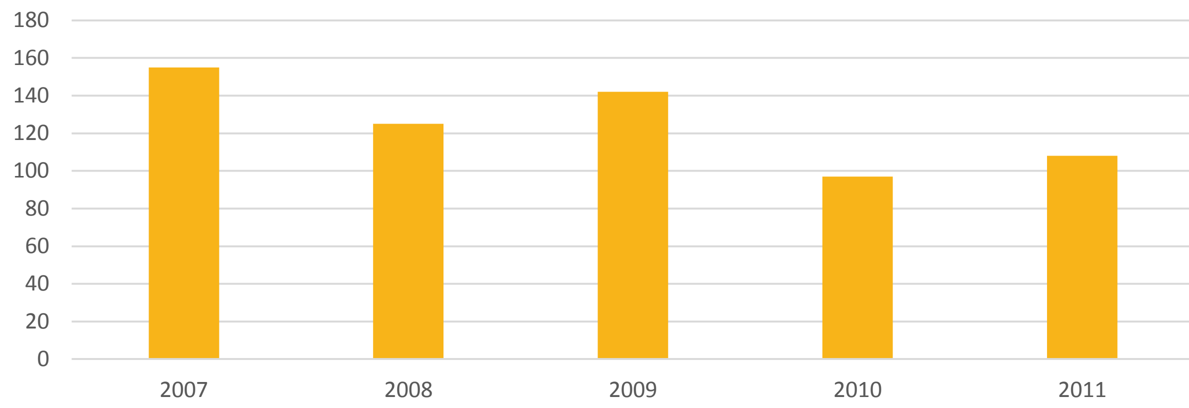


Figure 98: Total collisions by year

A7.2 Injury Severity

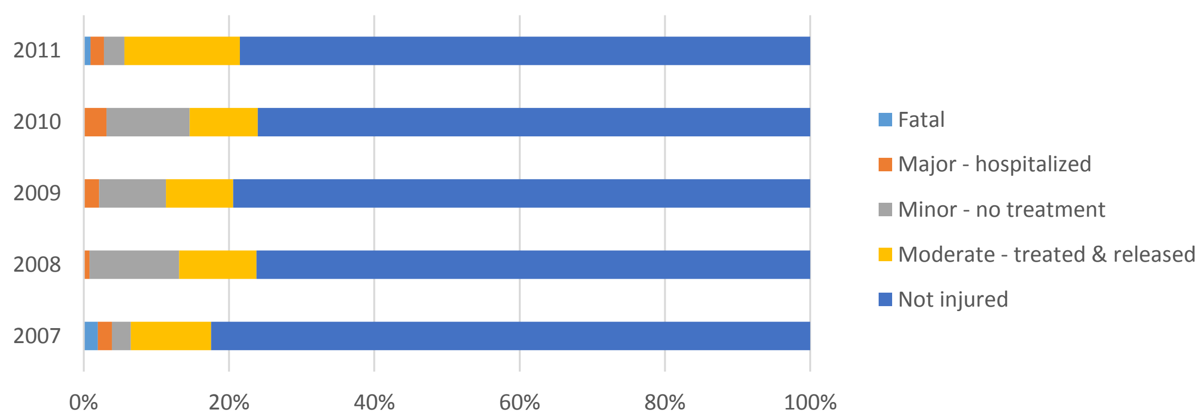


Figure 99: Injury severity of persons involved in collisions

A7.3 Age and Gender

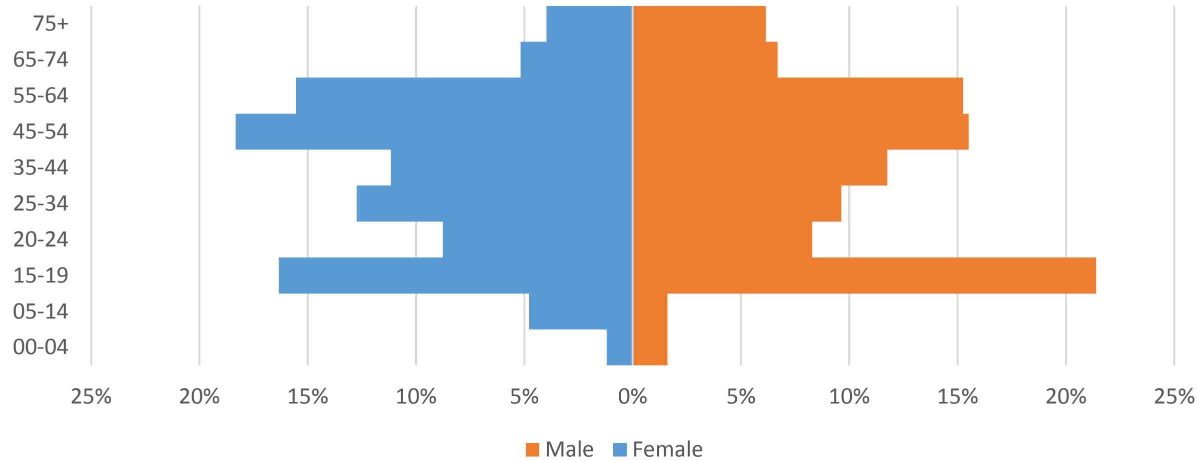


Figure 100: Age and gender distribution of persons involved in collisions

A7.4 Temporal Characteristics

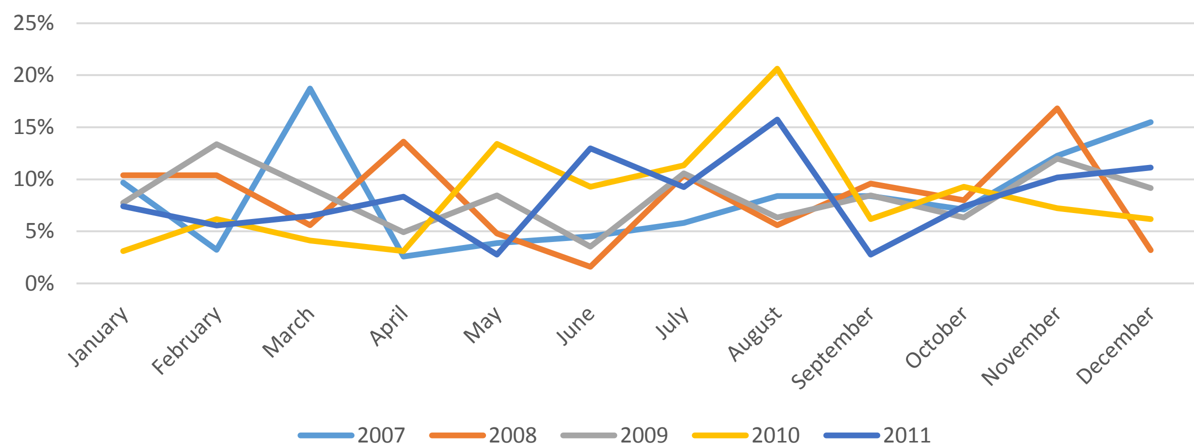


Figure 101: Monthly distribution of collisions

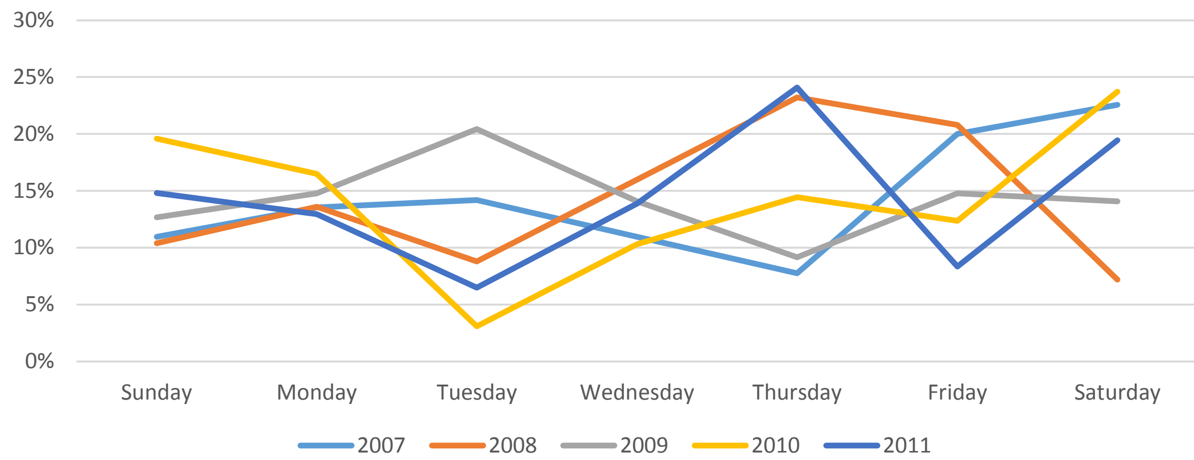


Figure 102: Day of week distribution of collisions

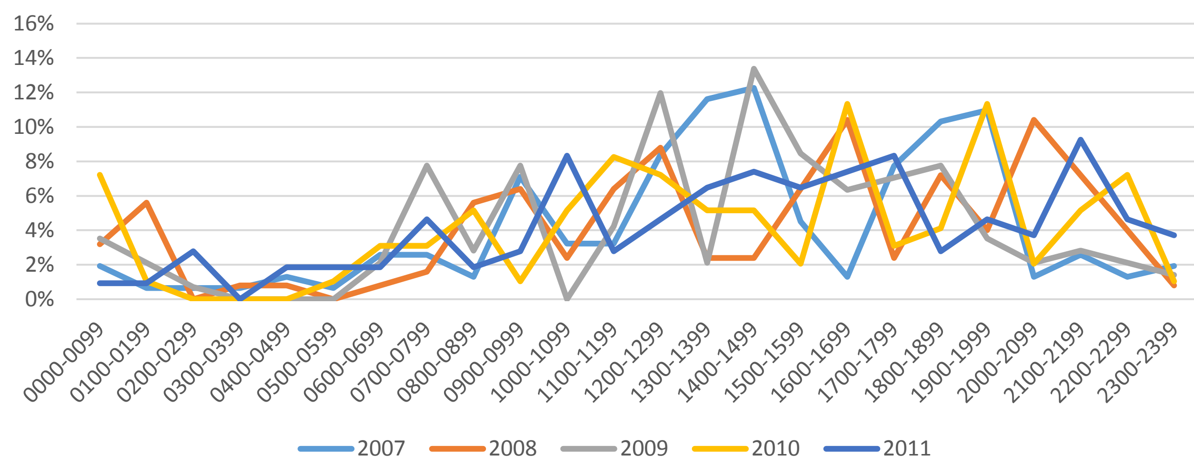


Figure 103: Time of day distribution of collisions

A7.5 Collision Frequency by Mode

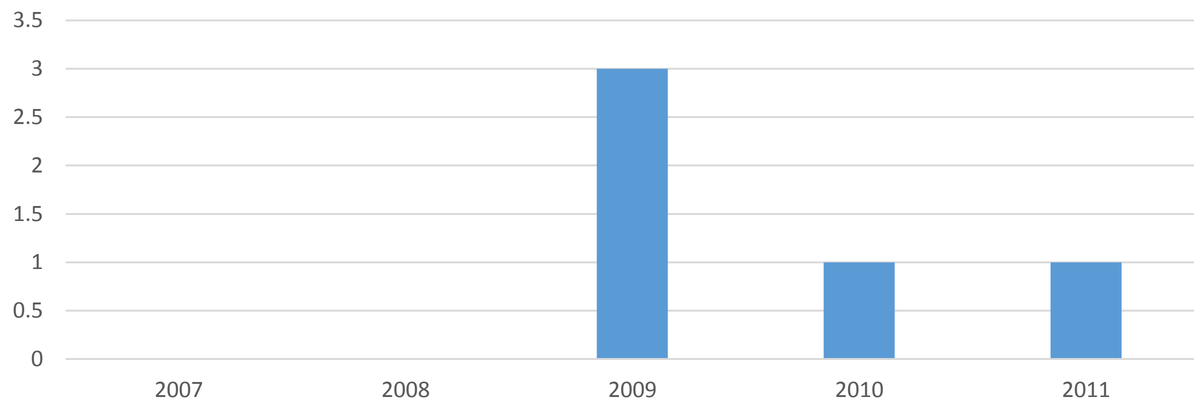


Figure 104: Number of pedestrians involved in collisions

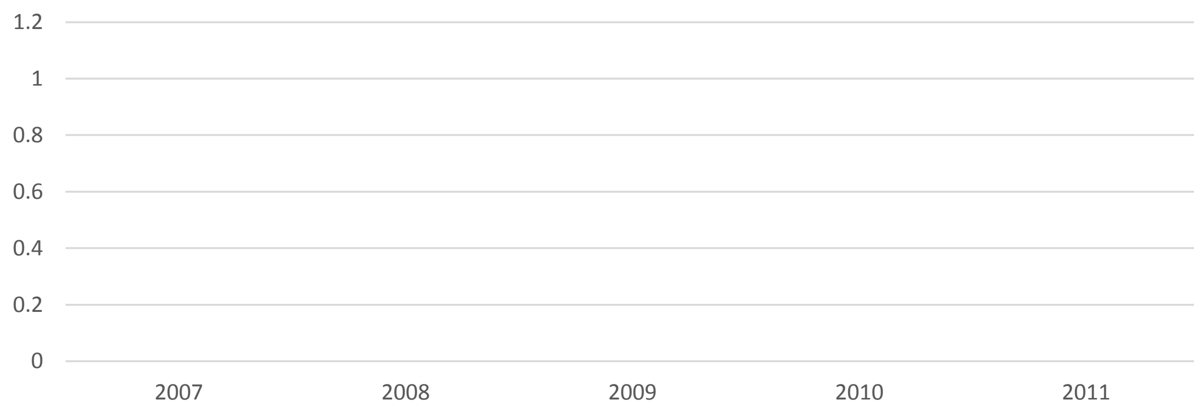


Figure 105: Number of cyclists involved in collisions

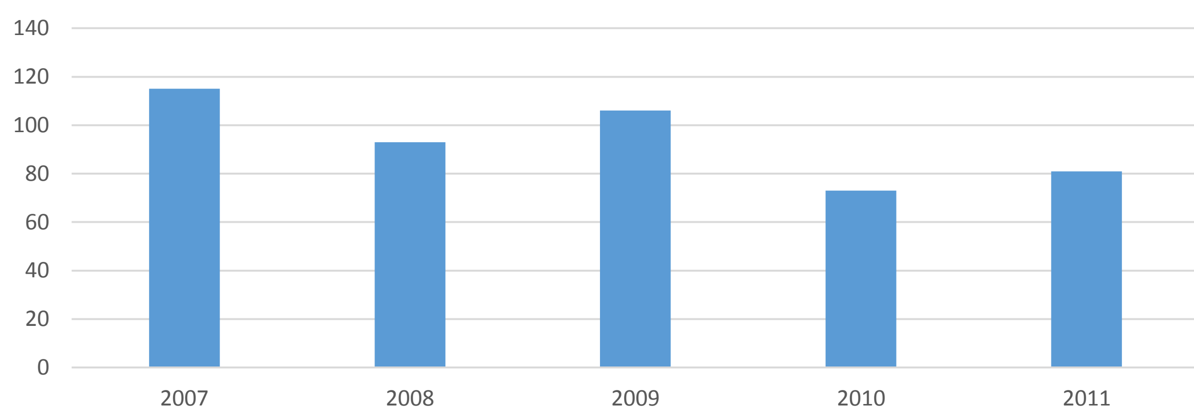


Figure 106: Number of drivers involved in collisions

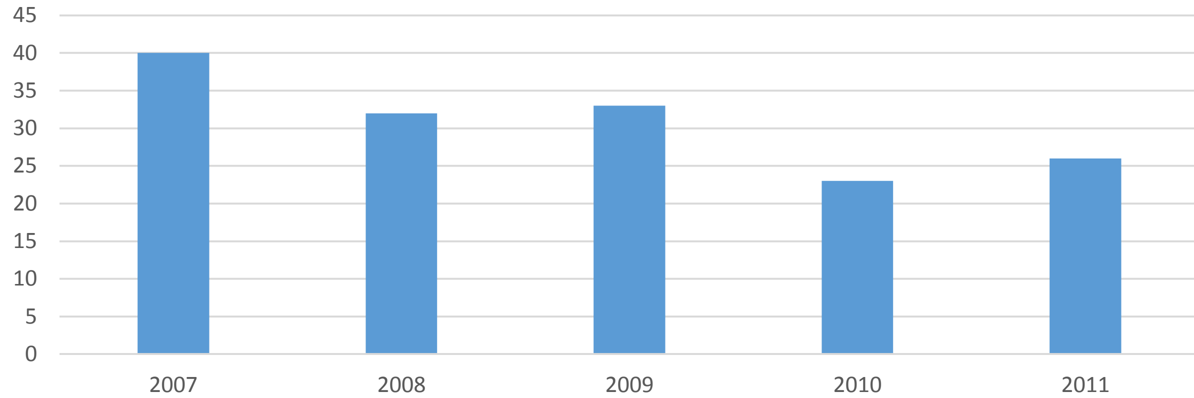


Figure 107: Number of passengers involved in collisions

A8 Halifax County

A8.1 Total Number of Collisions by Year

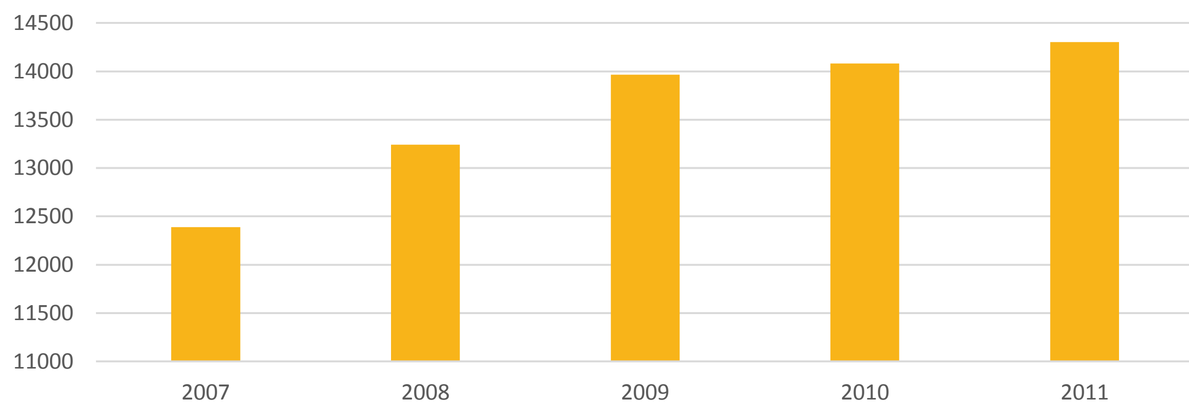


Figure 108: Total collisions by year

A8.2 Injury Severity

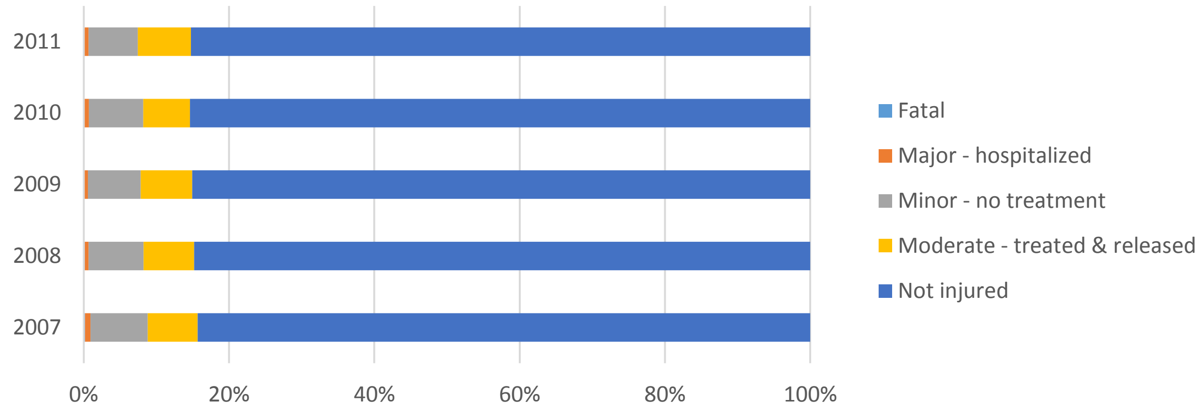


Figure 109: Injury severity of persons involved in collisions

A8.3 Age and Gender

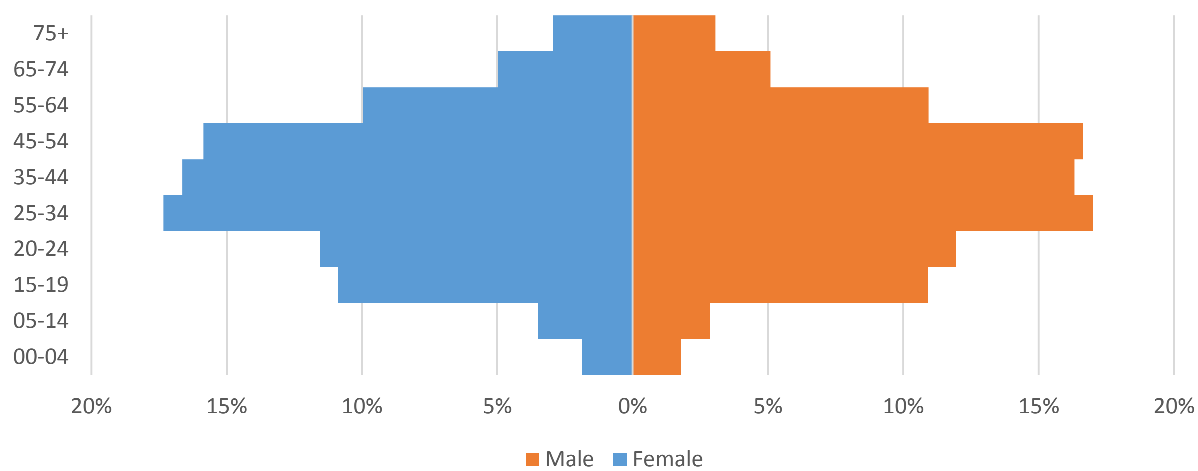


Figure 110: Age and gender distribution of persons involved in collisions

A8.4 Temporal Characteristics

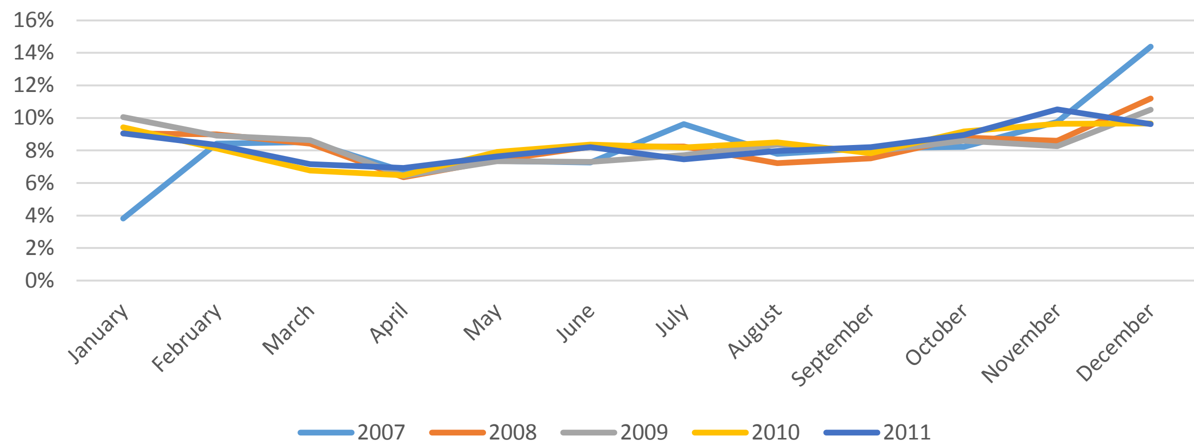


Figure 111: Monthly distribution of collisions

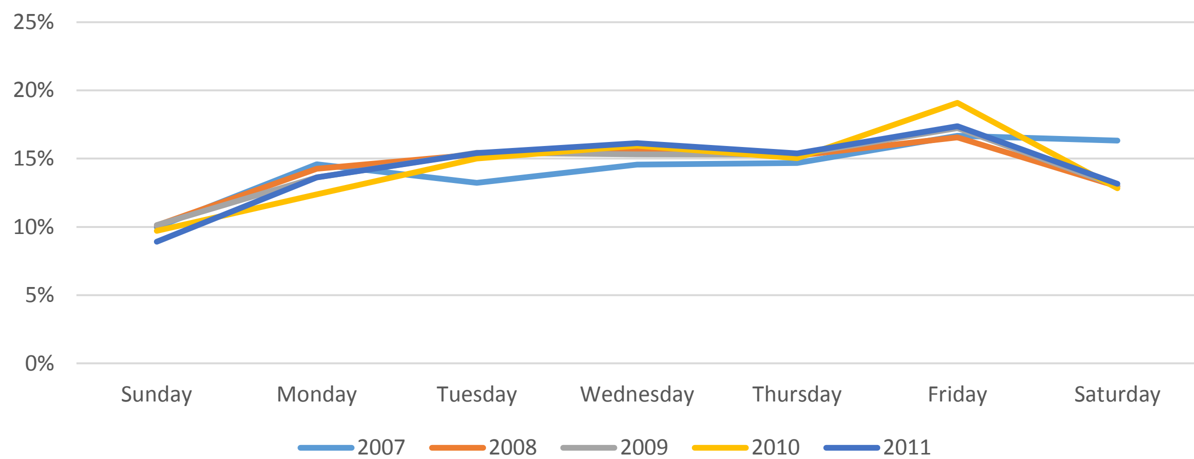


Figure 112: Day of week distribution of collisions

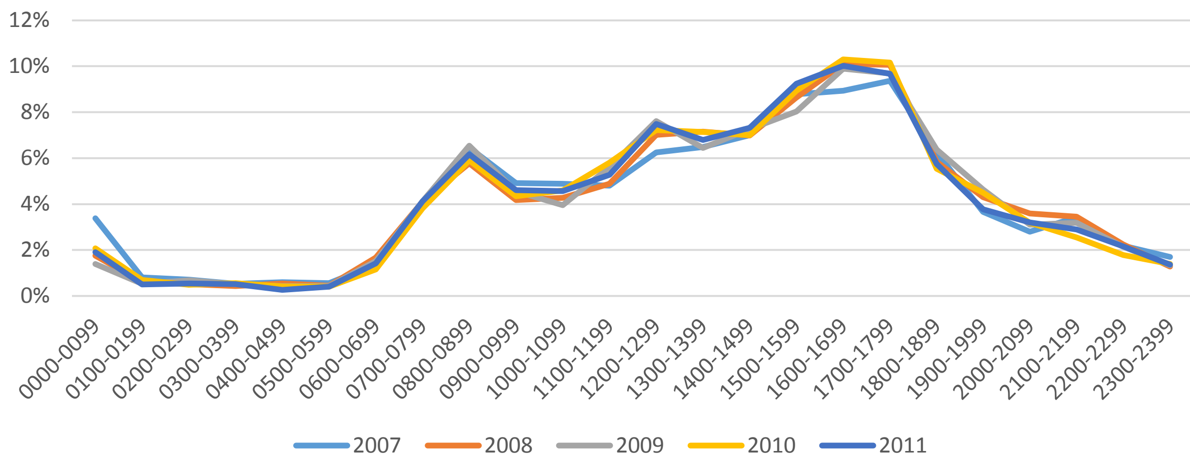


Figure 113: Time of day distribution of collisions

A8.5 Collision Frequency by Mode

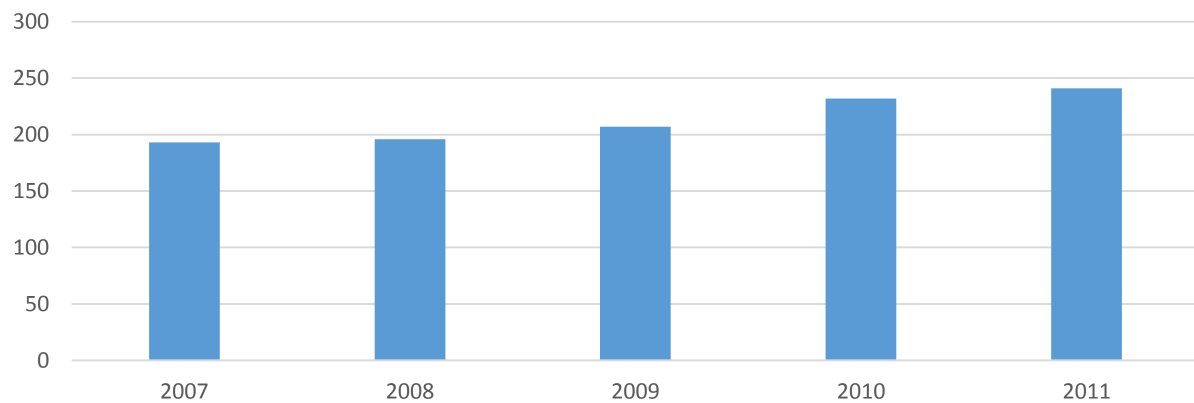


Figure 114: Number of pedestrians involved in collisions

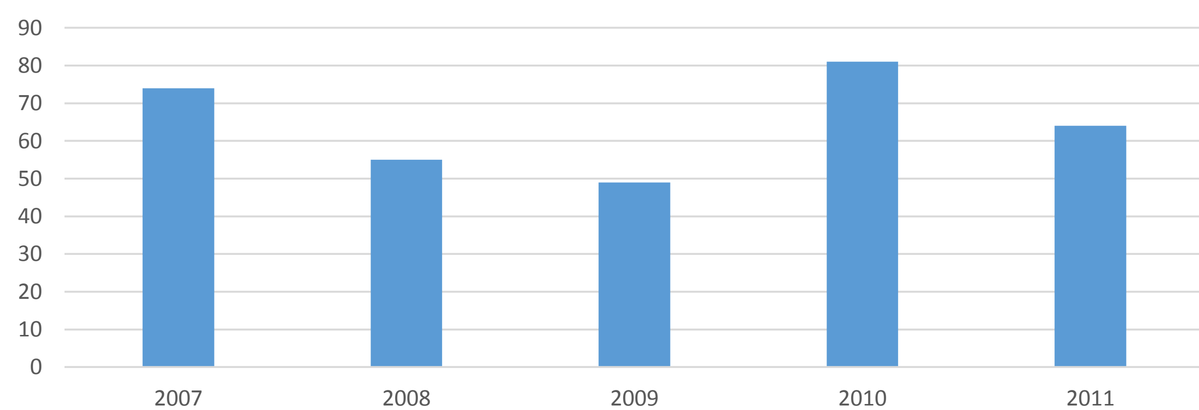


Figure 115: Number of cyclists involved in collisions

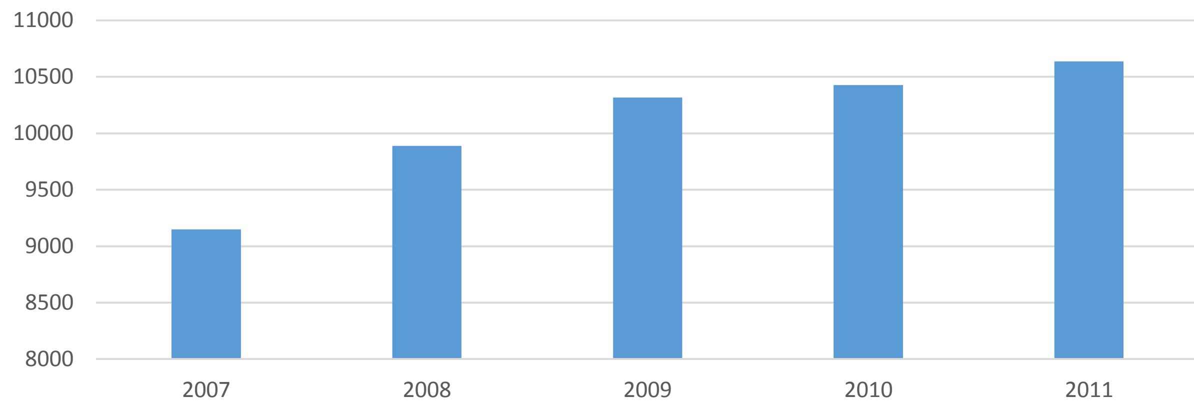


Figure 116: Number of drivers involved in collisions

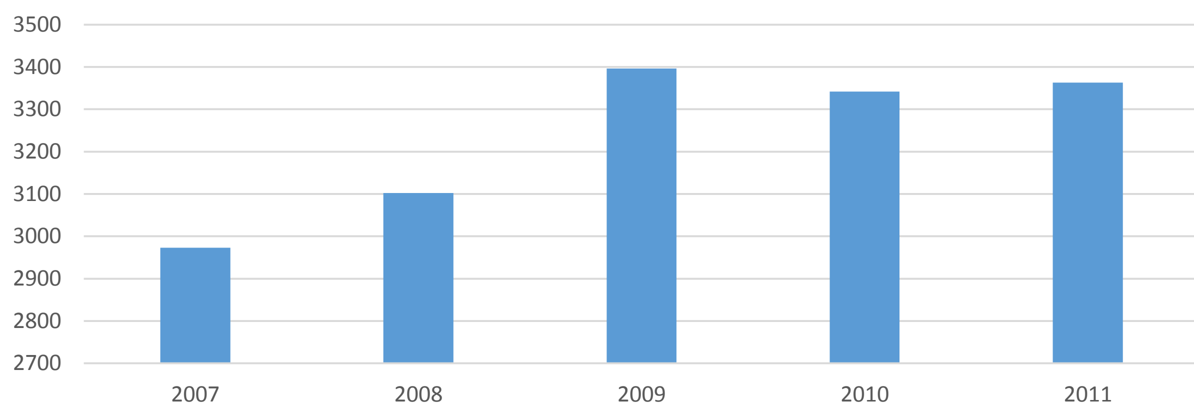


Figure 117: Number of passengers involved in collisions

A9 Hants County

A9.1 Total Number of Collisions by Year

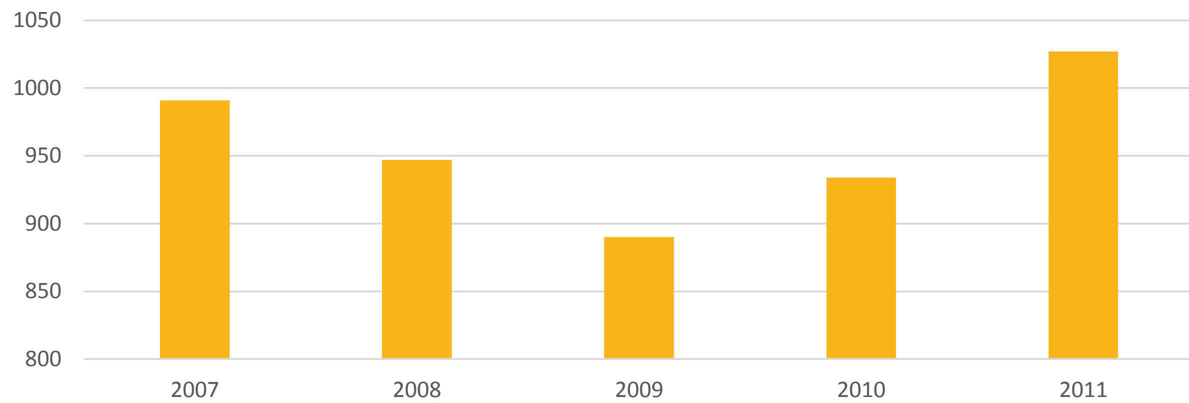


Figure 118: Total number of collisions by year

A9.2 Injury Severity

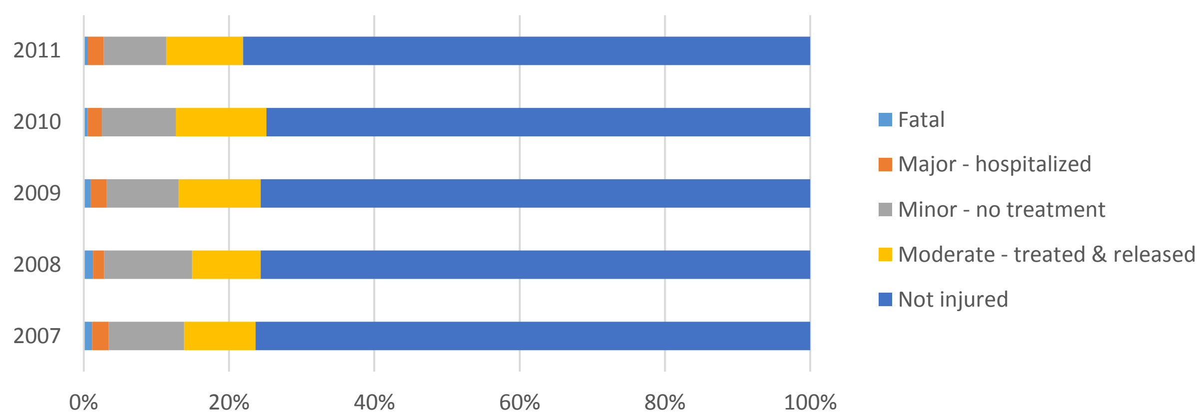


Figure 119: Injury severity of persons involved in collisions

A9.3 Age and Gender

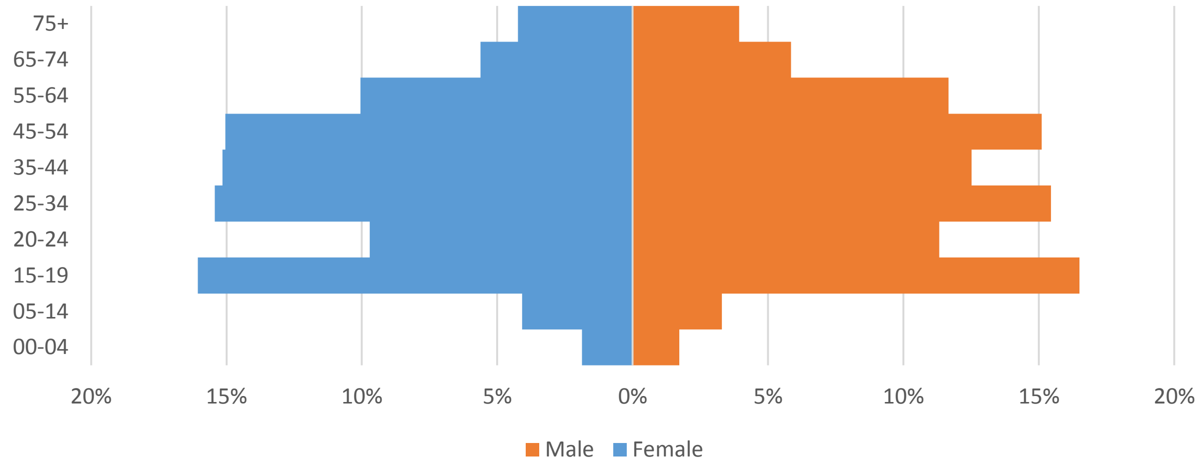


Figure 120: Age and gender distribution of persons involved in collisions

A9.4 Temporal Characteristics

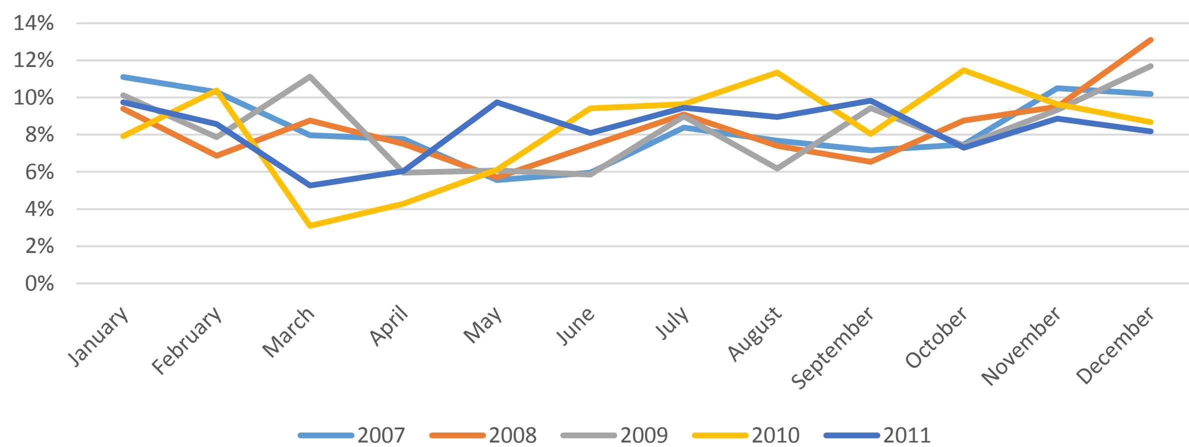


Figure 121: Monthly distribution of collisions

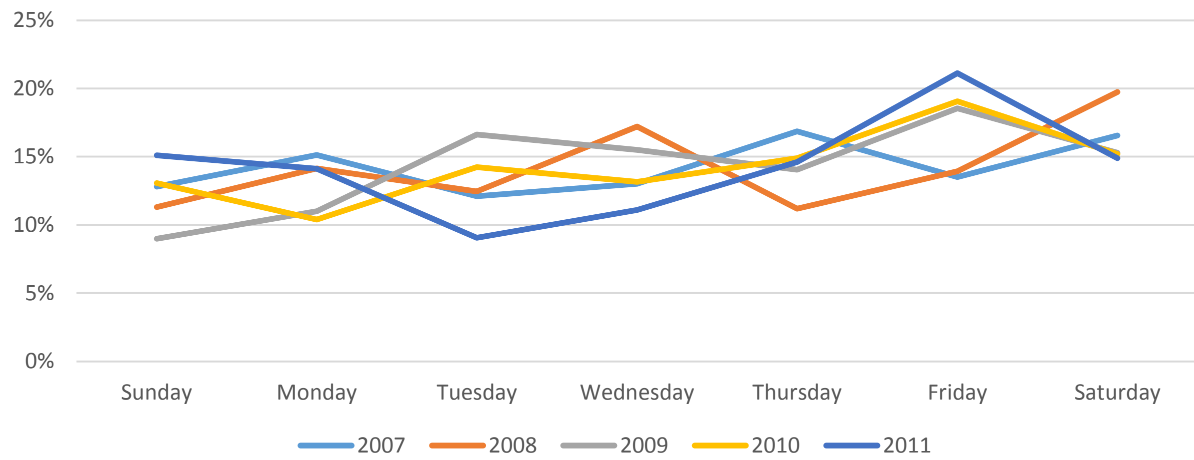


Figure 122: Day of week distribution of collisions

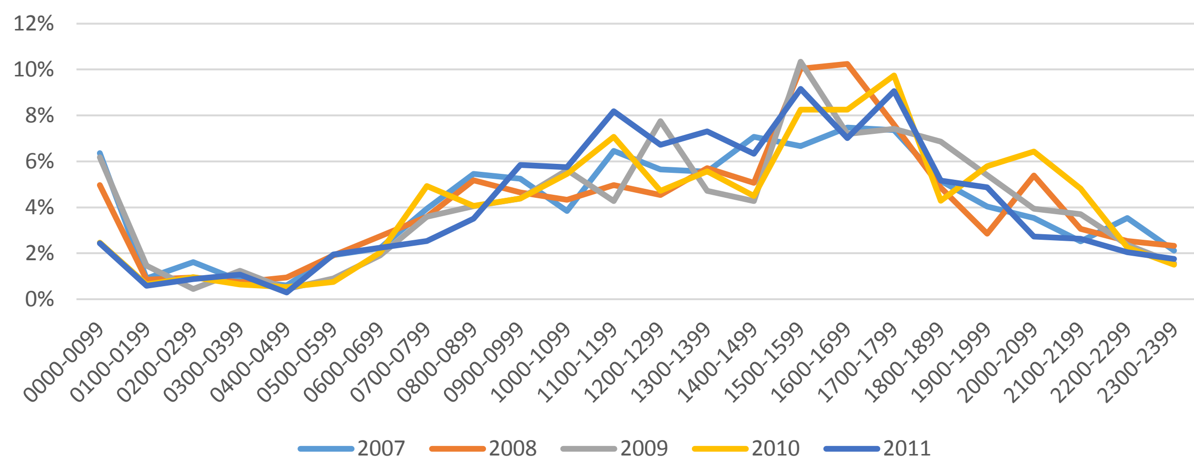


Figure 123: Time of day distribution of collisions

A9.5 Collision Frequency by Mode

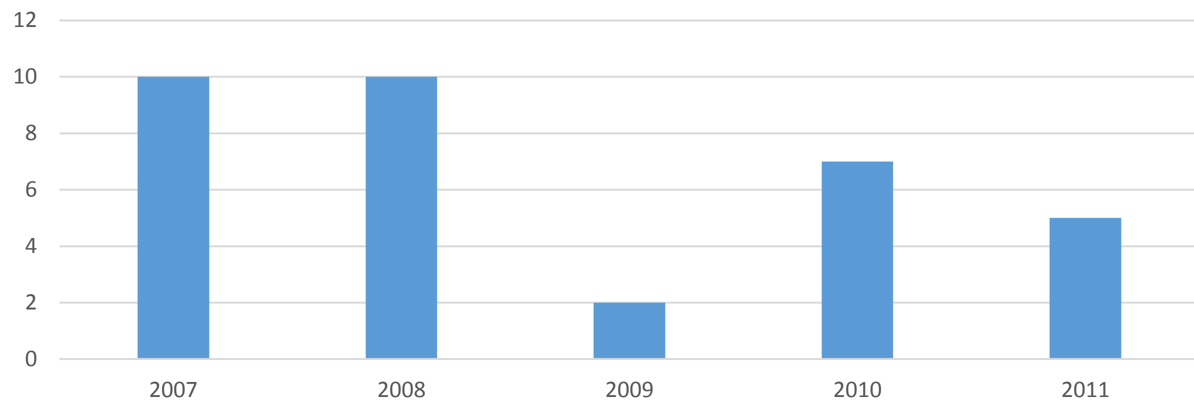


Figure 124: Number of pedestrians involved in collisions

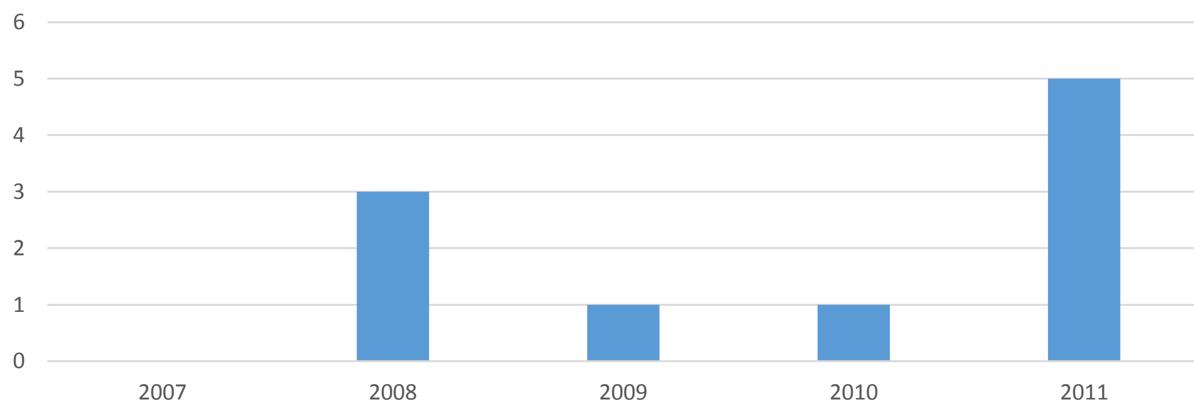


Figure 125: Number of cyclists involved in collisions

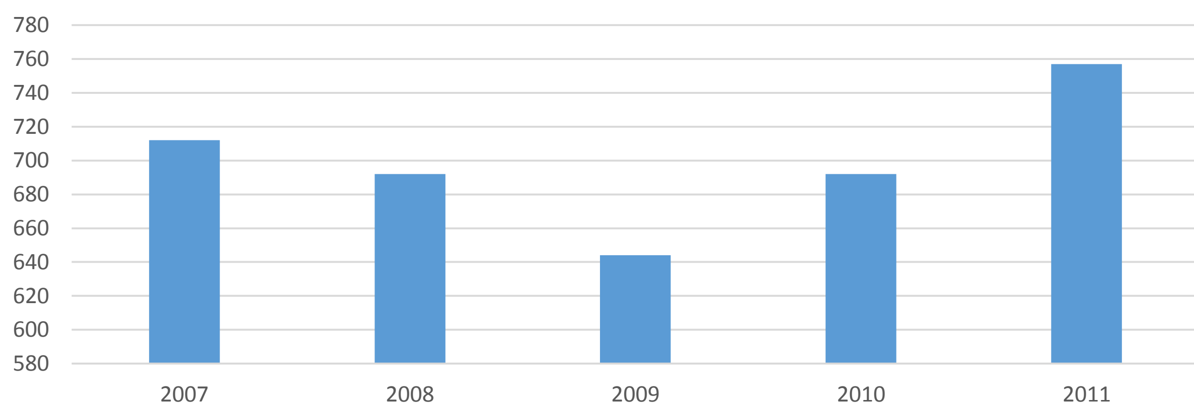


Figure 126: Number of drivers involved in collisions

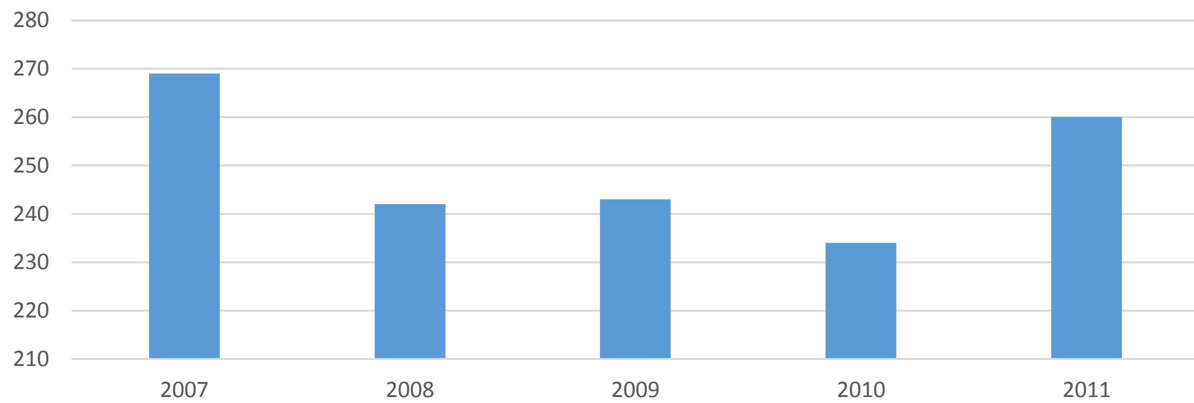


Figure 127: Number of passengers involved in collisions

A10 Inverness County

A10.1 Total Number of Collisions by Year

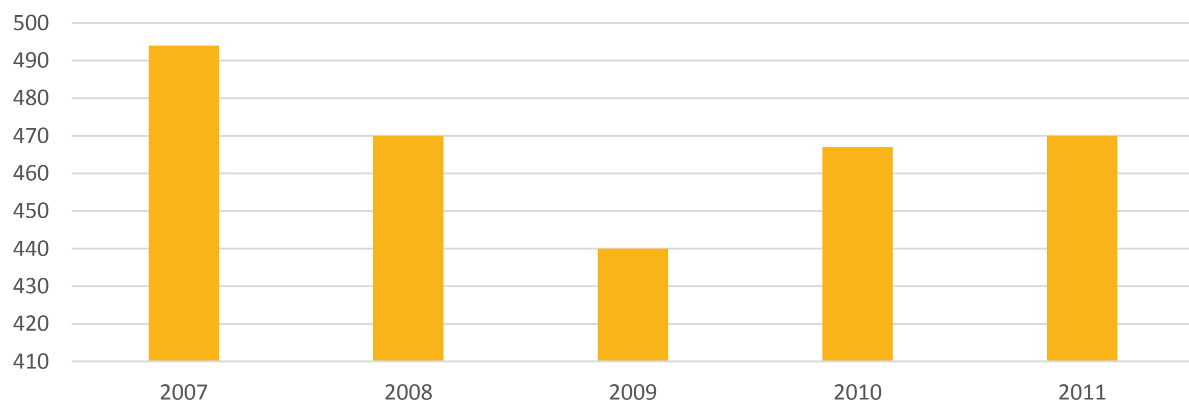


Figure 128: Total collisions by year

A10.2 Injury Severity

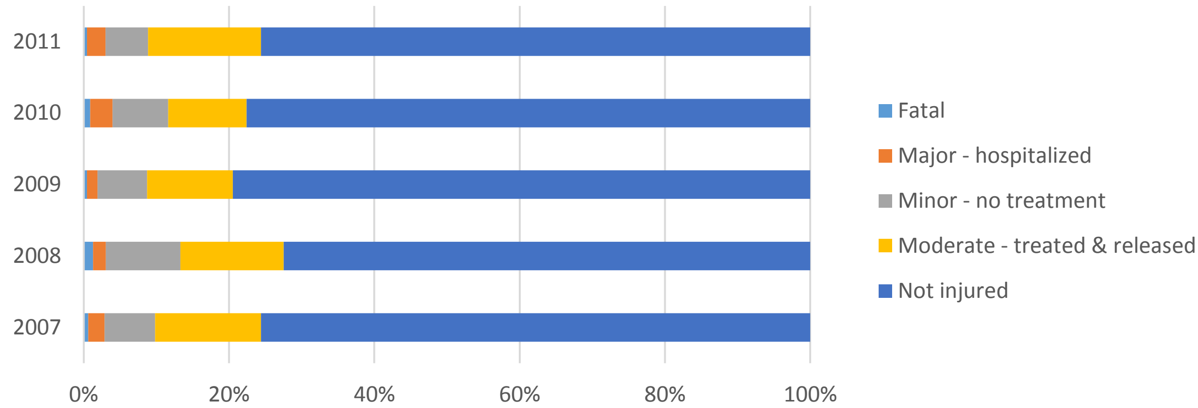


Figure 129: Injury severity of persons involved in collisions

A10.3 Age and Gender

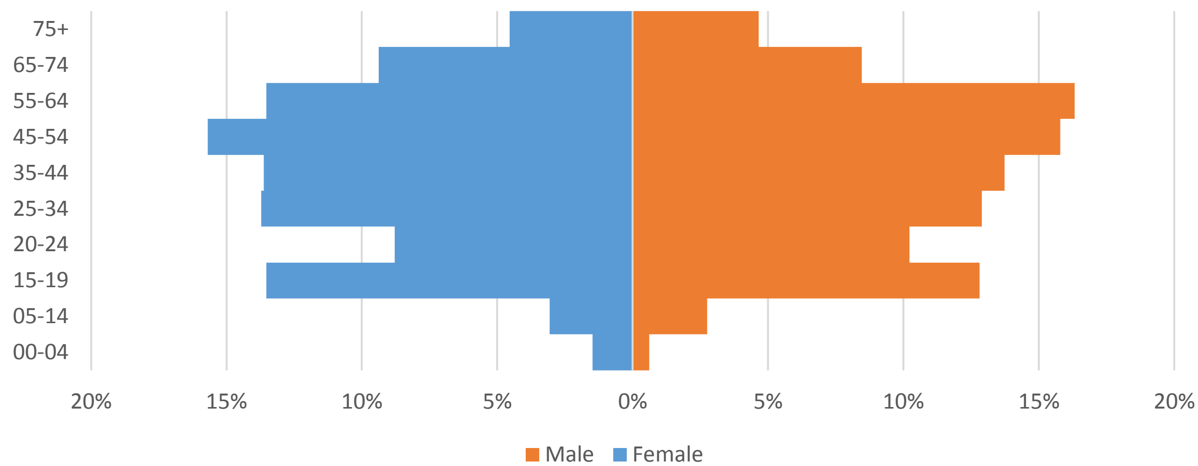


Figure 130: Age and gender distribution of persons involved in collisions

A10.4 Temporal Characteristics

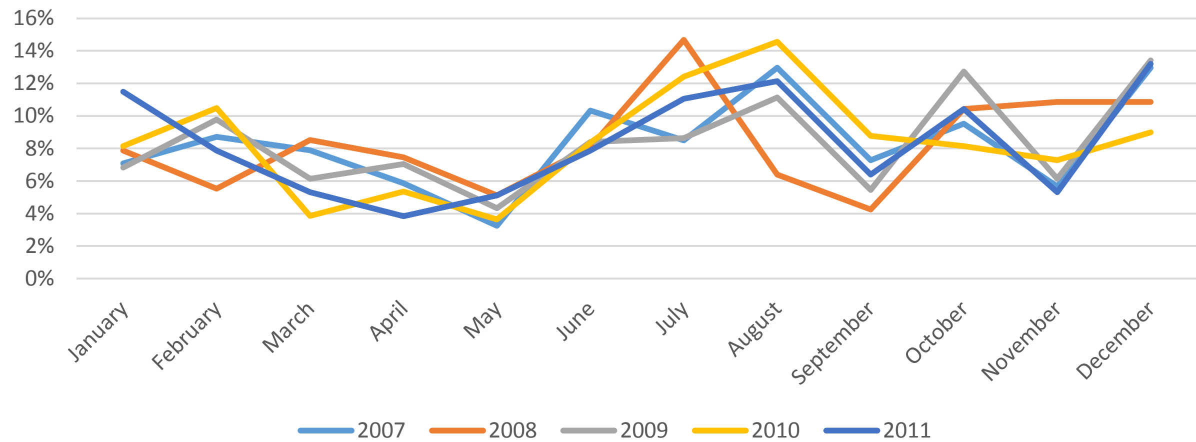


Figure 131: Monthly distribution of collisions

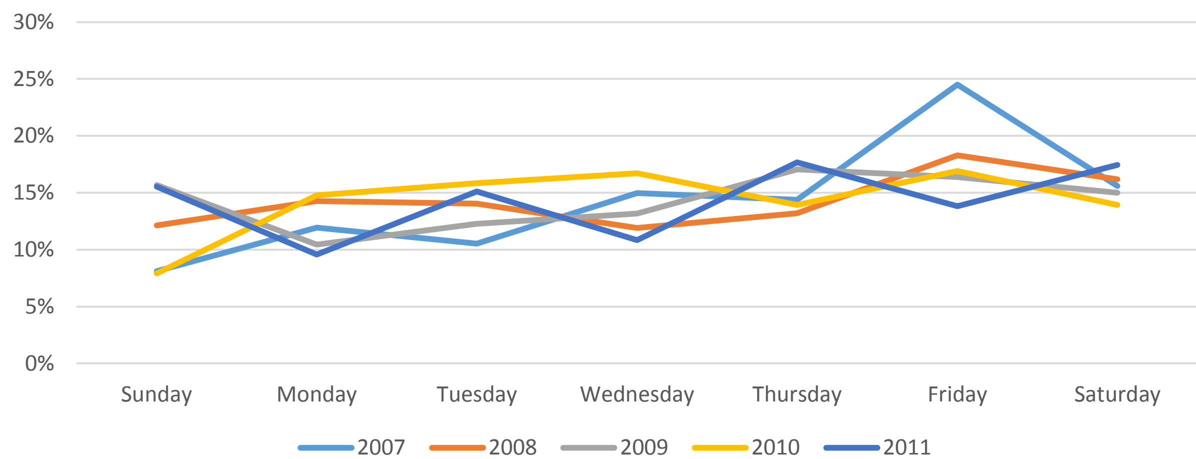


Figure 132: Day of week distribution of collisions

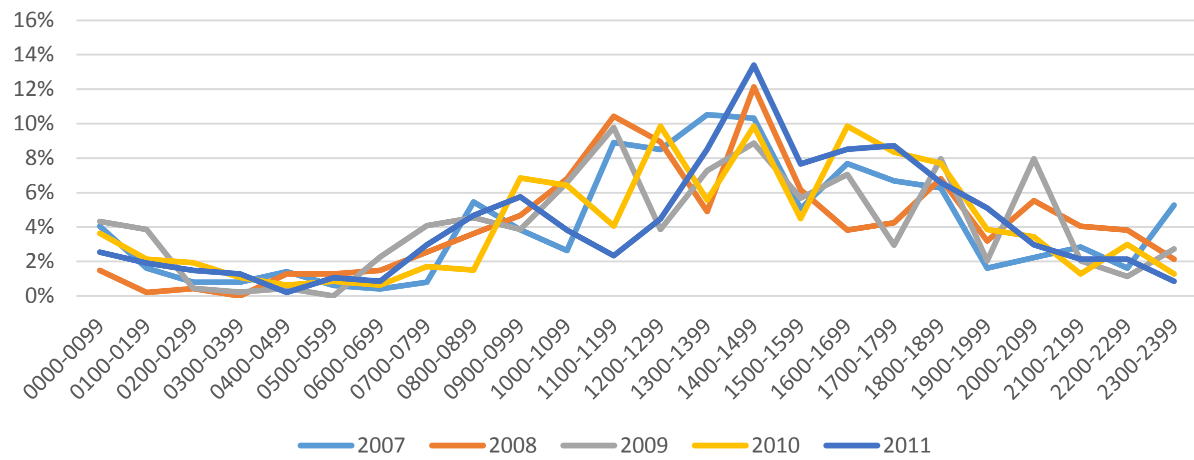


Figure 133: Time of day distribution of collisions

A10.5 Collision Frequency by Mode

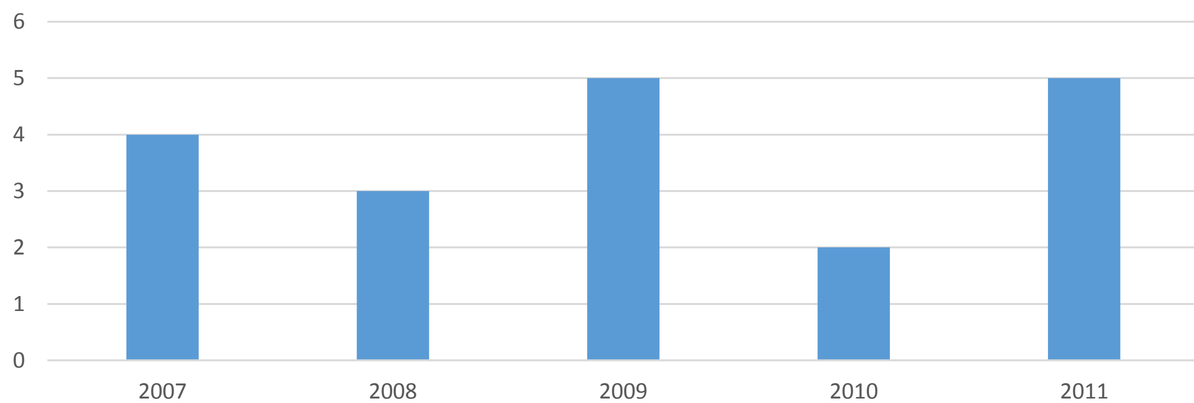


Figure 134: Number of pedestrians involved in collisions

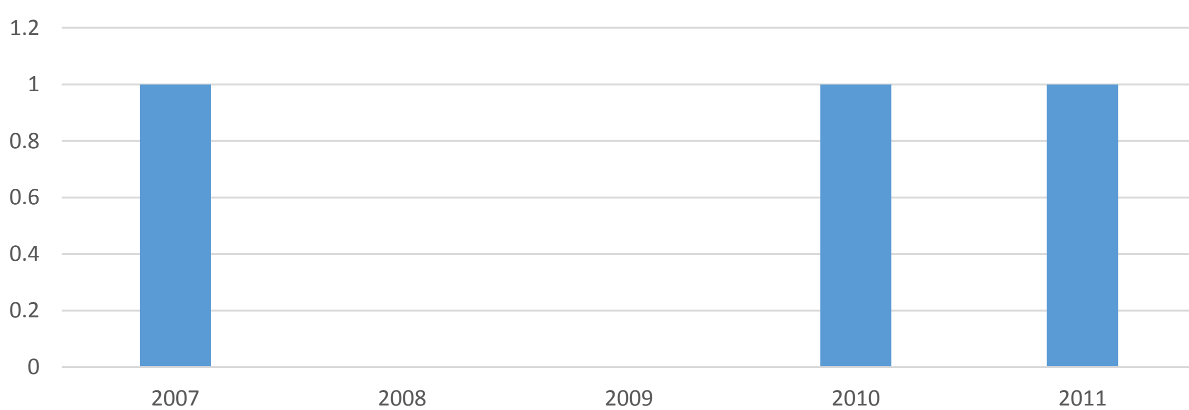


Figure 135: Number of cyclists involved in collisions

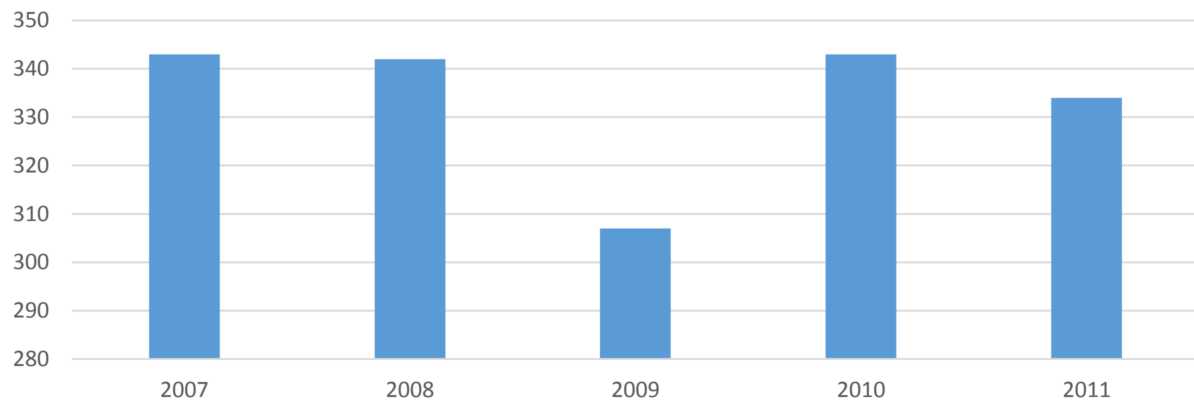


Figure 136: Number of drivers involved in collisions

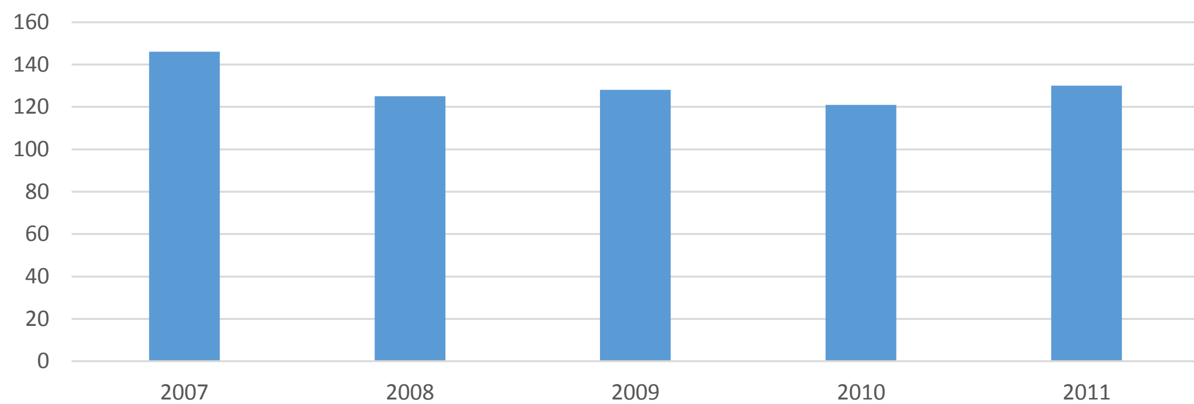


Figure 137: Number of passengers involved in collisions

A11 Kings County

A11.1 Total Number of Collisions by Year

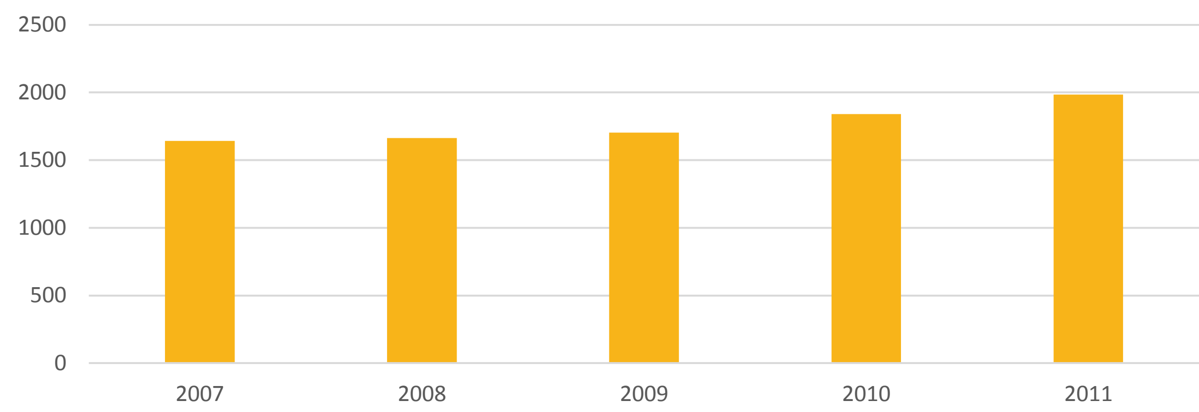


Figure 138: Total collisions by year

A11.2 Injury Severity

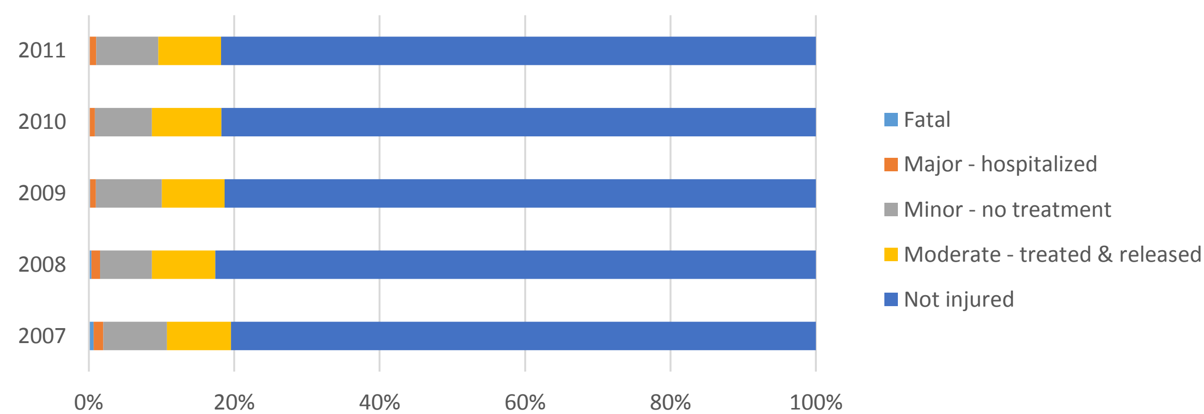


Figure 139: Injury severity of persons involved in collisions

A11.3 Age and Gender

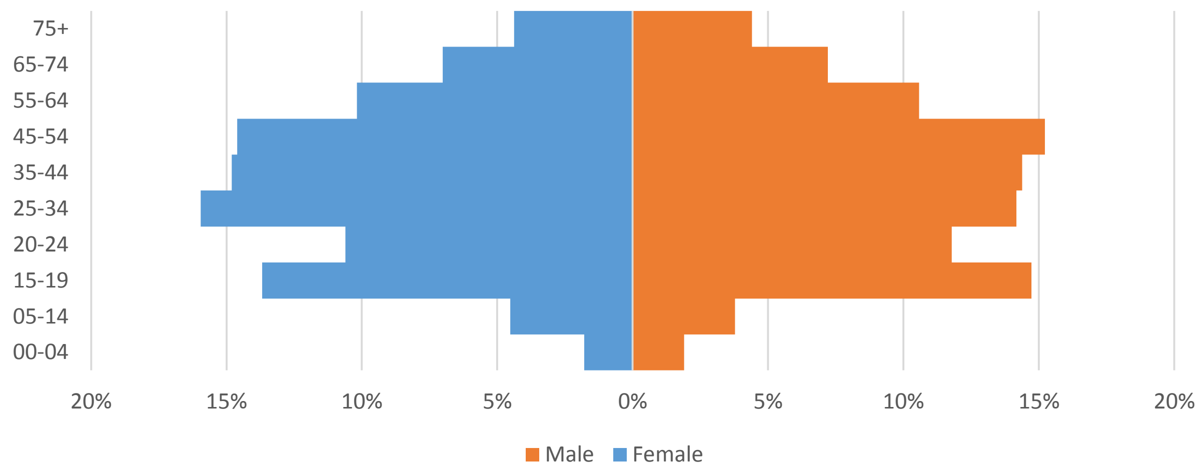


Figure 140: Age and gender distribution of persons involved in collisions

A11.4 Temporal Characteristics

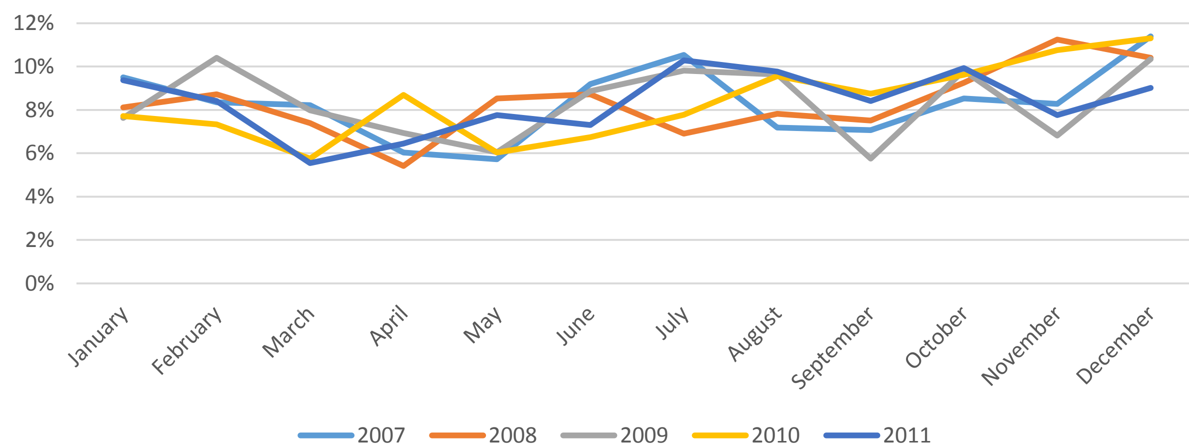


Figure 141: Monthly distribution of collisions

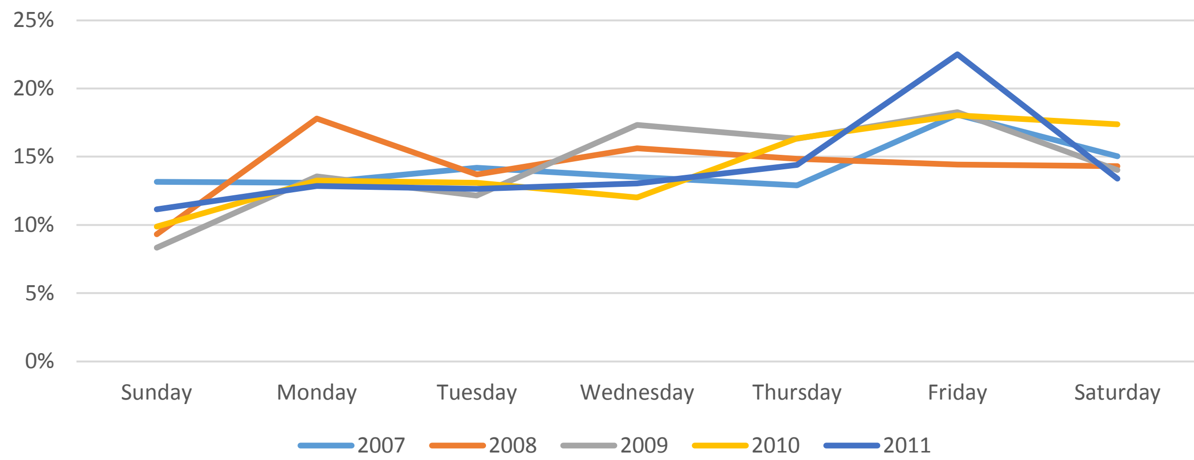


Figure 142: Day of week distribution of collisions

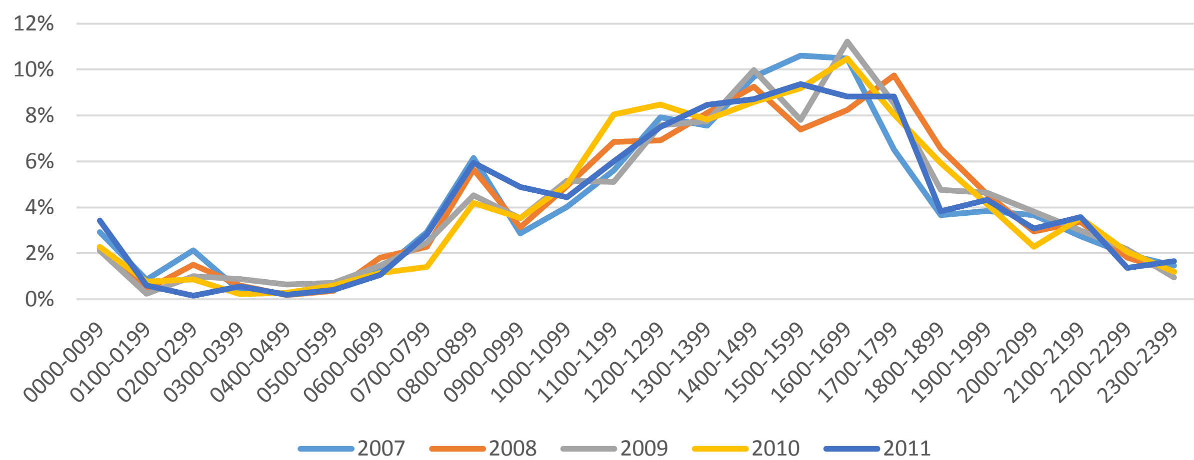


Figure 143: Time of day distribution of collisions

A11.5 Collision Frequency by Mode

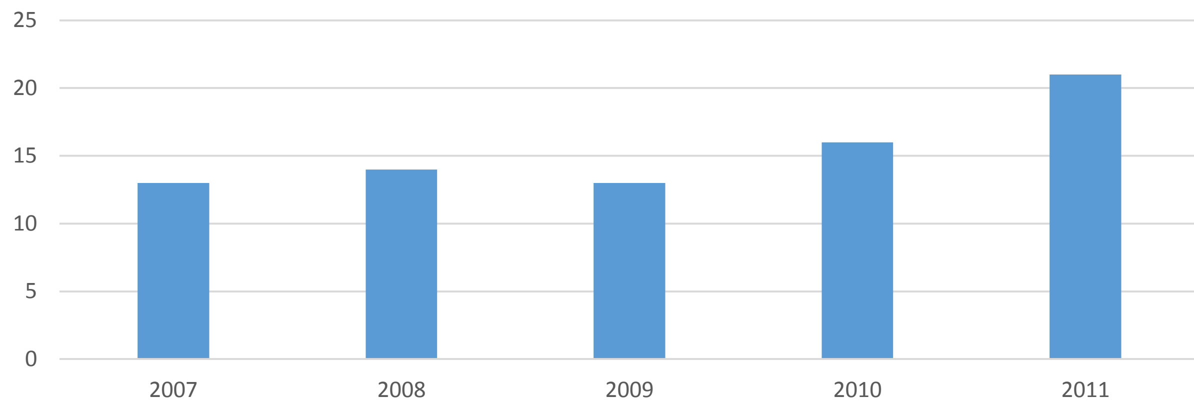


Figure 144: Number of pedestrian collisions involved in collisions

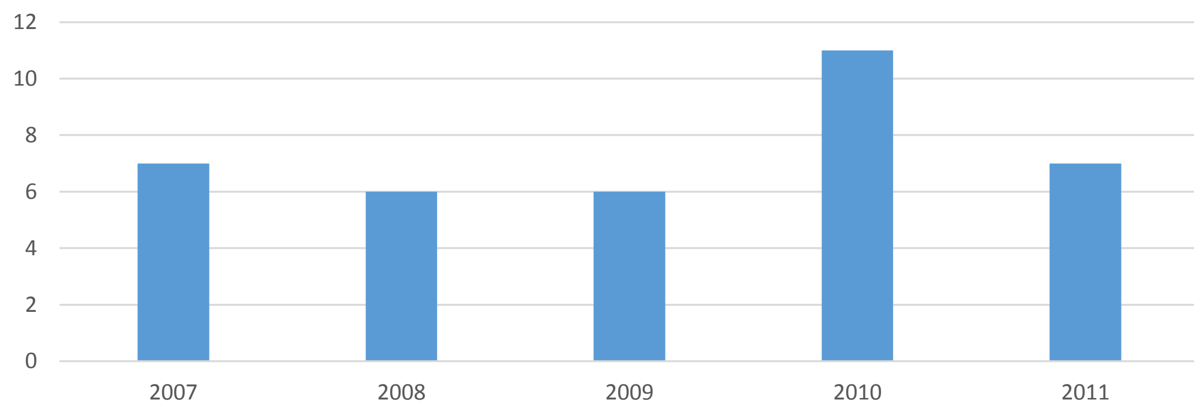


Figure 145: Number of cyclists involved in collisions

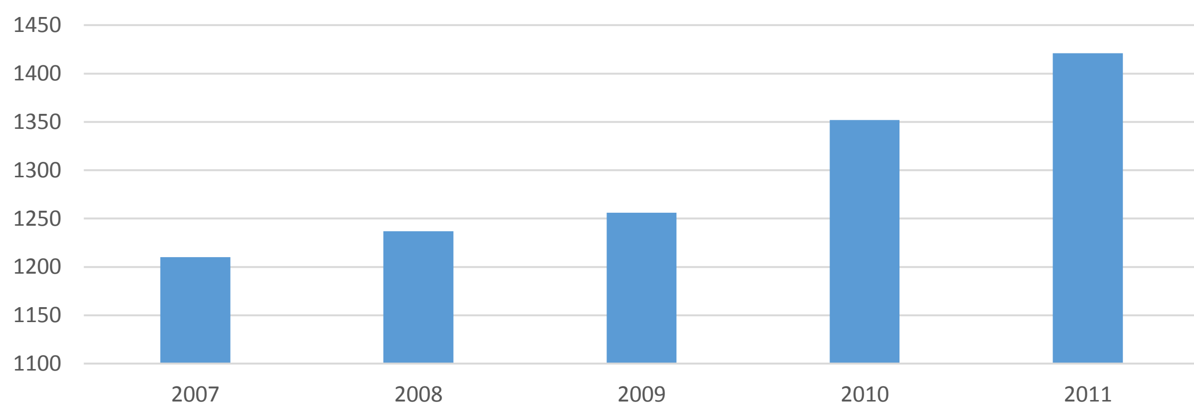


Figure 146: Number of drivers involved in collisions

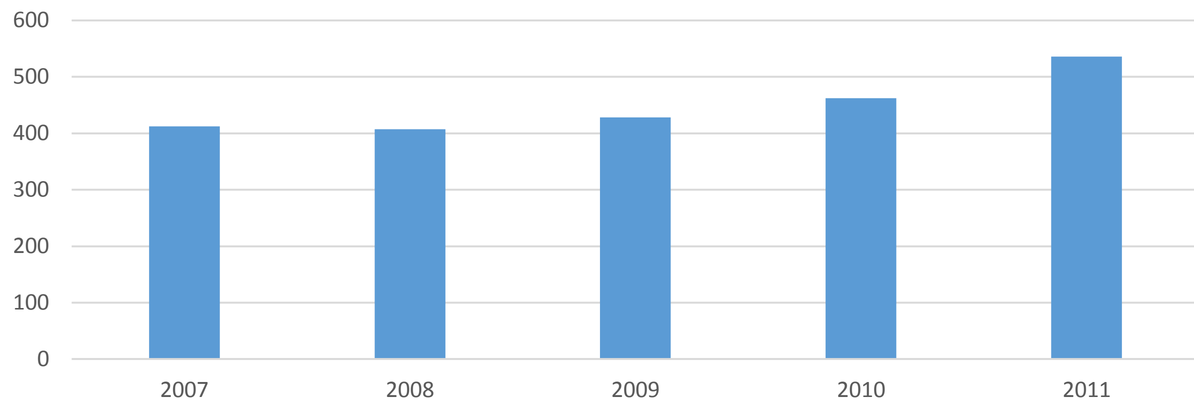


Figure 147: Number of passengers involved in collisions

A12 Lunenburg County

A12.1 Total Number of Collisions by Year

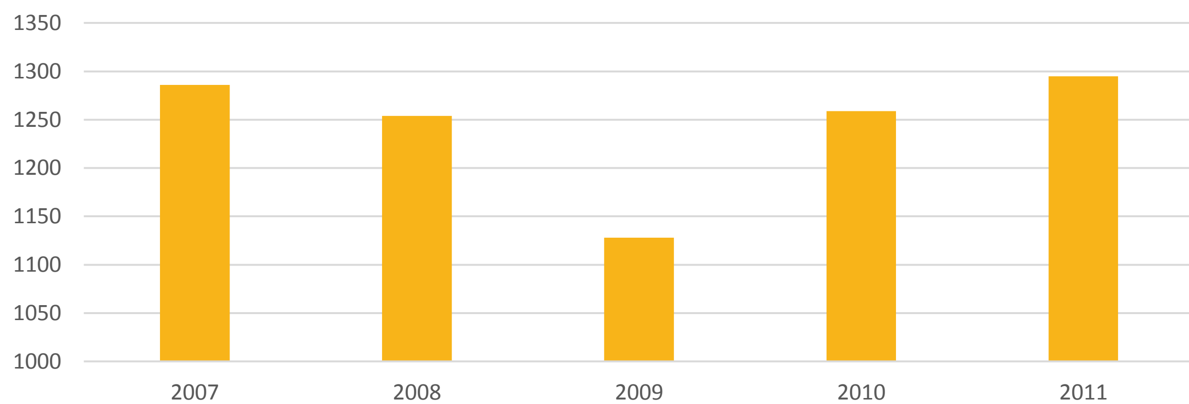


Figure 148: Total number of collisions

A12.2 Injury Severity

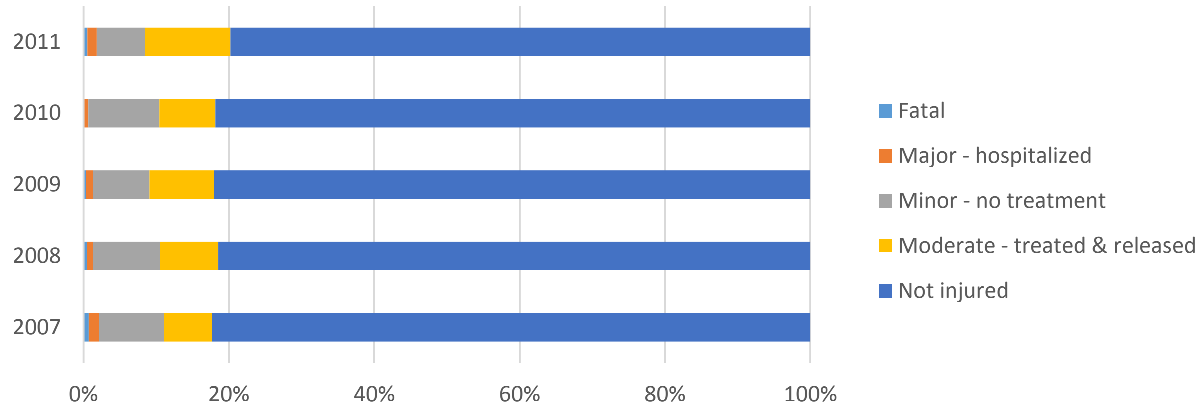


Figure 149: Injury severity of persons involved in collisions

A12.3 Age and Gender

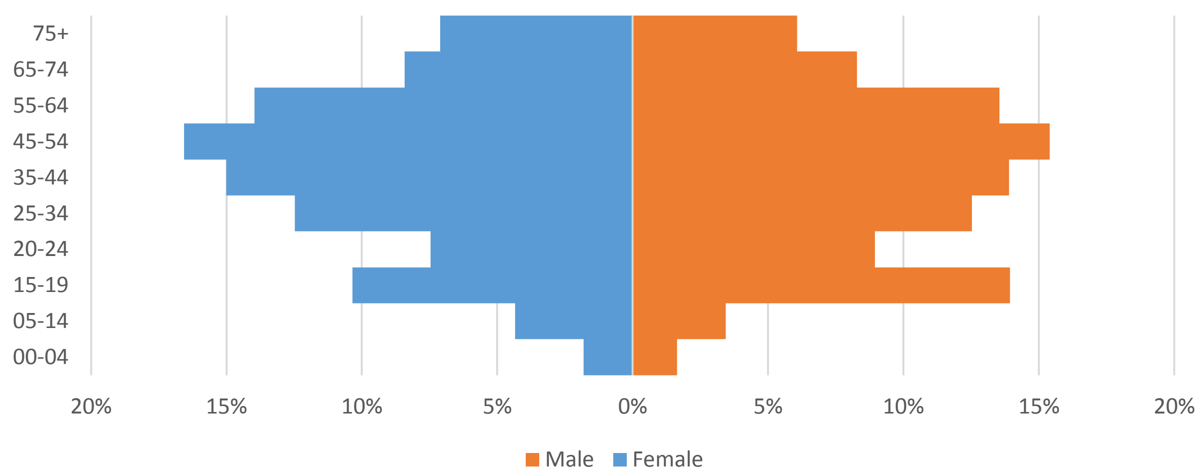


Figure 150: Age and gender distribution of persons involved in collisions

A12.4 Temporal Characteristics

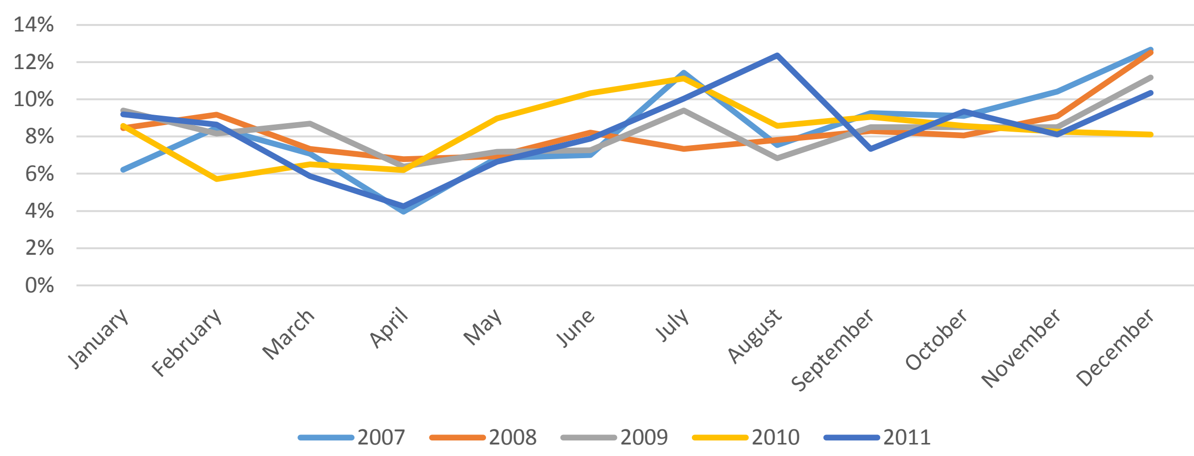


Figure 151: Monthly distribution of collisions

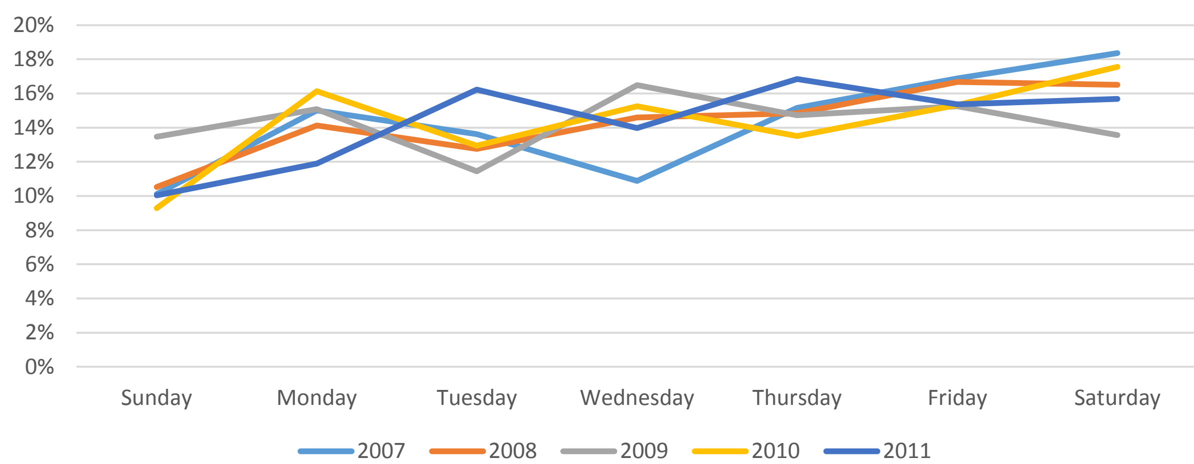


Figure 152: Day of week distribution of collisions

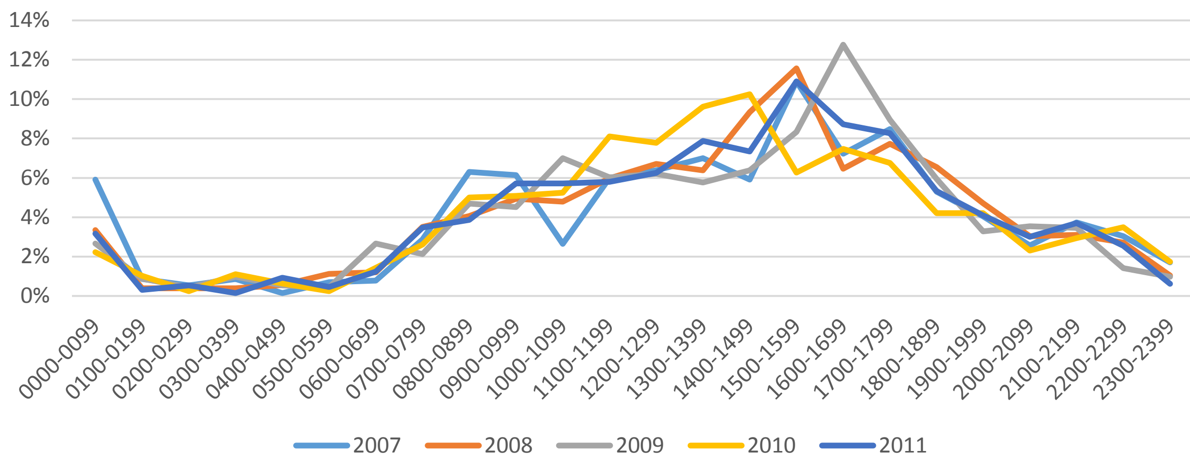


Figure 153: Time of day distribution of collisions

A12.5 Collision Frequency by Mode

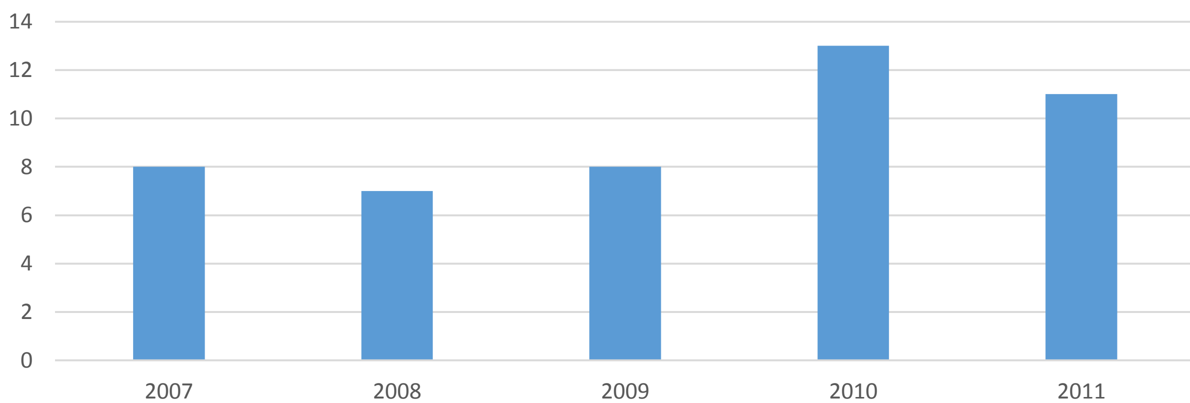


Figure 154: Number of pedestrians involved in collisions

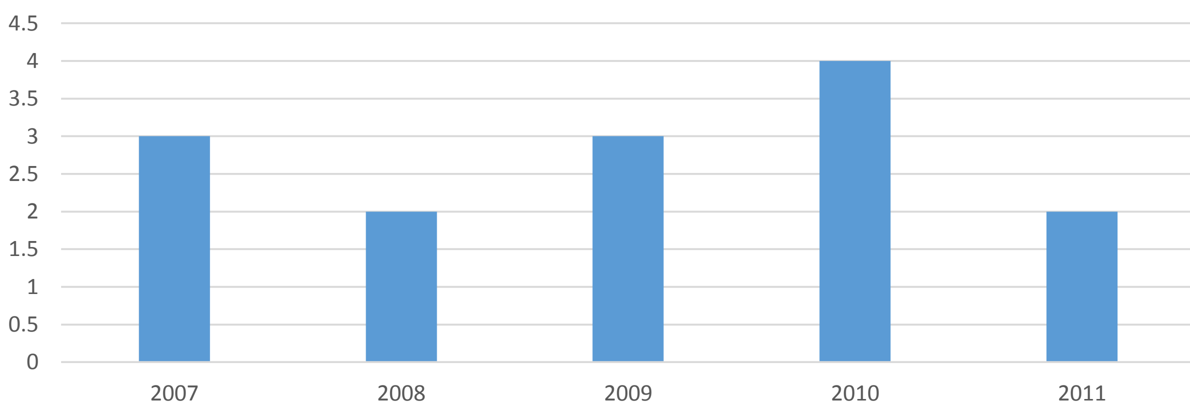


Figure 155: Number of cyclists involved in collisions

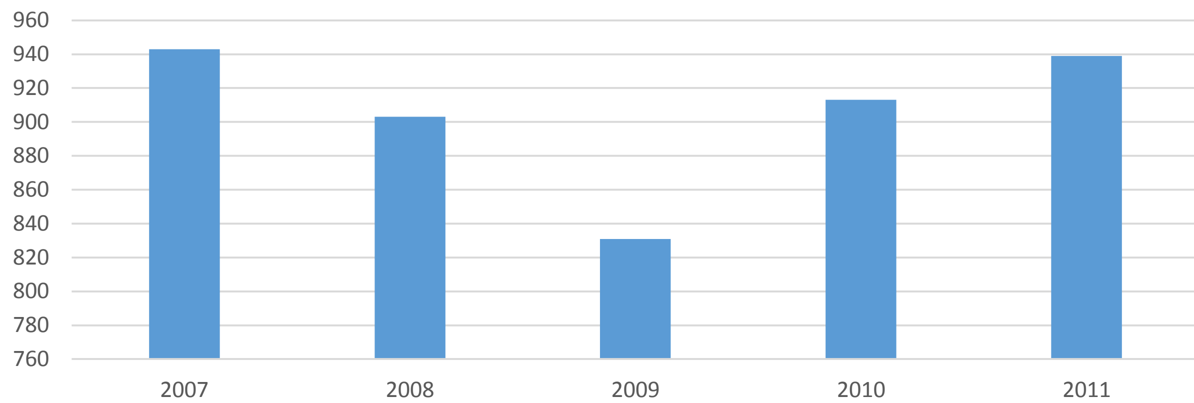


Figure 156: Number of drivers involved in collisions

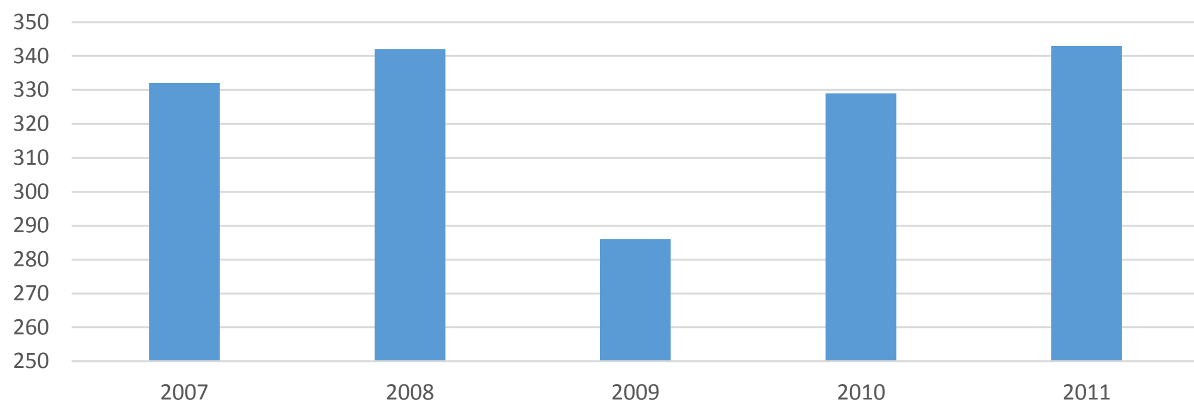


Figure 157: Number of passengers involved in collisions

A13 Pictou County

A13.1 Total Number of Collisions by Year

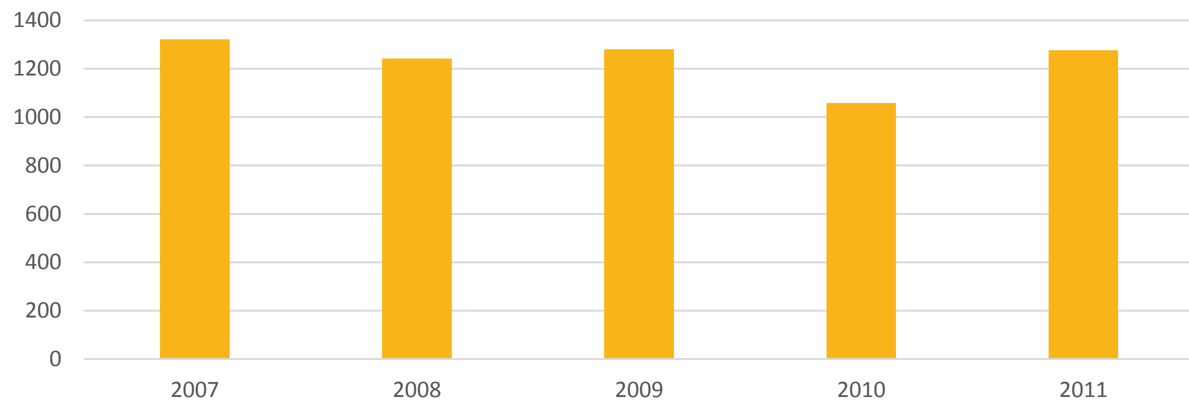


Figure 158: Total number of collisions

A13.2 Injury Severity

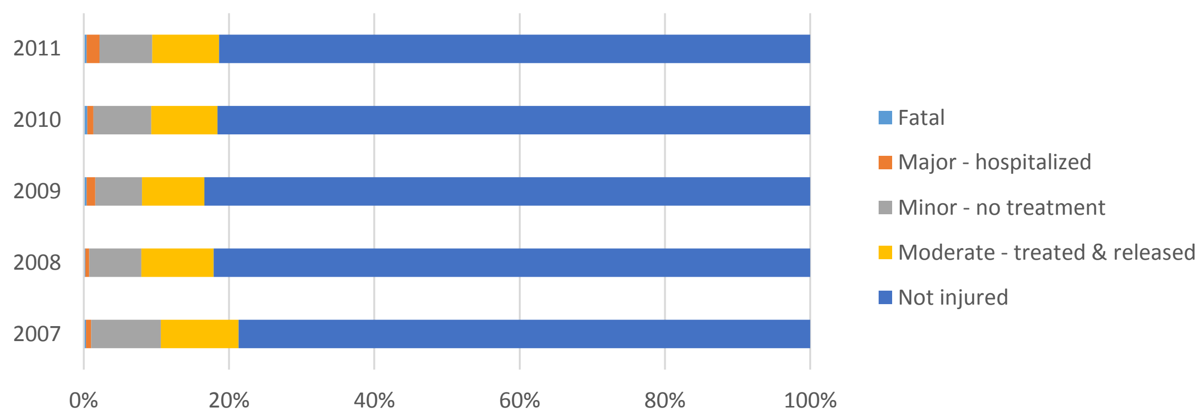


Figure 159: Injury severity of persons involved in collisions

A13.3 Age and Gender

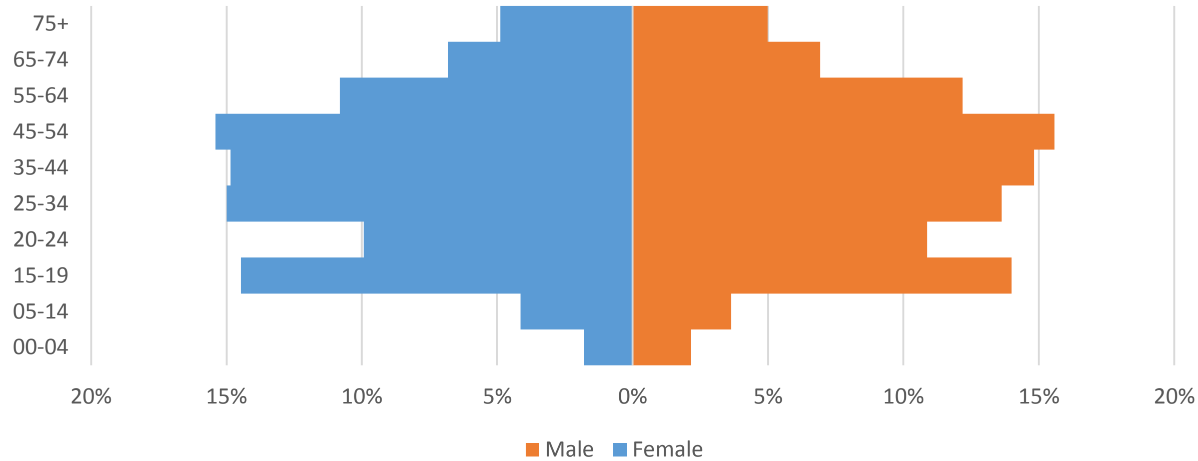


Figure 160: Age and gender distribution of persons involved in collisions

A13.4 Temporal Characteristics

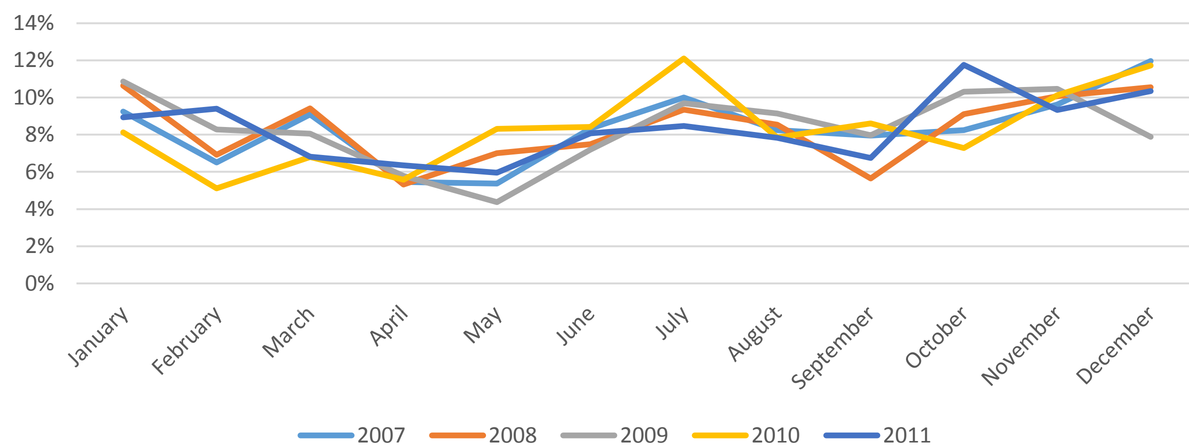


Figure 161: Monthly distribution of collisions

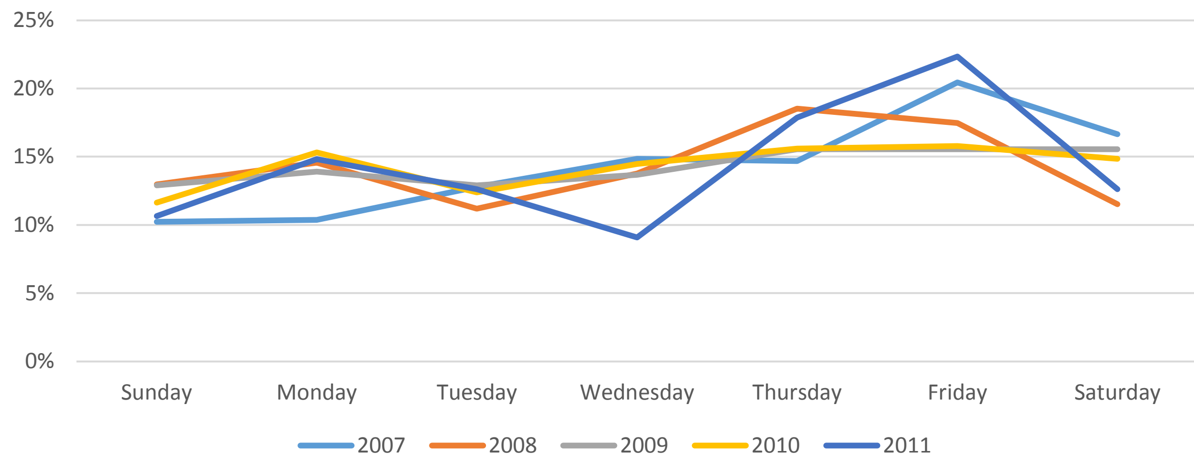


Figure 162: Day of week distribution of collisions

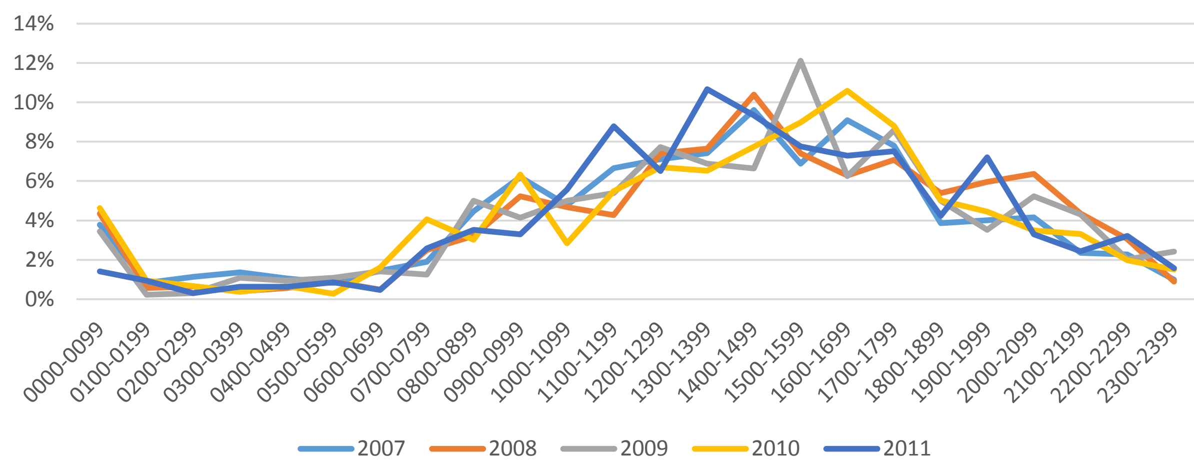


Figure 163: Time of day distribution of collisions

A13.5 Collision Frequency by Mode

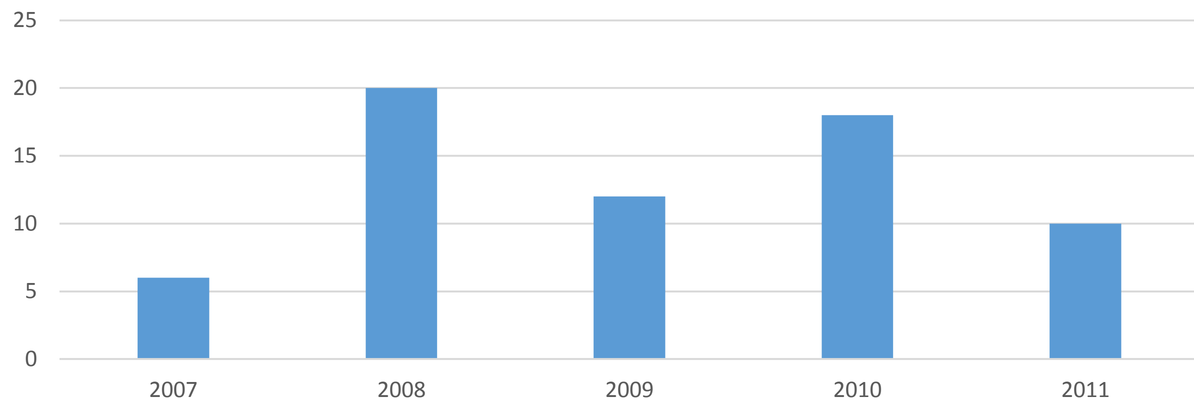


Figure 164: Number of pedestrians involved in collisions

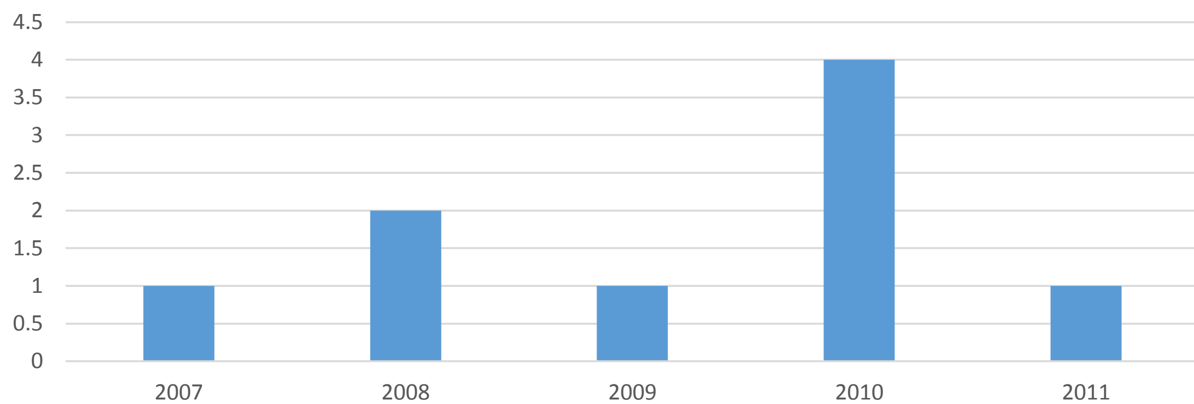


Figure 165: Number of cyclists involved in collisions

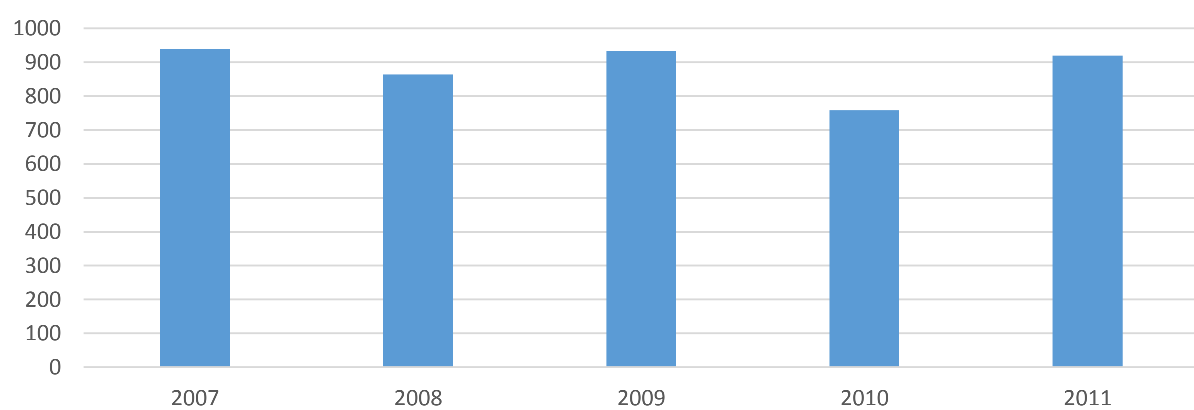


Figure 166: Number of drivers involved in collisions

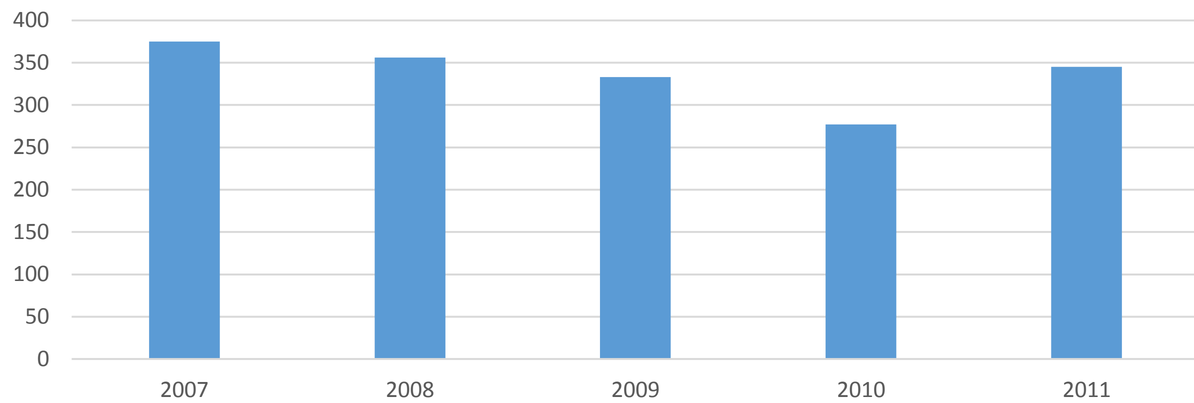


Figure 167: Number of passengers involved in collisions

A14 Queens County

A14.1Total Number of Collisions by Year

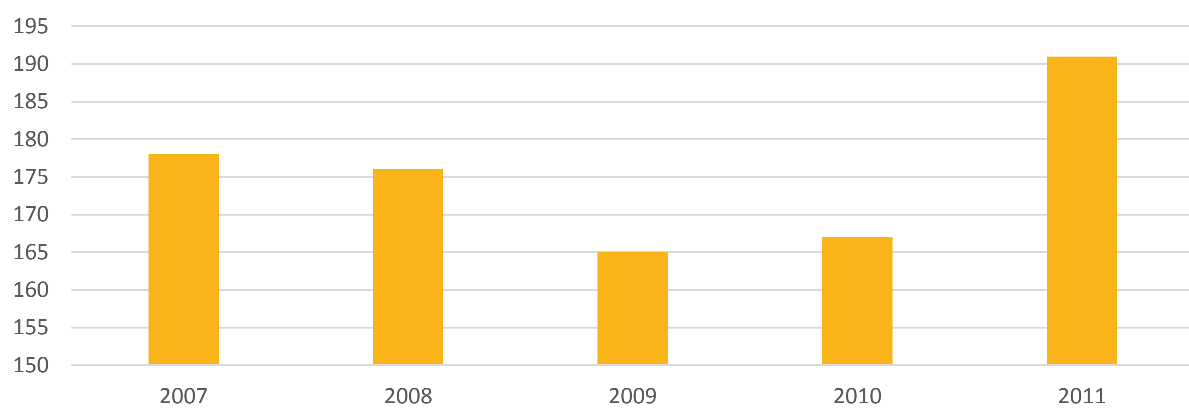


Figure 168: Total number of collisions

A14.2 Injury Severity

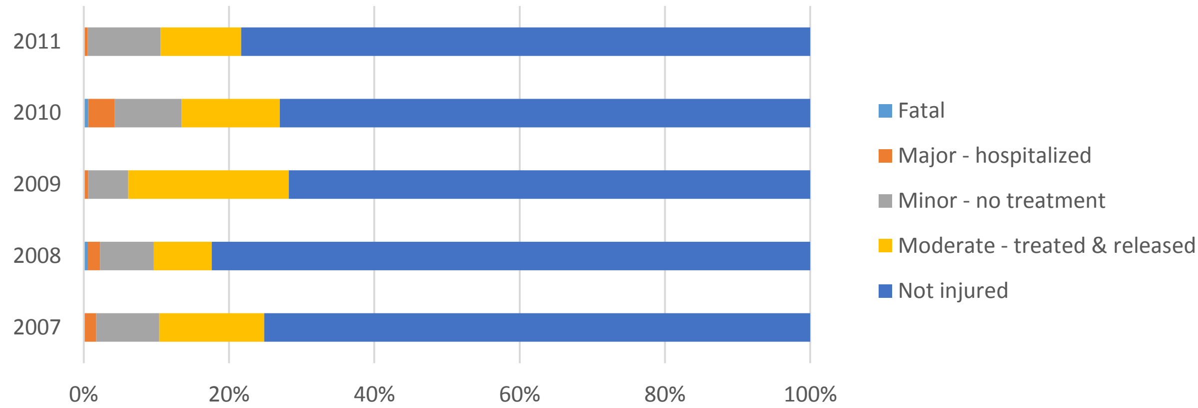


Figure 169: Injury severity of persons involved in collisions

A14.3 Age and Gender

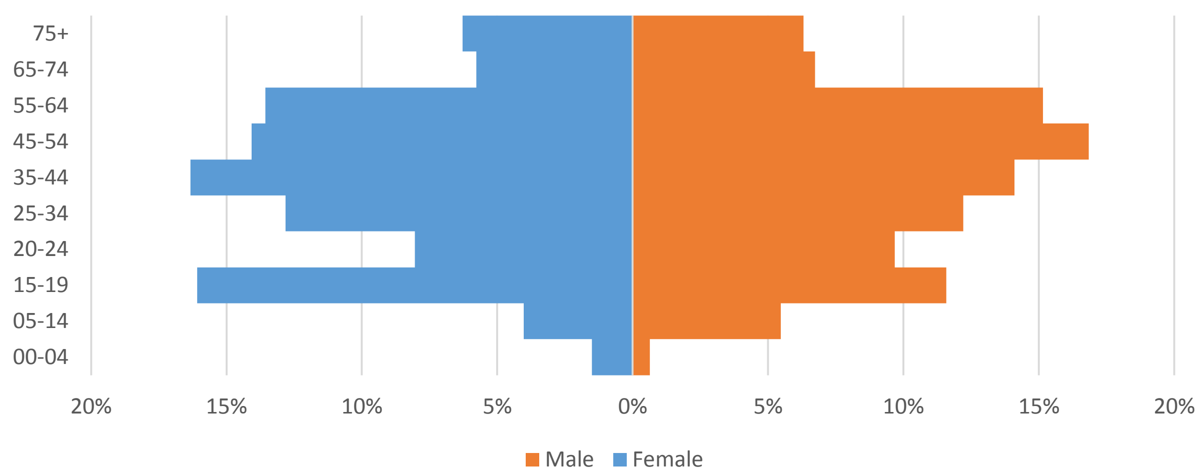


Figure 170: Age and gender distribution of persons involved in collisions

A14.4 Temporal Characteristics

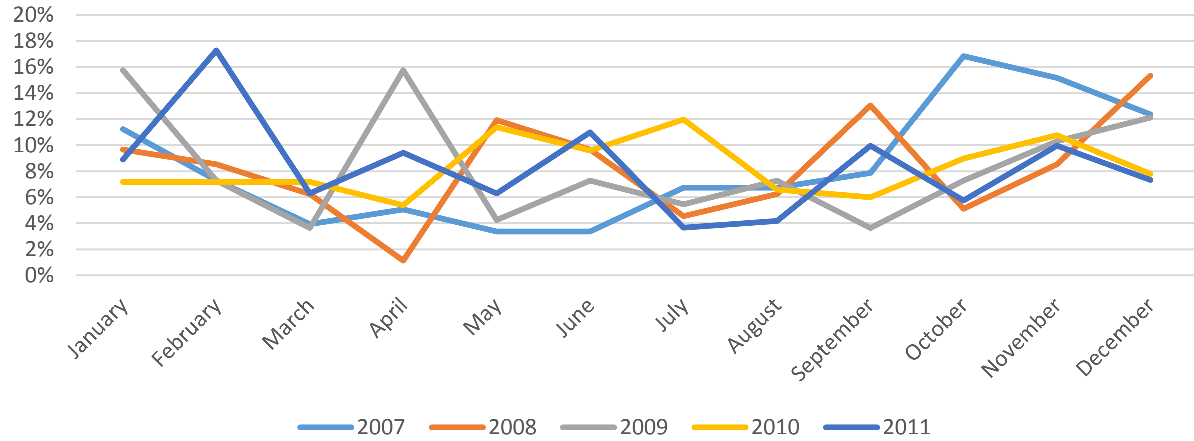


Figure 171: Monthly distribution of collisions

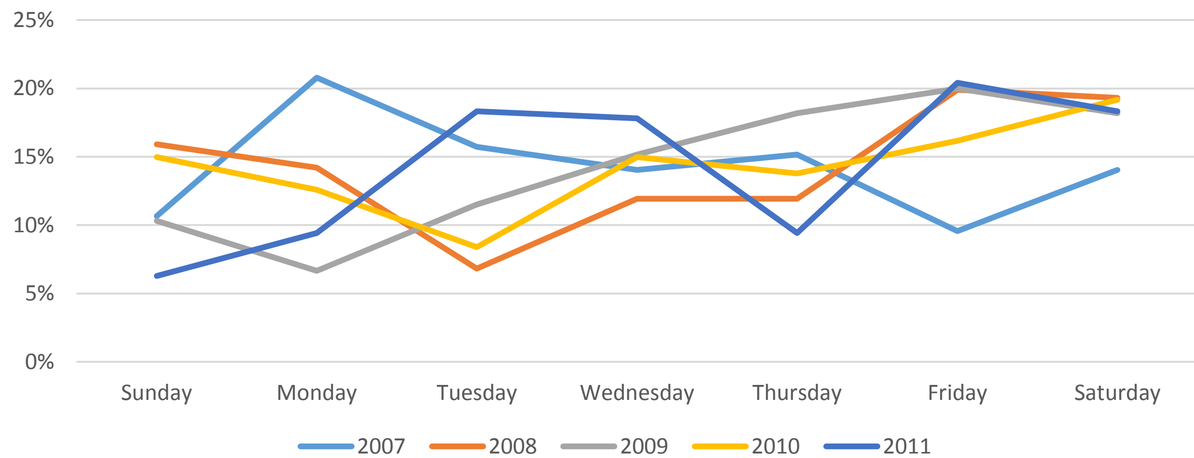


Figure 172: Day of week distribution of collisions

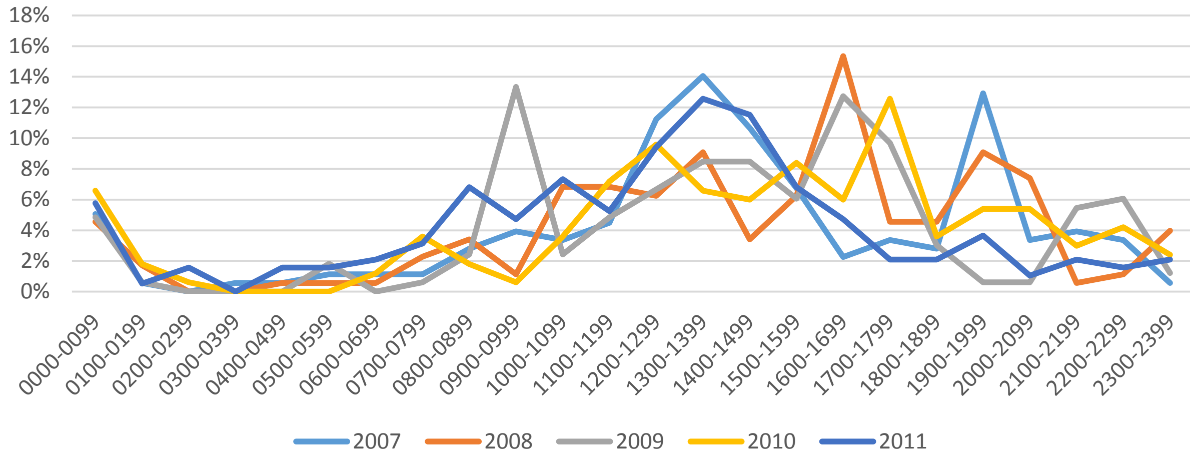


Figure 173: Time of day distribution of collisions

A14.5 Collision Frequency by Mode

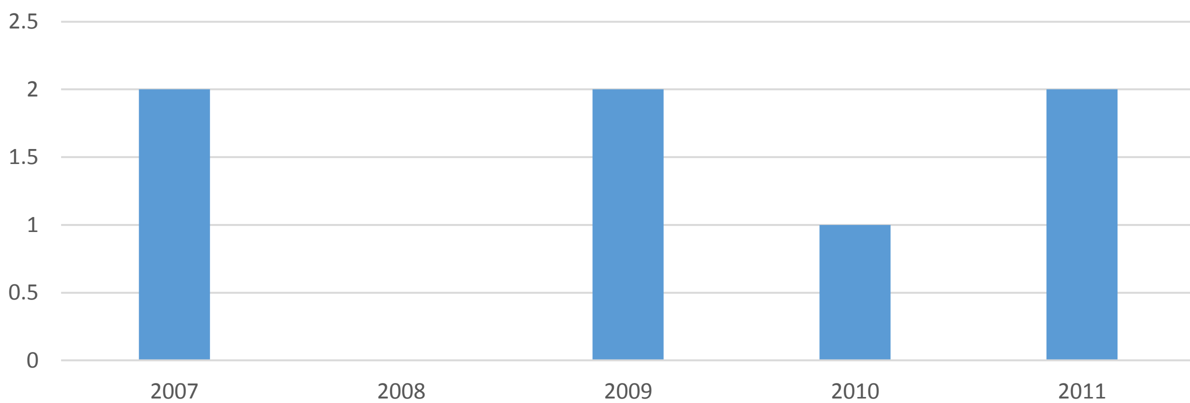


Figure 174: Number of pedestrians involved in collisions

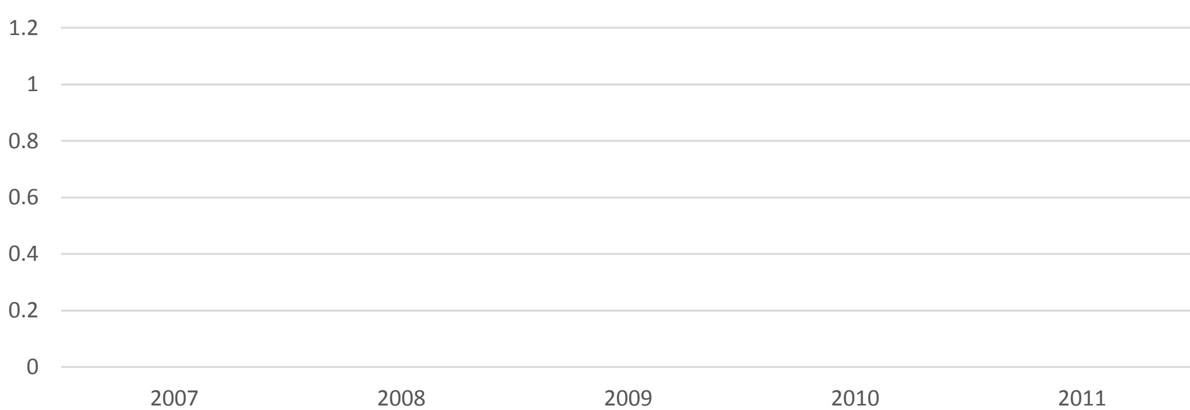


Figure 175: Number of cyclists involved in collisions

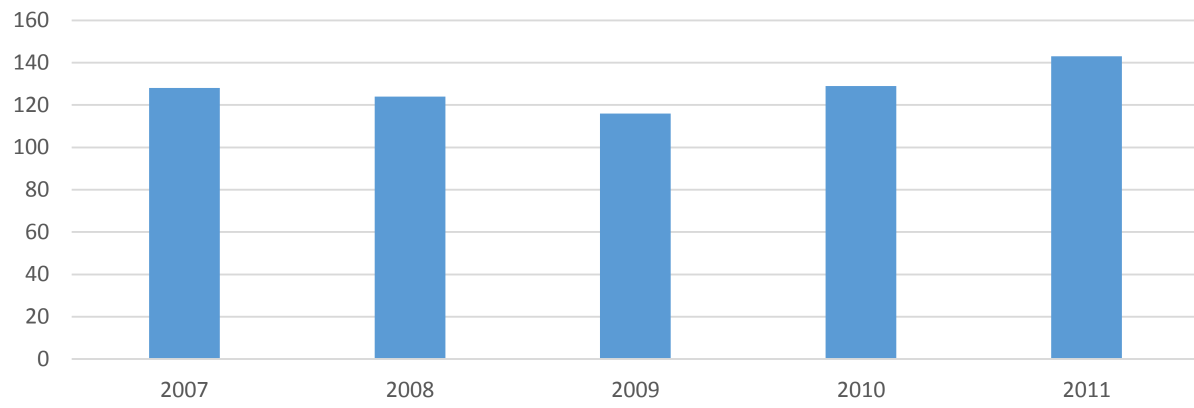


Figure 176: Number of drivers involved in collisions

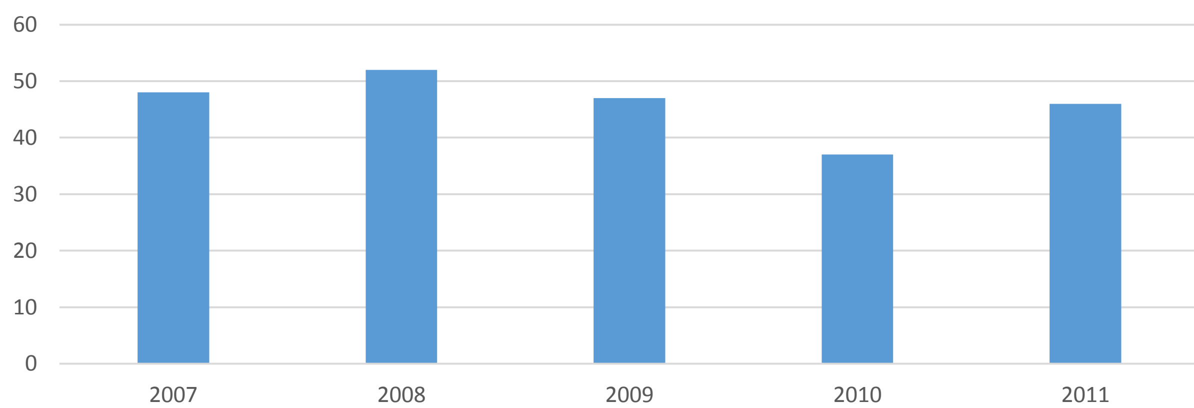


Figure 177: Number of passengers involved in collisions

A15 Richmond County

A15.1 Total Number of Collisions by Year

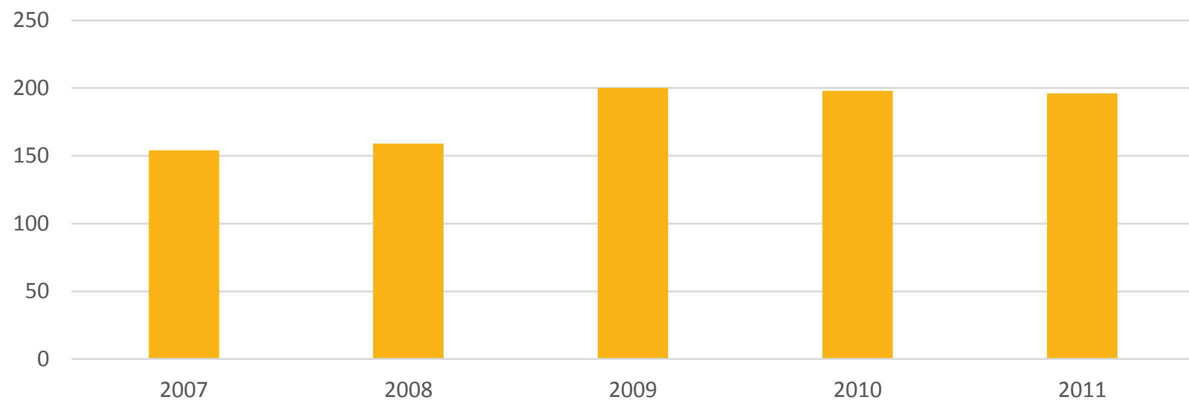


Figure 178: Total number of collisions

15.2 Injury Severity

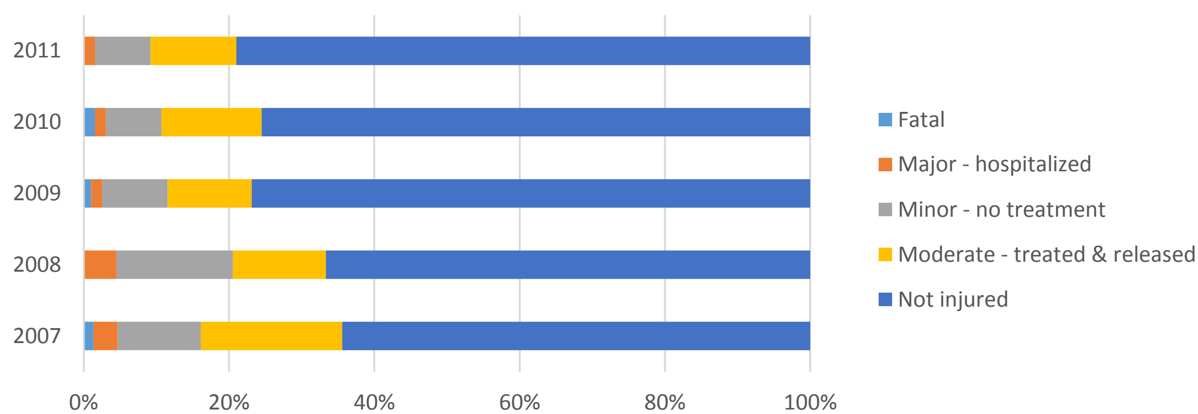


Figure 179: Injury severity of persons involved in collisions

15.3 Age and Gender

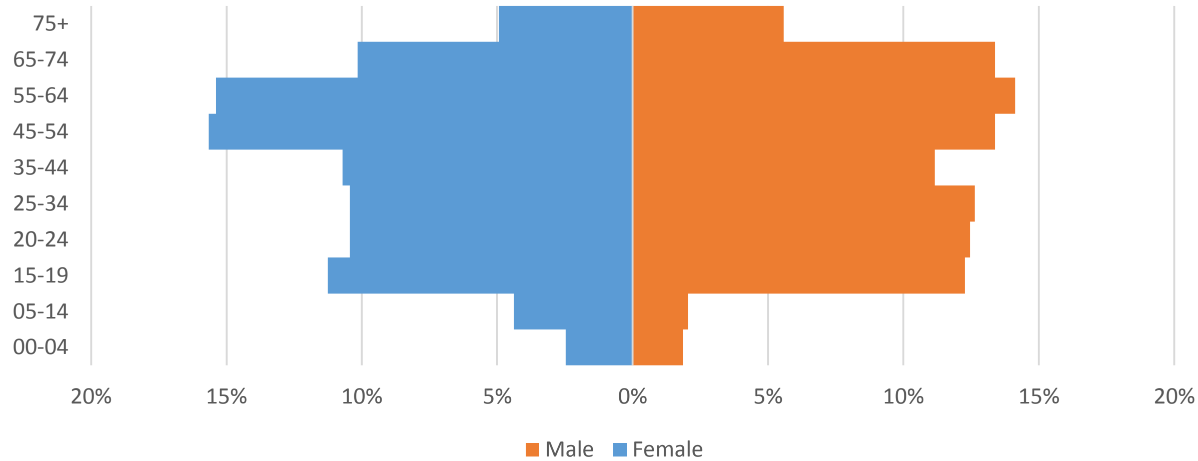


Figure 180: Age and gender distribution of persons involved in collisions

15.4 Temporal Characteristics

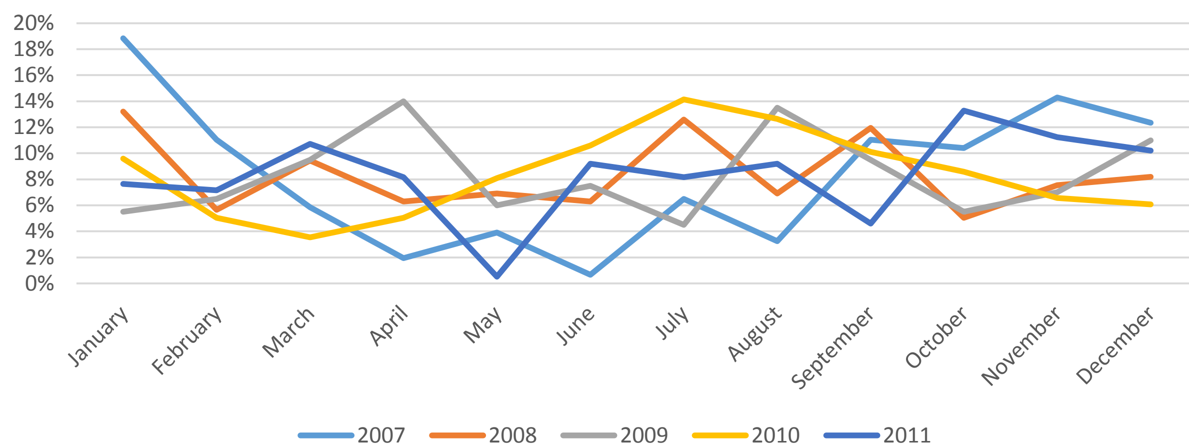


Figure 181: Monthly distribution of collisions

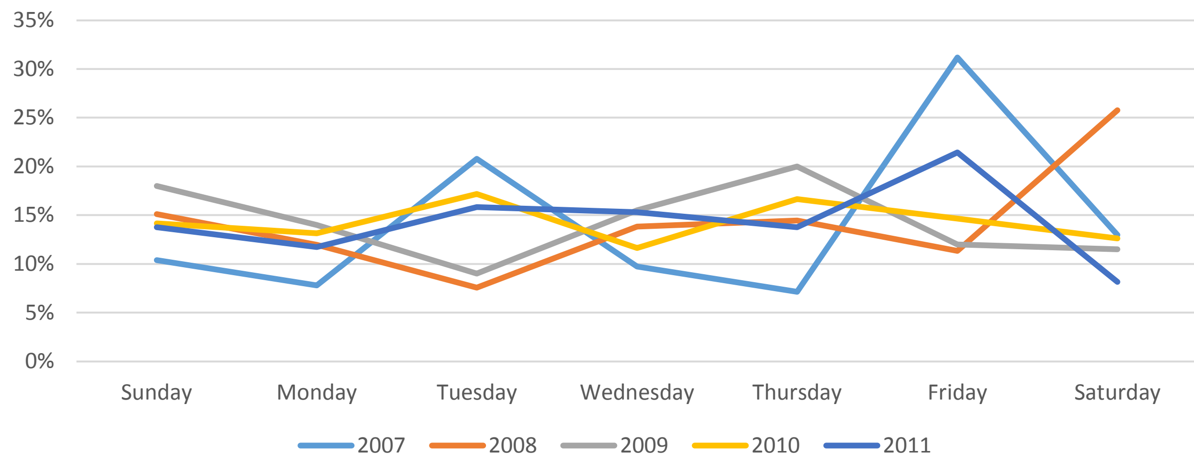


Figure 182: Day of week distribution of collisions

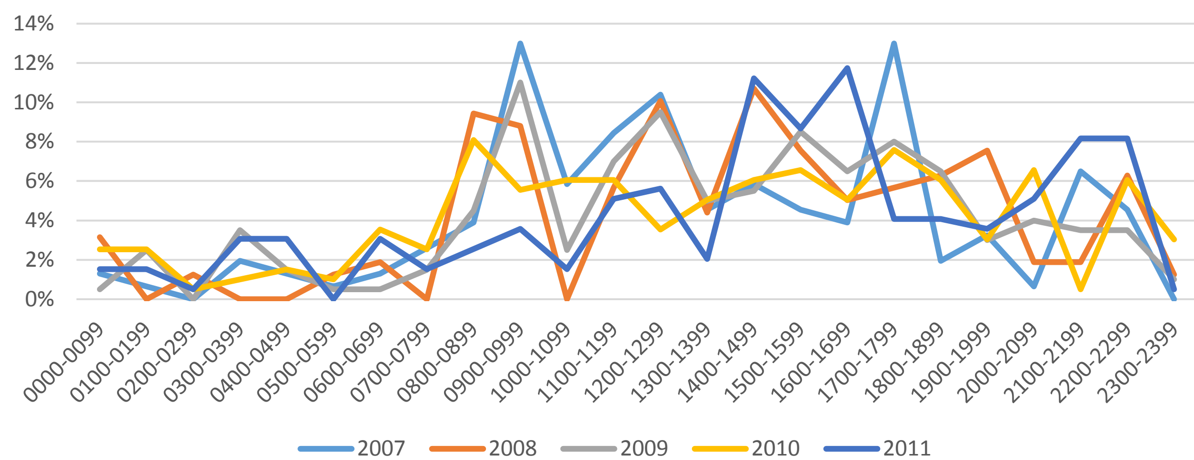


Figure 183: Time of day distribution of collisions

15.5 Collision Frequency by Mode

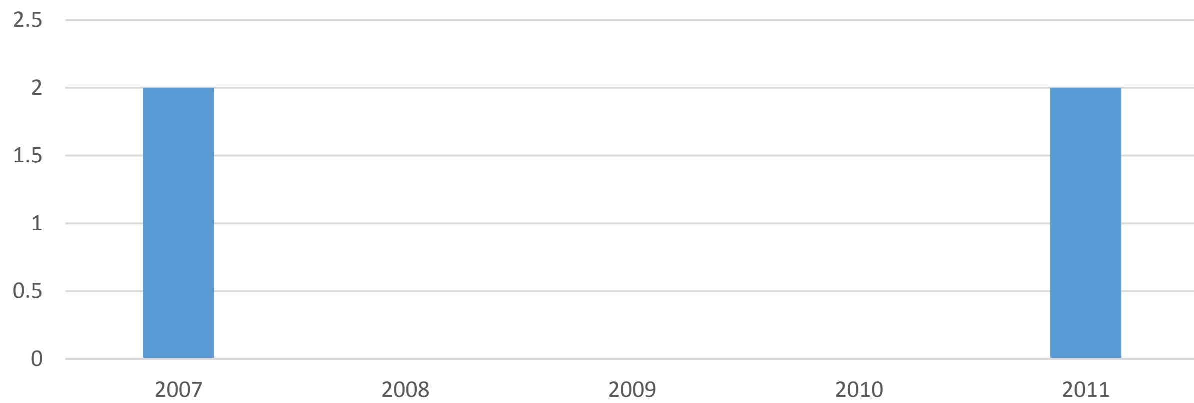


Figure 184: Number of pedestrians involved in collisions

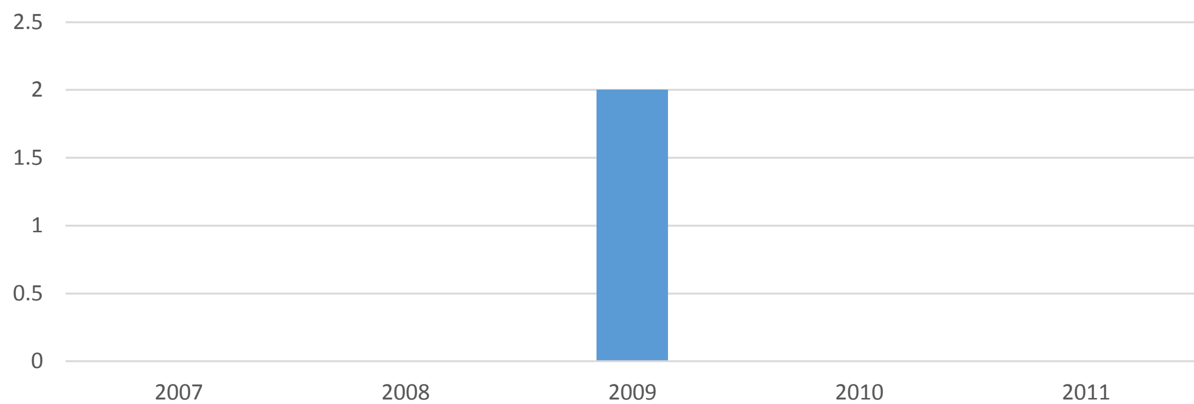


Figure 185: Number of cyclists involved in collisions

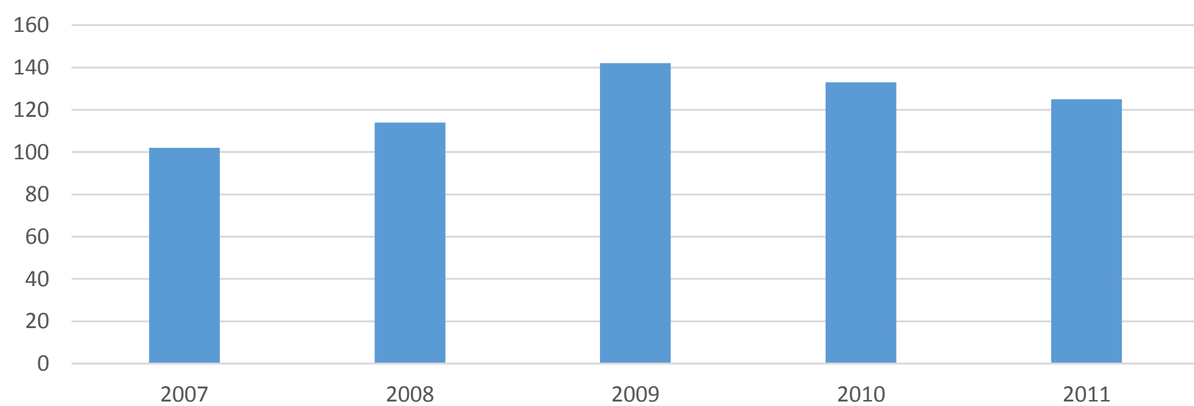


Figure 186: Number of drivers involved in collisions

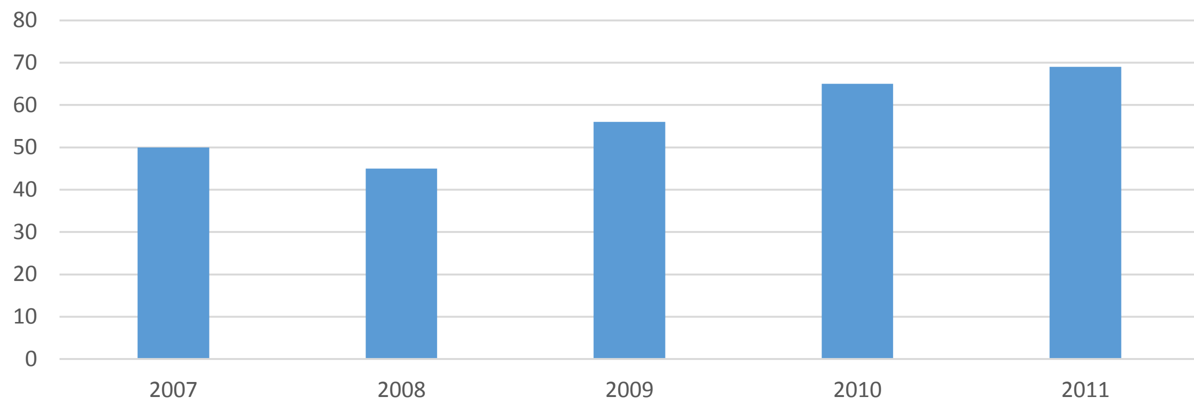


Figure 187: Number of passengers involved in collisions

A16 Shelburne County

A16.1 Total Number of Collisions by Year

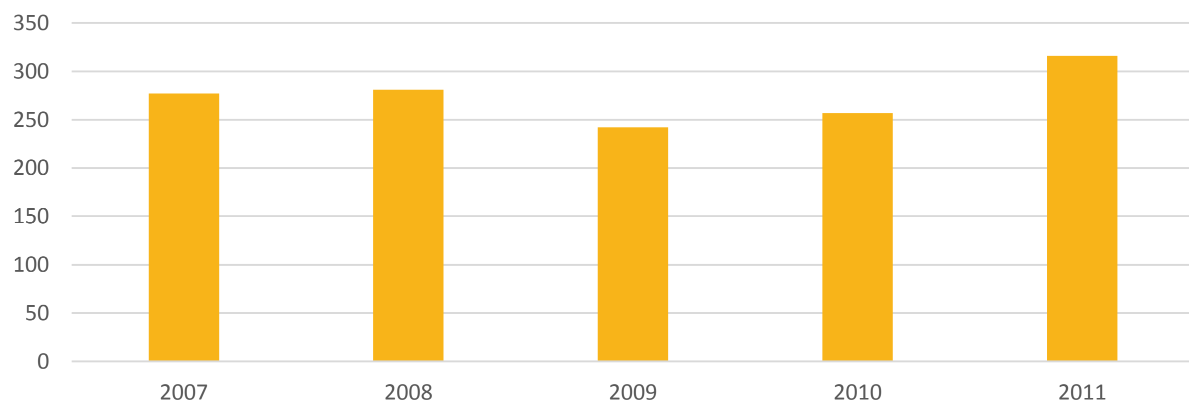


Figure 188: Total number of collisions

A16.2 Injury Severity

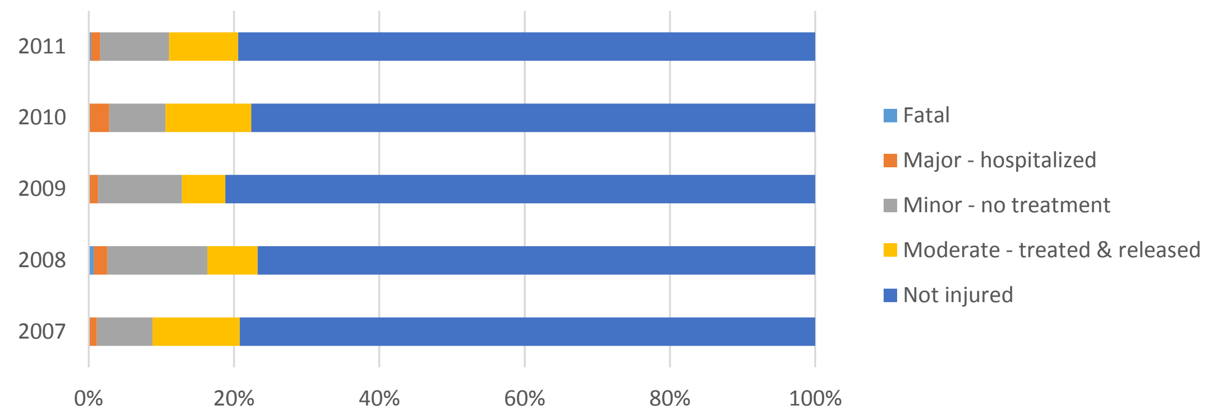


Figure 189: Injury severity of persons involved in collisions

A16.3 Age and Gender

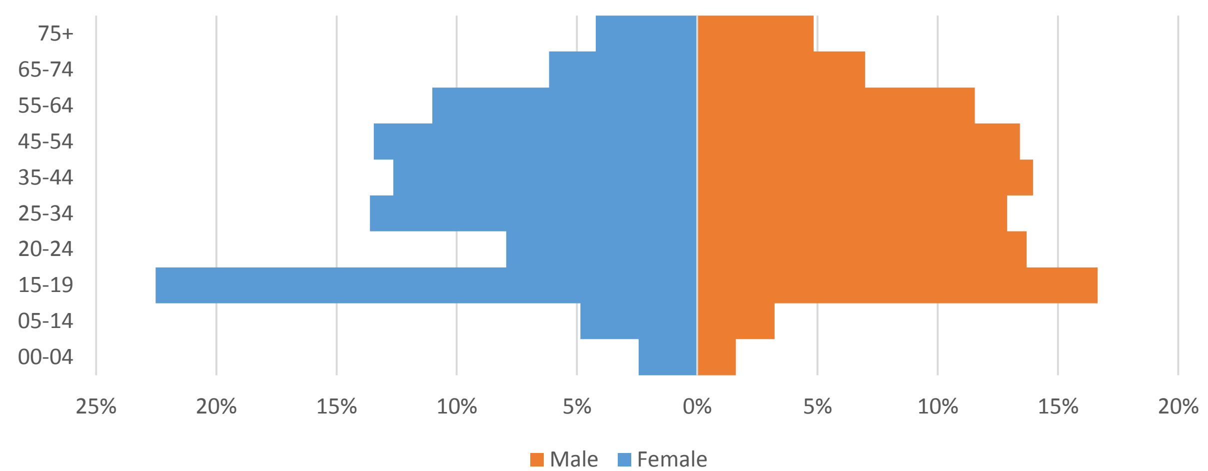


Figure 190: Age and gender distribution of persons involved in collisions

A16.4 Temporal Characteristics

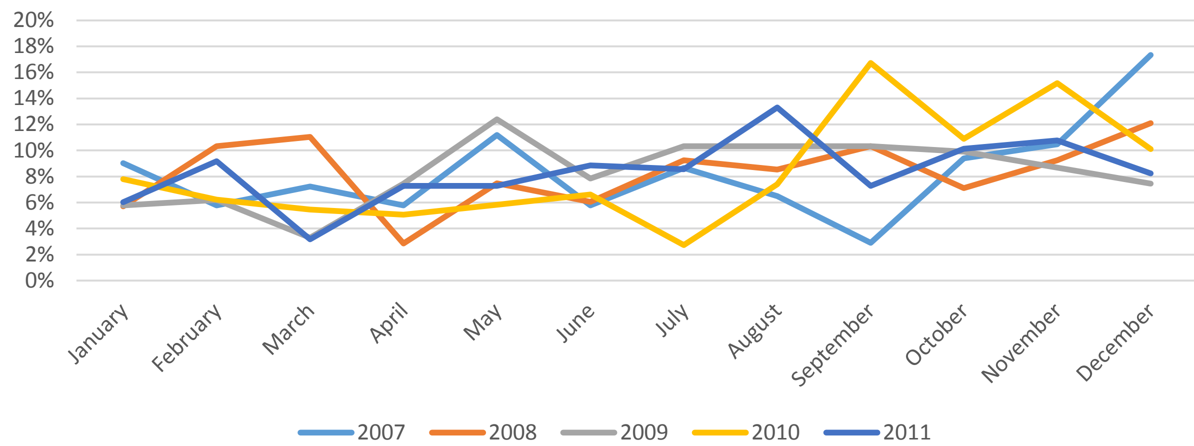


Figure 191: Monthly distribution of collisions

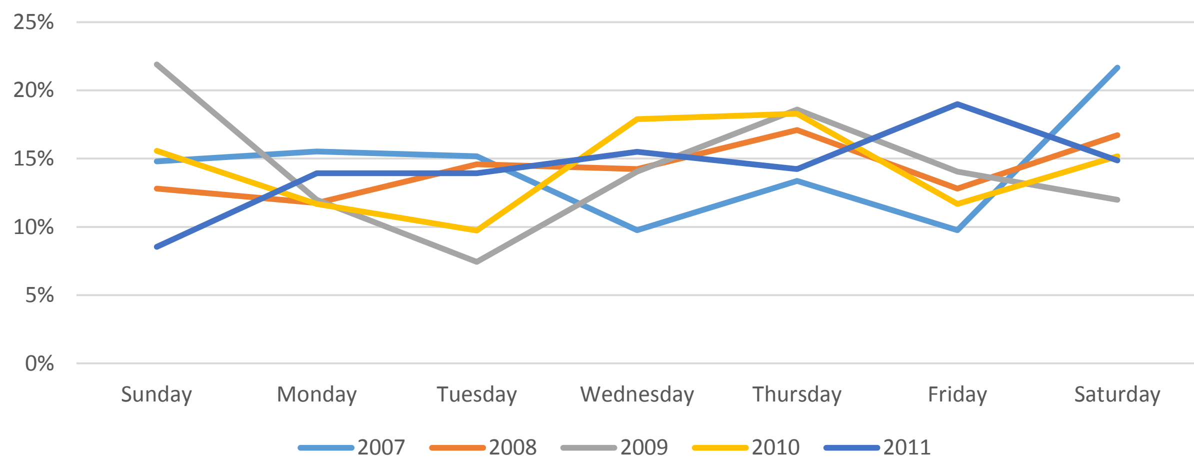


Figure 192: Day of week distribution of collisions

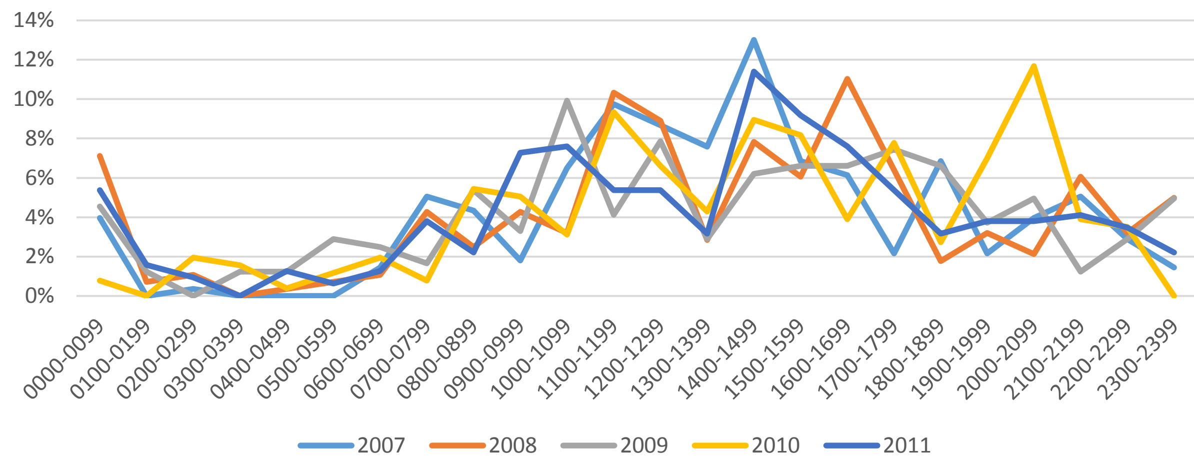


Figure 193: Time of day distribution of collisions

A16.5 Collision Frequency by Mode

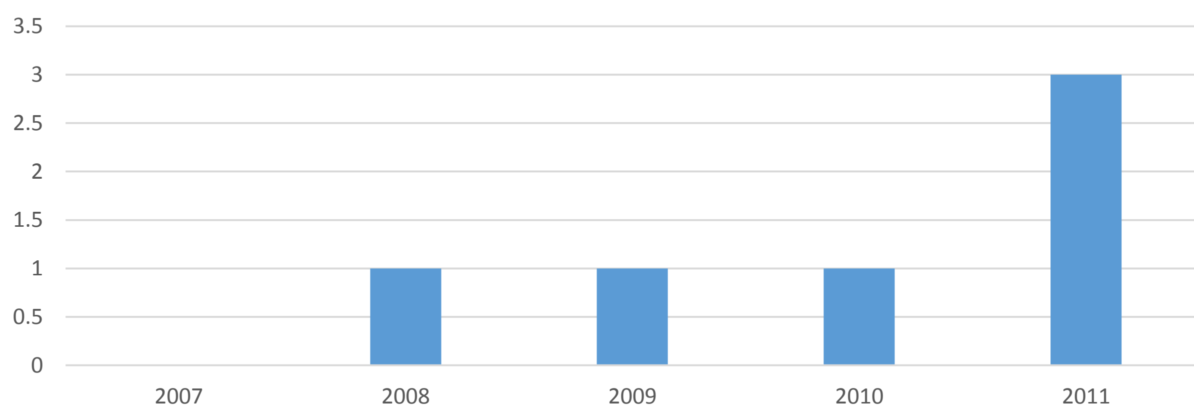


Figure 194: Number of pedestrians involved in collisions

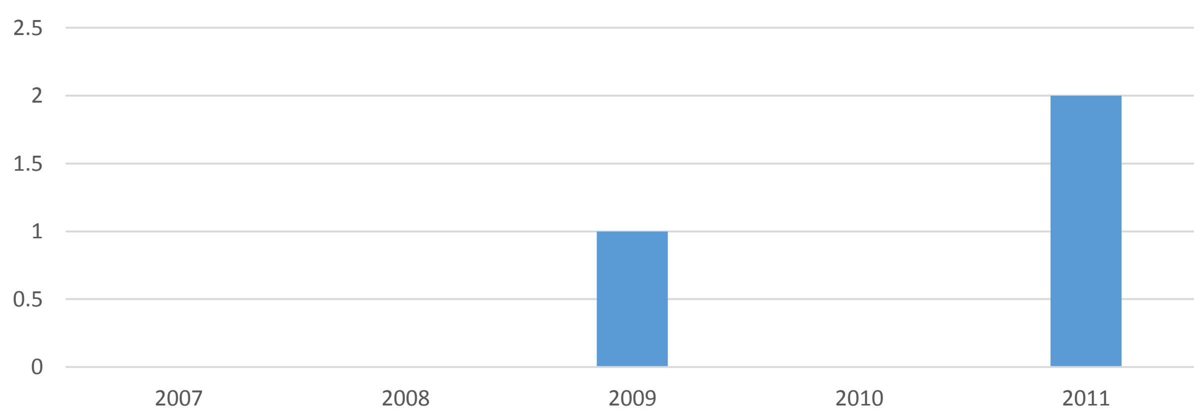


Figure 195: Number of cyclists involved in collisions

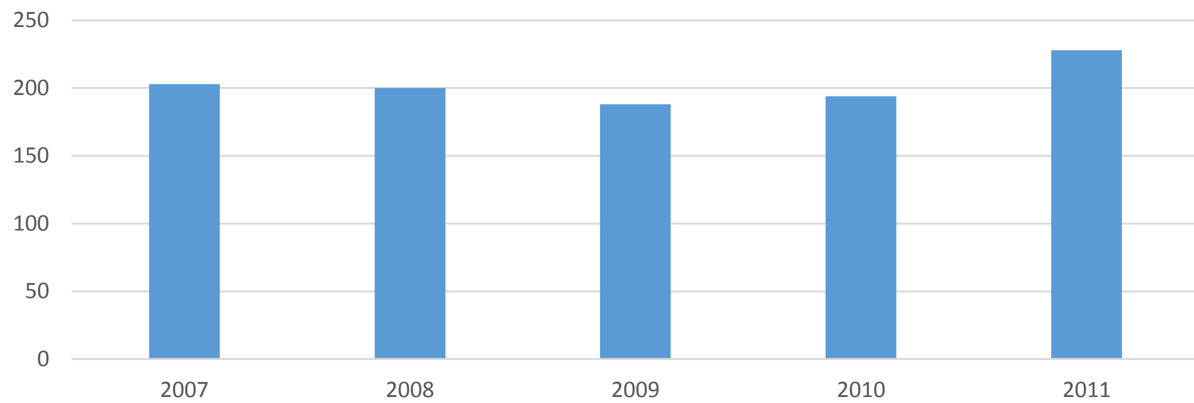


Figure 196: Number of drivers involved in collisions

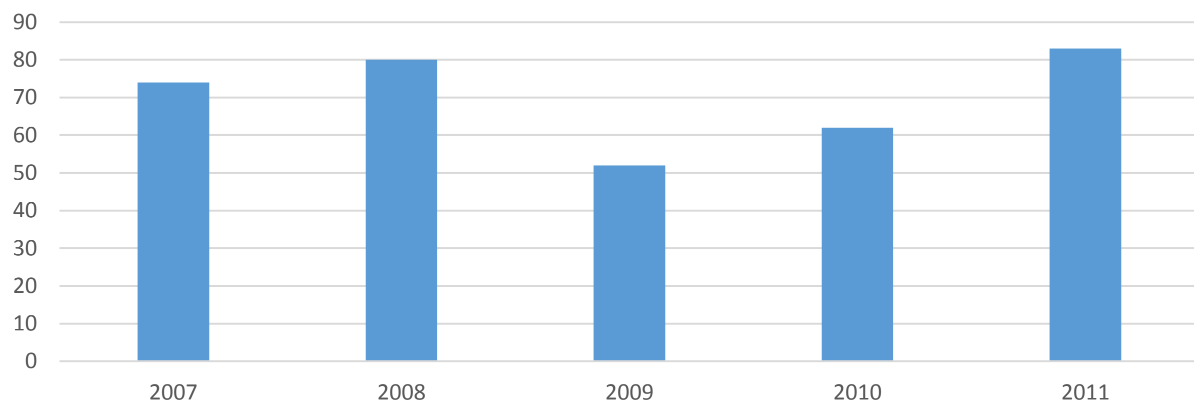


Figure 197: Number of passengers involved in collisions

A17 Victoria County

A17.1 Total Number of Collisions by Year

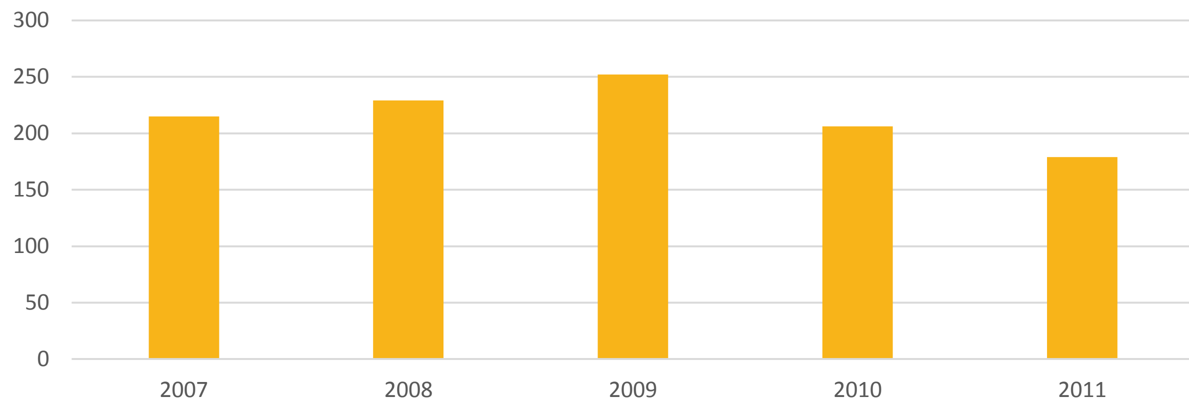


Figure 198: Total number of collisions

A17.2 Injury Severity

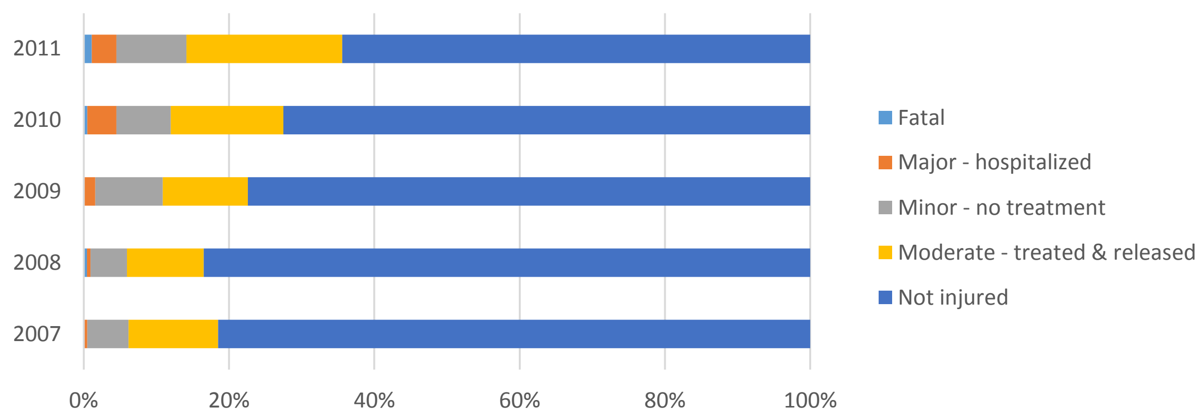


Figure 199: Injury severity of persons involved in collisions

A17.3 Age and Gender

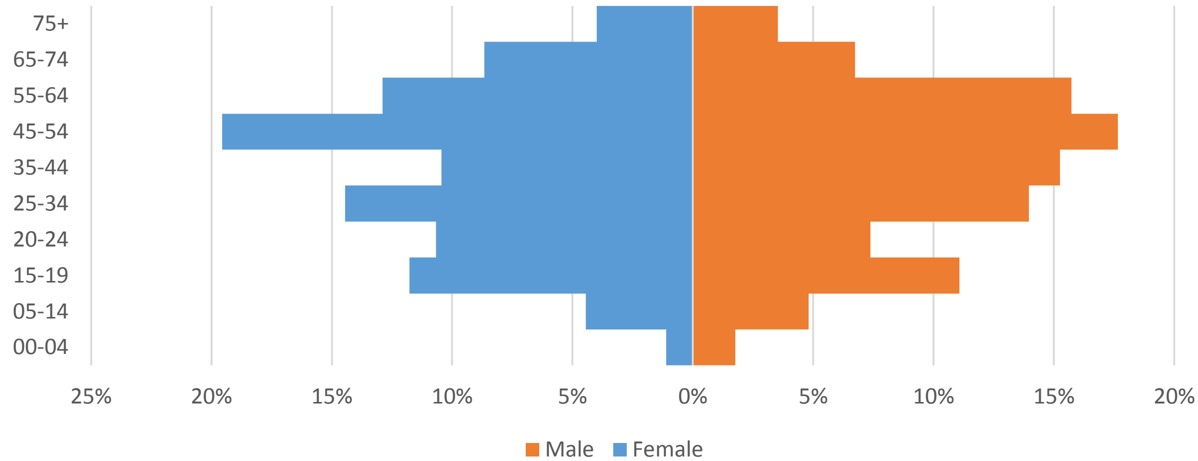


Figure 200: Age and gender distribution of persons involved in collisions

A17.4 Temporal Characteristics

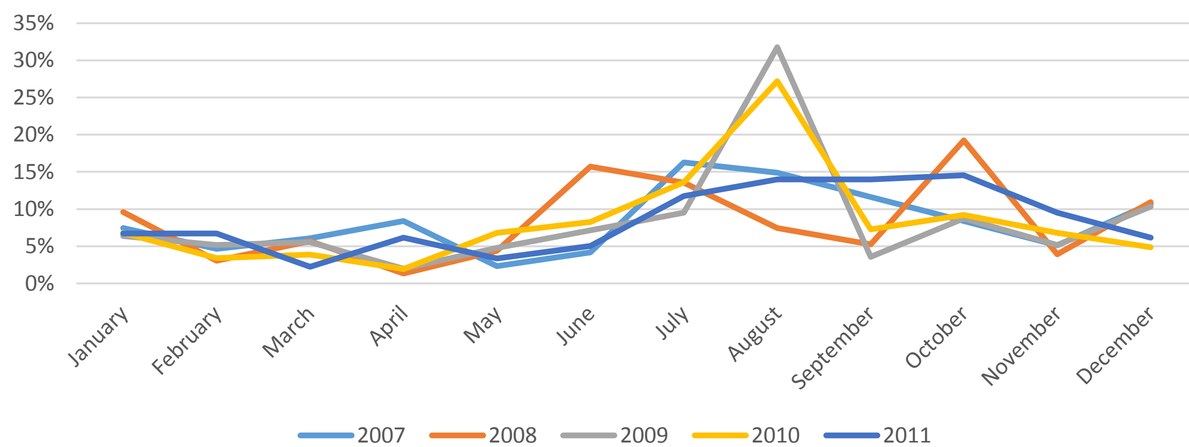


Figure 201: Monthly distribution of collisions.

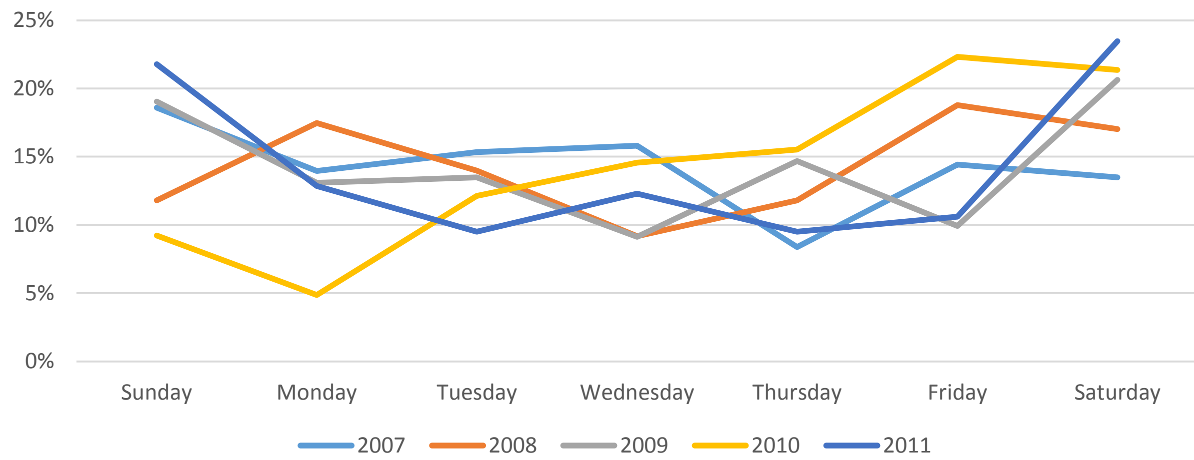


Figure 202: Day of week distribution of collisions

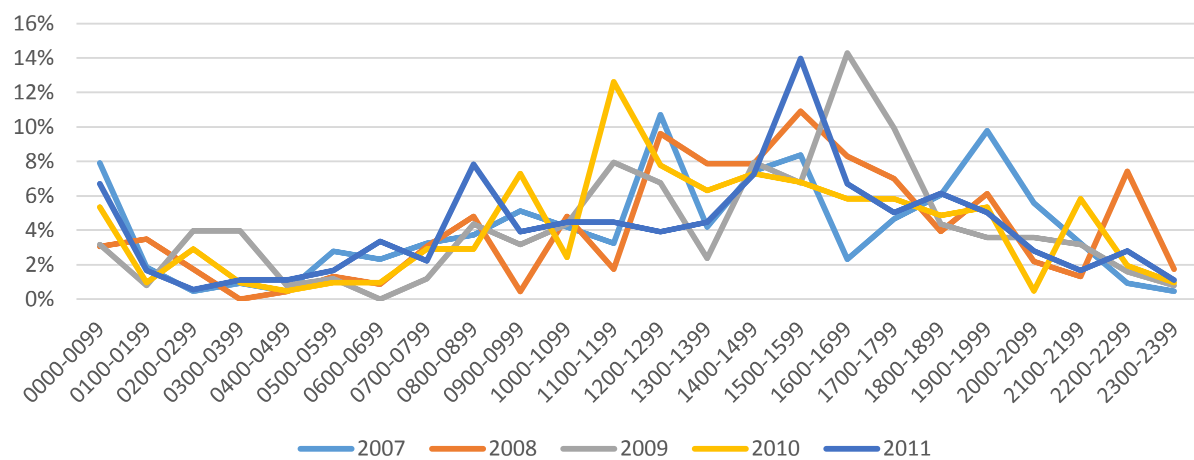


Figure 203: Time of day distribution of collisions

A17.5 Collision Frequency by Mode

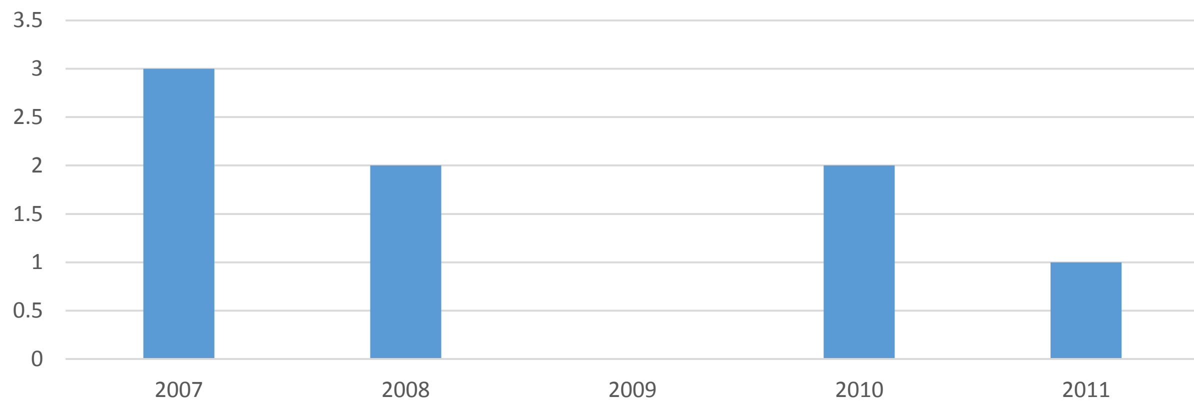


Figure 204: Number of pedestrians involved in collisions

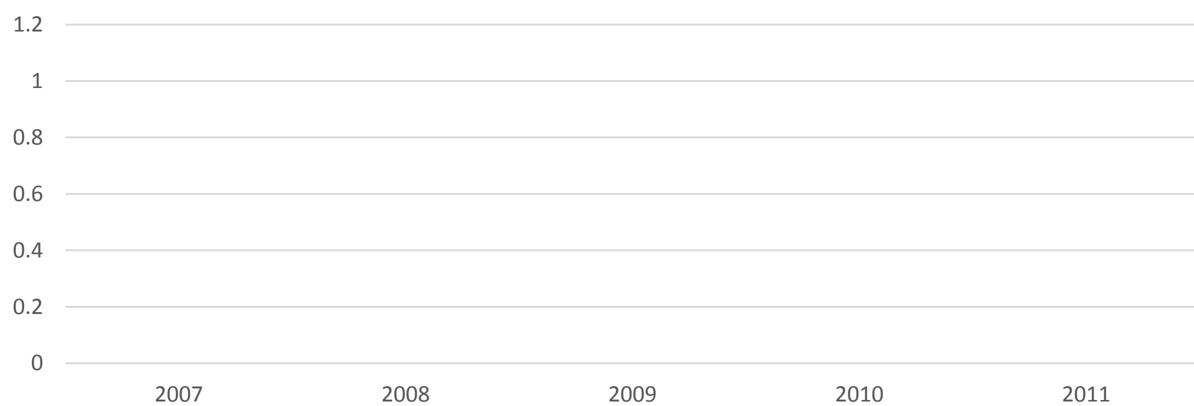


Figure 205: Number of cyclists involved in collisions

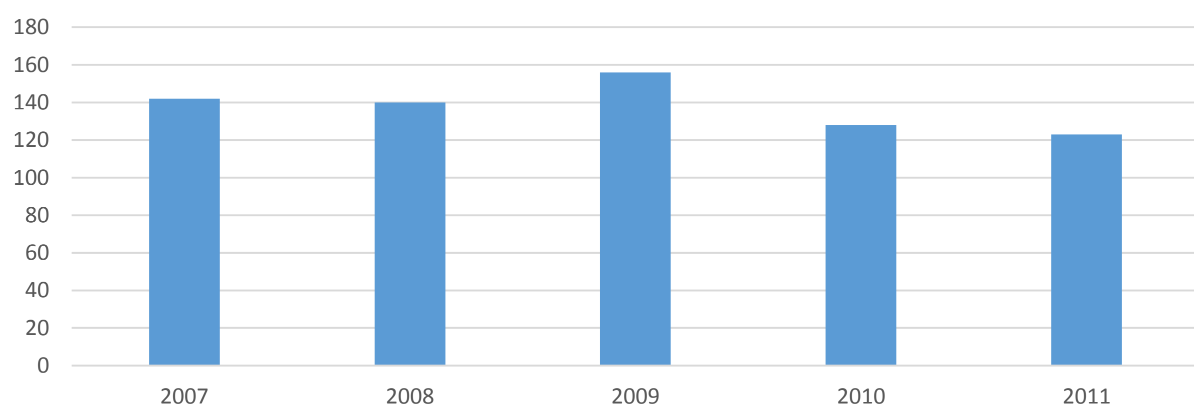


Figure 206: Number of drivers involved in collisions

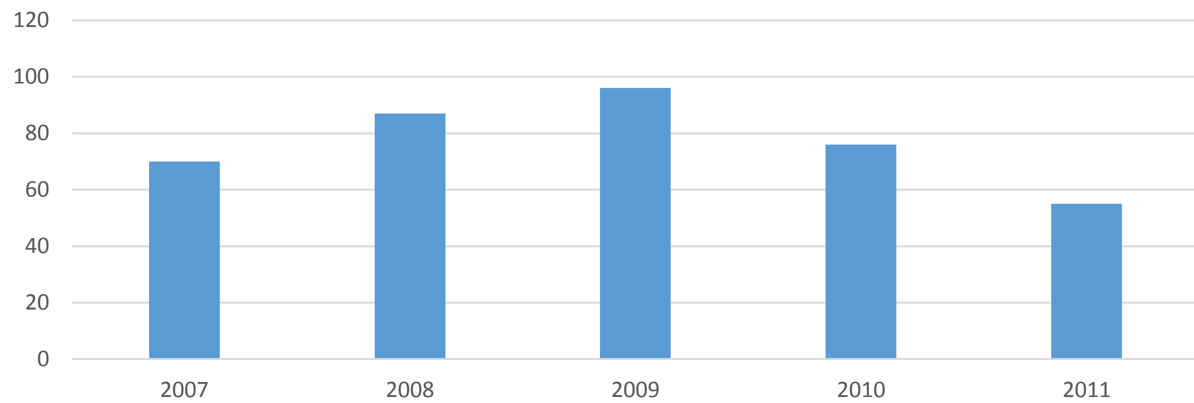


Figure 207: Number of passengers involved in collisions

A18 Yarmouth County

A18.1 Total Number of Collisions by Year

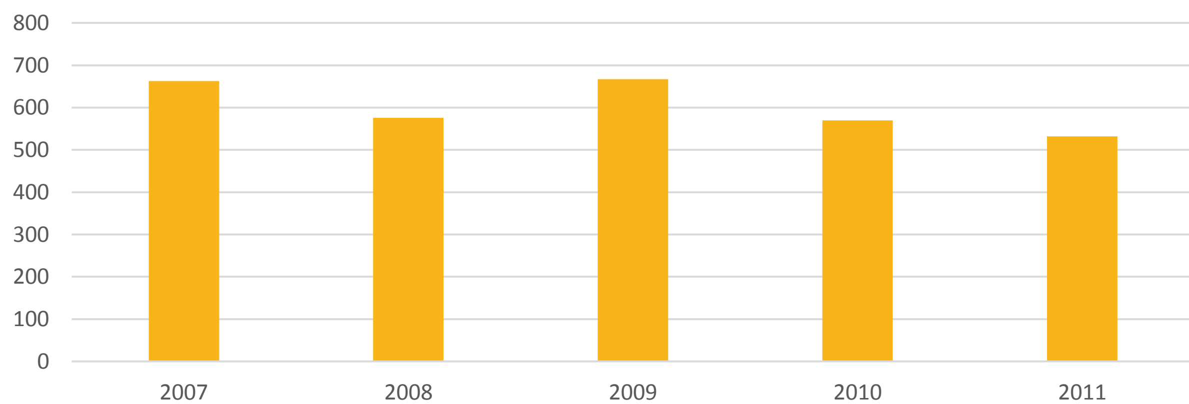


Figure 208: Total number of collisions

A18.2 Injury Severity

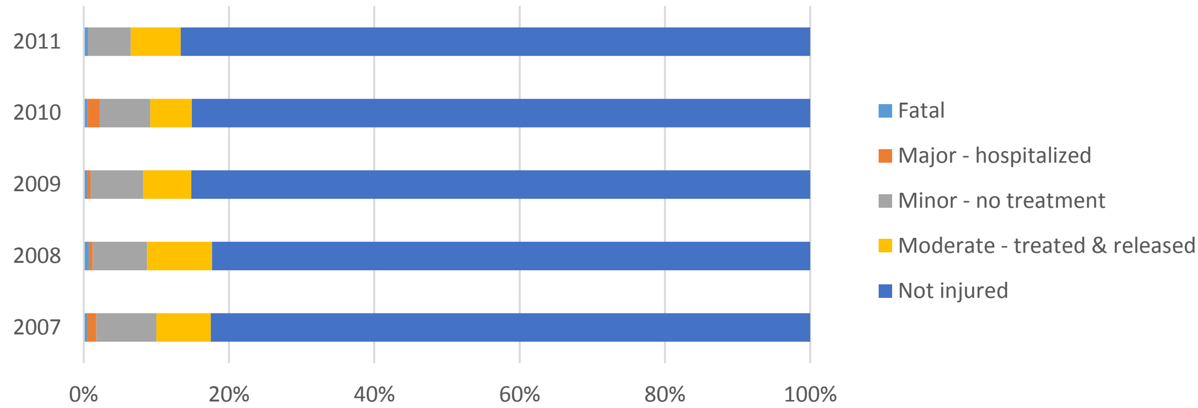


Figure 209: Injury severity of persons involved in collisions

A18.3 Age and Gender

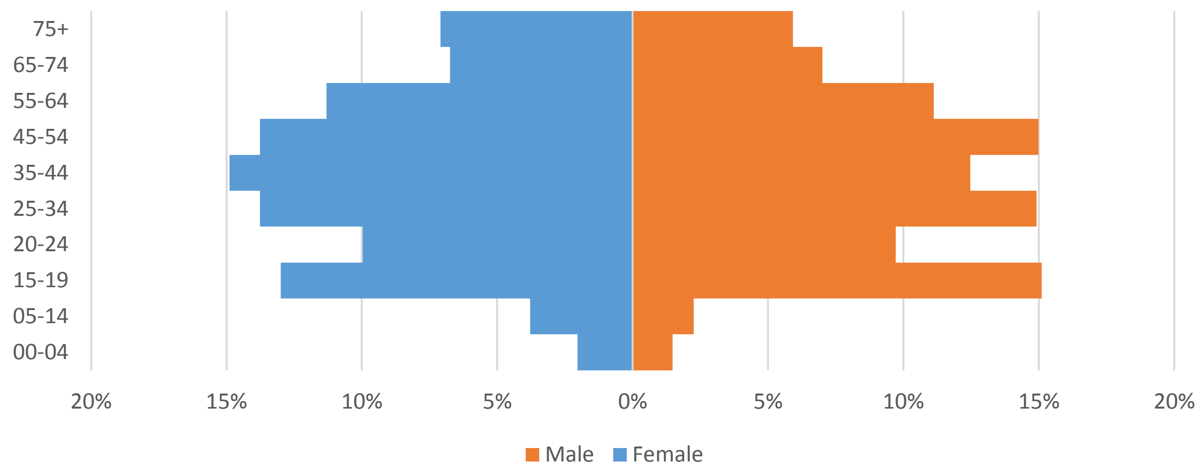


Figure 210: Age and gender distribution of persons involved in collisions

A18.4 Temporal Characteristics

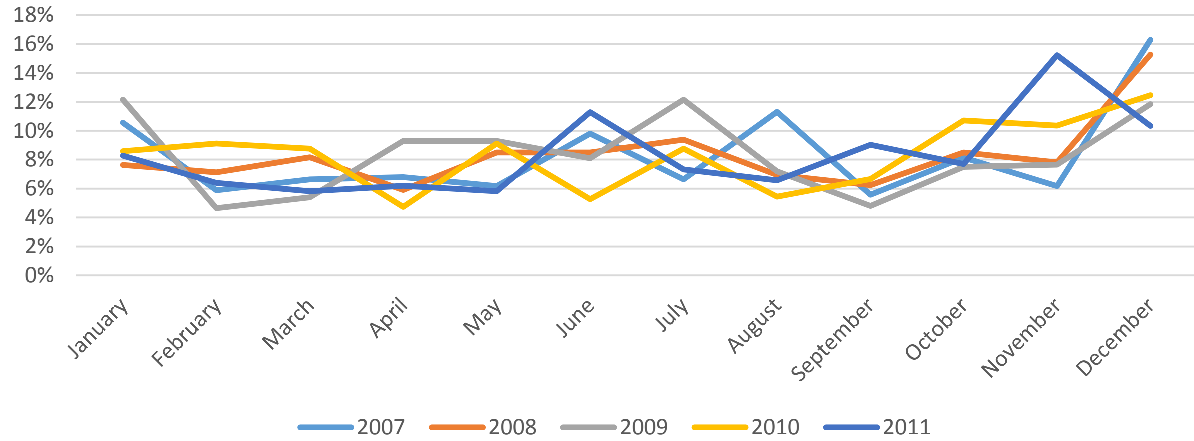


Figure 211: Monthly distribution of collisions

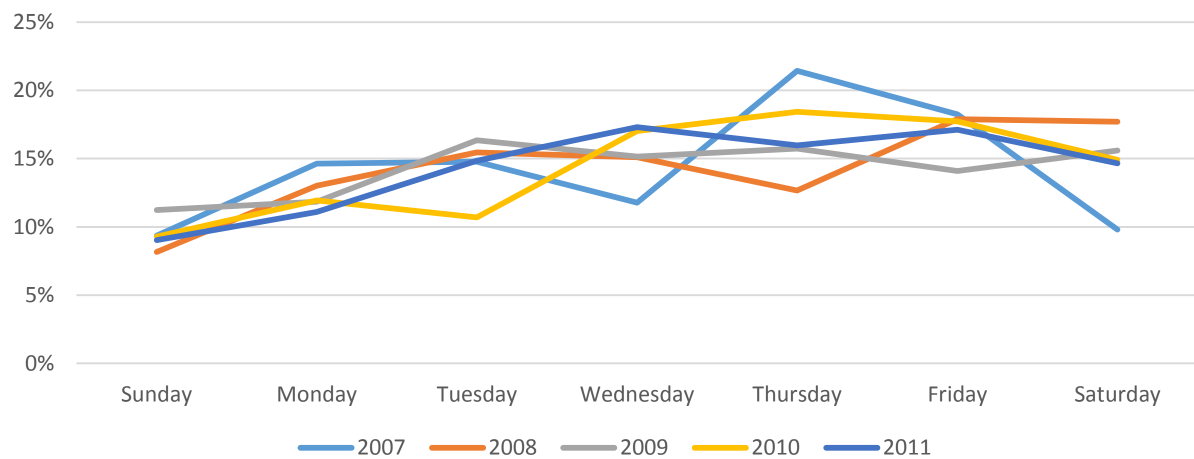


Figure 212: Day of week distribution of collisions

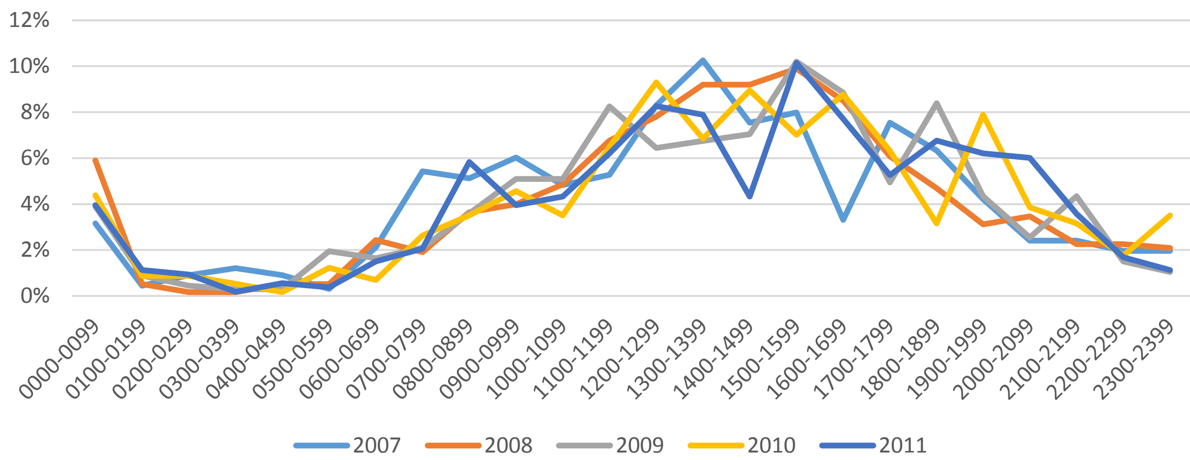


Figure 213: Time of day distribution of collisions

A18.5 Collision Frequency by Mode

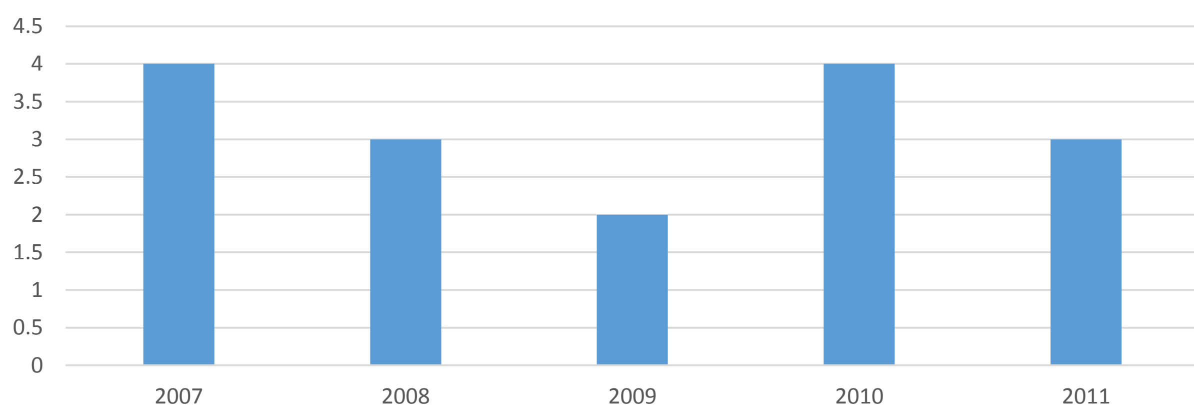


Figure 214: Number of pedestrians involved in collisions

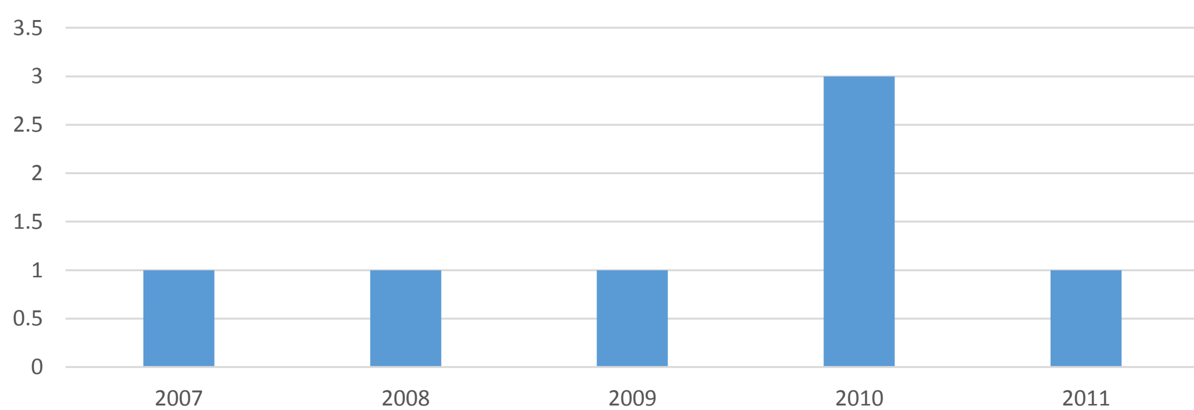


Figure 215: Number of cyclists involved in collisions

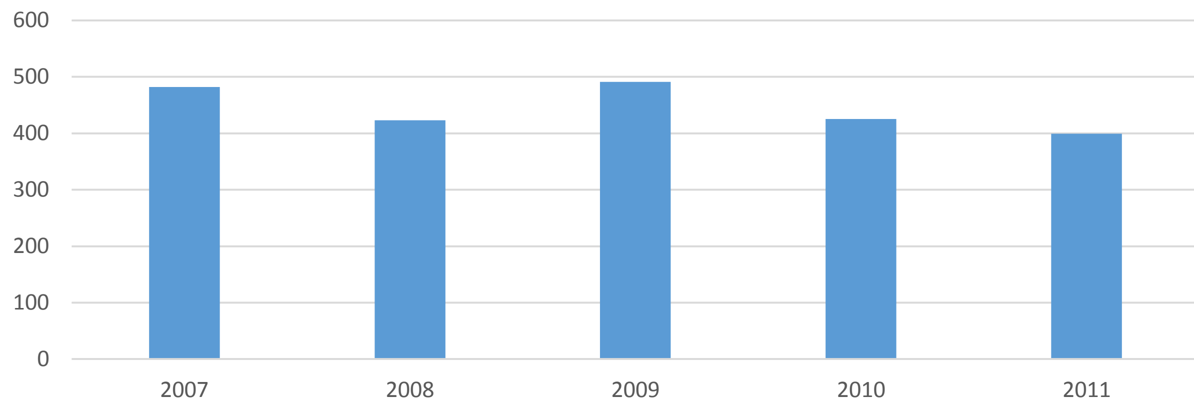


Figure 216: Number of drivers involved in collisions

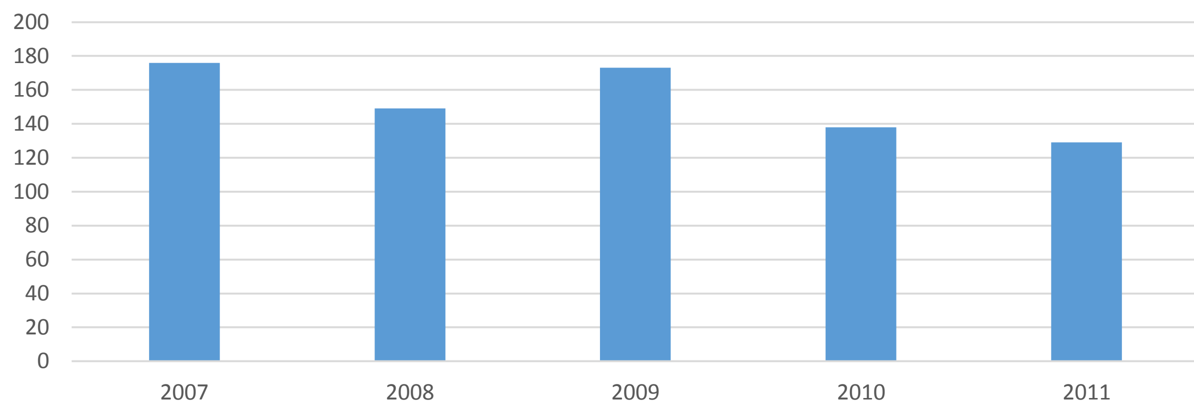


Figure 217: Number of passengers involved in collisions