ABSTRACT

Title of Thesis:	ANALYSIS OF THE CONTRIBUTORY FACTORS TO THE SEVERITY OF BICYCLE, PEDAL-CYCLE, AND PEDESTRIAN RELATED CRASHES IN MARYLAND
	Livingstone Imonitie, Master of Science, 2023
Thesis Directed By:	Professor, Cinzia Cirillo, Department of Civil and Environmental Engineering

Walking and cycling have numerous health benefits, but these popular modes of transportation are prone to numerous collisions with motor vehicles.

The goal of this study is to examine some of the factors that contribute to the severity of crashes in Maryland, which include property crashes, injury crashes, and fatal crashes. The light condition, junction condition, road surface condition, lane type, road condition, road division type, weather condition, time of day, population density, and the presence of schools were all considered. To demonstrate the relationship between each variable and the severity of the crash, the ordered logistic regression model was used. According to the findings, there was a positive significant relationship between the severity of crashes and crashes that occurred in areas with no lighting, at non-intersections, and on roadways with a positive median barrier. The frequency of crashes in various regions was also influenced by population density, time of day, and the presence of schools.

ANALYSIS OF THE CONTRIBUTORY FACTORS TO THE SEVERITY OF
BICYCLE, PEDAL-CYCLE, AND PEDESTRIAN RELATED CRASHES
IN MARYLAND

by

Livingstone Imonitie

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Dedication

I dedicate this study to families who have lost love ones on the roadway in Maryland.

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List of Abbreviations

CCD	Common Core of Data
DUI	Driving Under the Influence
MDOT	Maryland Department of Transportation
MSA	Maryland State Archives
MSPD	Maryland State Police Department
NCES	National Center for Education Statistics
OLR	Ordinal Logistic Regression
QGIS	Quantum Geographic Information System

Chapter 1: Introduction

1.1 Background

Although it is known that walking and cycling have great health advantages such as strengthening the heart muscles, lowering resting pulse, and reducing blood fat levels, individuals in the United State still prefer to use their motor vehicles to commute (Geng 2021). When choosing a mode of transportation, one of the considerations is safety. The user, the mode, the road, and the surroundings are all factors in safety (Alessandrini 2018). In a case of a collision between a motor vehicle and a pedestrian or a bicyclist, the driver of the vehicle tends to have more protective gear in comparison to the pedestrian or a bicyclist. The motorist has airbags and seat belts for protection. The vehicle structure also serves as protective gear. But pedestrians and bicyclists have nothing to protect themselves with in case of a collision. The bicyclist may choose to wear a helmet but this only protects the head from a head injury and the other part of the body is left unprotected. The pedestrian has no protective gear in case of collision. This, therefore, makes them the most vulnerable road users. Because they lack protective gear, bicyclists and pedestrians involved in collisions are more likely to sustain severe injuries and even pass away than drivers of motor vehicles (Hoglund 2018). In 2020, there were an estimated amount of 4.8 million car crashes in the US, and of those, 47,000 cyclists and 76,000 pedestrians sustained injuries. Every day, the number keeps increasing (NHTSA 2020). Some of the crashes are fatal and lead to loss of lives. A mode that has numerous health benefits has become one with the most recorded fatalities in the States. The risk of death when cycling or walking has been estimated to be 12 times greater than when driving a motor vehicle in the United States (NHTSA 2020).

In comparison with European countries where cycling and walking are the most used mode of commuting, they recorded a lower fatality rate during crashes. There has been an inverse relationship between the number of people walking and cycling and the frequency of crashes. This concept is known as a safety-in-numbers effect. The motorist become accustomed to sharing the road with other vulnerable road users as their number increased (Saad M. et al. 2019). This study tends to investigate the reason behind the high frequency of pedestrian and bicycle-related crashes.

There are more than 127,000 accidents involving bicycles and pedestrians in the US yearly. More than 6,000 pedestrians and 843 cyclists were killed on the road in 2019 (NHTSA 2019). Most of the fatalities were people in their 20s and older, and among them, there were more men than women (Sacks et al., 1991). Each year, these crashes claim the lives of about 38,000 people. Every 88 minutes, a pedestrian is killed in a collision with a car and this has been the greatest cause of death for children under 15 years old (Insurance Institute of Highway Safety, IIHS 2022).

Some researchers believe that the drivers are at fault for the collisions as more crashes occur as a result of driver speeding, intoxication or distraction (Asgarzadeh M., Verma S., & Mekary R. A. 2017). Other researchers believe that pedestrians and bicyclists are to be blamed for the crashes as they do not obey the traffic signals at intersections or follow safety measures (Lee, C., & Abdel-Aty, M. 2005).

This study tends to focus on other contributing factors such as road infrastructures, land use, and environmental factors in relation to the severity of crashes in Maryland. In the last five years, there have been 110,745 collisions on average in the state of Maryland. Of which 548 fatalities and an average of 45,527 injuries were recorded. A total of 782 collisions involving bicycles or pedal cycles on average have occurred, and 10 of those crashes have resulted in fatalities. Also, there have been 2,962 pedestrian-related crashes, with 125 fatalities (Maryland Department of Transportation’s Highway Safety Office 2022).

The roadway implies safety worsened over time for road users and the factors responsible for the high frequency of crashes need to be addressed before it is too late.

1.2 Research Objective

The objective of this study is to analyze the factors responsible for the severity of bicyclists, pedal-cyclists, and pedestrians-related crashes on the roadway in the state of Maryland. To achieve the research objective, certain tasks were identified and they include:

1) Evaluating the crash trend over the years using the available crash data,
2) Identifying some of the causes of the crashes,
3) Evaluating factors responsible for the increased severity of crashes,
4) Developing an ordered logistic regression model to show the relationship of the severity of crashes to available variables,
5) Identifying the significant variables responsible for the fatalities of bicycle, pedal-cycle, and pedestrian-related crashes in Maryland.

1.3 Research Approach

The approach used in this study is to first get the crash data from the Maryland Statewide Vehicle Crash as reported by the Maryland State Police Department (MSPD). This research is in line with the ZeroDeath Maryland vision by the Maryland Department of Transportation (MDOT).

After cleaning the data and adding variables such as population density and number of schools in each county, the ordered logit regression model will be used to estimate the probability of variables responsible for the severity of bicycle, pedal-cycle, and pedestrian crashes in Maryland. The different variables will be evaluated and compared with available studies and approaches already in use. Then, different measures will be proposed based on the model results to alleviate the frequency of crashes and fatalities on roadways.

1.4 Research Outline

This thesis has 6 chapters starting with chapter 1 as the introduction. Here, is an introduction to the traffic safety condition of road users, research objectives, approach, and contributions. Chapter 2 introduces the literature review and studies that have been done on traffic safety in the United States and Europe. Here, the limitations of these studies are identified and the unique contribution of this research which is to focus on land use and road infrastructure is addressed. Chapter 3 shows the various datasets used and their sources. Then, chapter 4 describes the methodology used to evaluate the data and what model was used in estimating the factors responsible for the severity of crashes. Following that is chapter 5 which shows the results and the comparison of various hypotheses in the research. These hypotheses will be evaluated against the results obtained. Finally, chapter 6 gives recommendations and conclusions of the study and its contribution to the transportation sector of the state of Maryland. Future research suggestions are also provided here.

Chapter 2: Literature Review

2.1 Mobility

Mobility has become an important aspect of human existence. Humans desire to move from one location to another either in search of food or for leisure and the mode of transportation used is generally determined by its cost, safety, reliability, speed, and comfort. The purpose of the trip also determines what mode to use. There are two major characteristics that influence the decision of a rider on what mode of transportation to use. They are (a) Personal characteristics and (b) Travel-based characteristics (Maduwanthi et. al. 2015).

2.1.1 Personal Characteristics

This has to do with the attributes of the individual choosing the mode. This includes income, age, and vehicle ownership. More people tend to use their own vehicles to commute. The income and age of the individual also influence the mode of transportation used. The more money individuals earn, the more they commute. Individuals with low income tend to walk to their destination rather than use public transport or personal vehicles. For the age attribute, older people prefer to use public transportation or personal vehicles to commute more than younger people.

2.1.2 Travel-based Characteristics

The factors influencing the travel-based mode of transportation include time, cost, safety, and comfort. A particular mode is used if it can get to the destination as quickly as possible with minimum cost and high safety. Personal vehicles and public transportation tend to be used more in the United States because of the time it takes to commute from origin to destination and the safety it gives. Safety is one of the most important factors when any mode is to be considered.

2.2 Mode of Transportation

The different transportation modes are available to enable commuters to decide which mode suits the nature of their daily trip. This can either be private vehicles, public transportation, carpooling, cycling, walking, etc. The vast majority of people in the United States commute in private cars. Owning a car in the US has become a necessity and almost every household has at least one private motor vehicle (Lange 2021).

In the State of Maryland, 80% of commuters use cars for their daily travels, 5% walk, and only 1% use bike (Regional Travel Survey 2018). These differences in mode of transportation make it difficult for motorists to familiarize themselves with sharing the roadway with bicyclists and pedestrians. Cities that do encourage walking and cycling do not have adequate infrastructure to protect vulnerable road users to prevent collisions. The biggest threat to bicyclists and pedestrians appears to be motor vehicles.

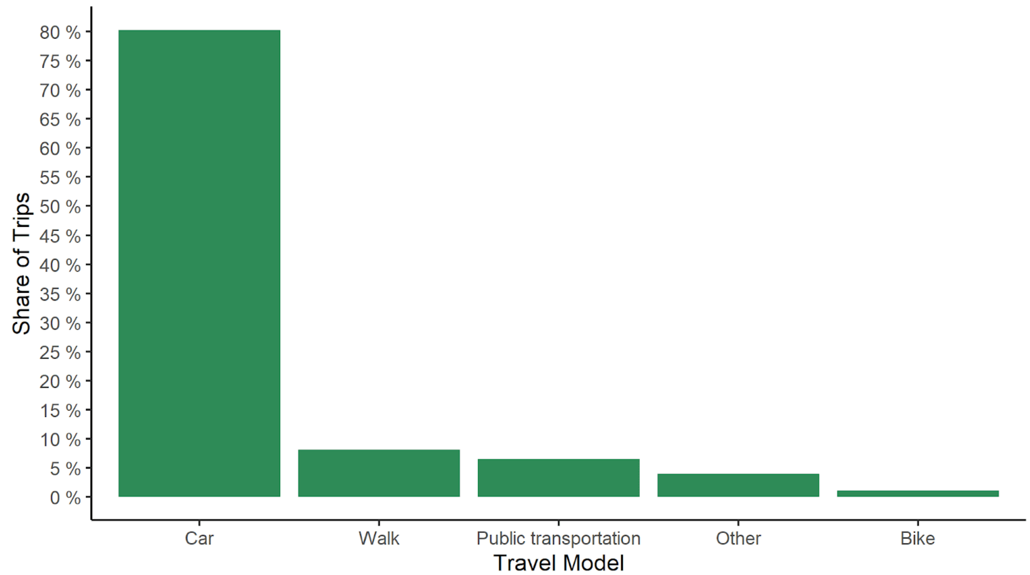


Figure 2.1: Travel mode in Maryland. Source (Regional Travel Survey 2018)

In comparison, in European countries, there are more commuters using bicycles for their daily travel. Although fewer Americans commute on bicycles than citizens of European nations, the rate of bicycle accidents in the U.S. is higher. This is due to the fact that a large portion of the population in Europe commutes by bicycle, and the number of bicycle owners grows yearly. Bicyclists and car drivers can easily share the road. However, in the United States, where most households own cars and commute daily, the situation is the opposite (Maness 2012). Drivers and bicycles on the road are not used to sharing the road with one another. Both parties might have unfounded expectations of what the other will do.

Cycling and walking have some health benefits that encourage commuters to use these modes. They help to lower blood fat levels, reduce resting pulse, and strengthen the cardiac muscles (Geng 2021) and are also a great mode for exercise and leisure. Despite all these benefits, both modes are more prone to fatality in an event of a collision with a motor vehicle.

In addition to health benefits, cycling and walking help the environment. The amount of carbon dioxide released into the atmosphere by burning fossil fuels in motors is reduced when more people commute by walking or biking. Air pollution and fuel consumption are reduced when cycling and walking are encouraged which is beneficial to the environment.

2.3 Crashes on the Roadway

Vehicle crashes have become one of the leading causes of death in America. There are an estimated 6 million vehicle crashes occurring every year on US roads and about 38,000 of those crashes include fatalities. Every 88 minutes, a pedestrian is killed by a vehicle collision, and children below the age of 15 years are killed yearly by such impacts (Insurance Institute of Highway Safety, IIHS 2020). In a crash involving a motorist and a pedestrian or bicyclist, the latter tend to suffer more from the collision because they have little or no protective gear. Motorists are protected by the vehicle structure and airbags in the vehicle, causing the impact to be less severe, while pedestrians have no such protection. A bicyclist may wear a head helmet but this only protects the head from brain injury. The other parts of the body are left unprotected. This makes them the most vulnerable road users (Reynolds, C.C., Harris, M.A., Teschke, K. et al. 2009). The risk of death when walking and cycling is seen to be higher than when driving a motor vehicle.

The safety of cyclists may be improved by higher ridership rates because higher cycling rates have been demonstrated to reduce injury rates. There is a non-linear relationship between the number of bicyclists at intersections with the frequency of crashes. This concept is referred to as Safety-in-Numbers (Saad et al. 2019). This is the reason why most European countries record fewer bicycle crashes on roads than the United States. The safety-in-number is accurate for bicyclists but not for pedestrians. It has been observed that more pedestrian-related crashes occur in areas with high population densities. Also, more crashes occur at intersections with more pedestrians than intersections without pedestrians.

A study done in the state of Florida using the crash information compiled in the Florida Traffic Crash Records Database from 1992 - 2002 and analyzing the vehicle-pedestrian crashes at intersections identified higher pedestrian crashes at intersections with high traffic volume. The study uses an ordered probit model to compute the probability of severe pedestrian injury at the impact. It appears that intersections with higher average traffic volumes have more pedestrian crashes (Lee, C., & Abdel-Aty, M. 2005).

In Maryland, there have been an average of 110,745 collisions on roads. Out of these, there have been 548 fatalities and an average of 45,527 injuries. 782 of these collisions involve bicyclists or pedal-cyclists and an average of 10 of those crashes resulted in fatalities. The pedestrians who are more vulnerable have an average of 2,962 pedestrian-related crashes on average, with 125 fatalities (Maryland Department of Transportation's Highway Safety Office MDOT 2022).

Bicycle or Other Pedalcycle Involved
Crash Summary

	2017	2018	2019	2020	2021	5 Year AVG.	%
Fatal Crashes	11	6	10	16	6	10	1.3
Injury Crashes	717	603	686	580	583	634	81.0
Property Damage Crashes	139	133	153	122	145	138	17.7
Total Crashes	867	742	849	718	734	782	100.0
Total of All Fatalities	11	6	10	16	6	10	
Total Number Injured	767	634	728	616	613	672	

Figure 2.2: Bicycle and pedal cycle crash summary for Maryland. Source (MDOT 2022)

Pedestrian On Foot Involved
Crash Summary

	2017	2018	2019	2020	2021	5 Year AVG.	%
Fatal Crashes	109	130	124	130	125	124	4.2
Injury Crashes	3,111	2,931	2,750	2,000	2,185	2,595	87.6
Property Damage Crashes	246	248	264	217	238	243	8.2
Total Crashes	3,466	3,309	3,138	2,347	2,548	2,962	100.0
Total of All Fatalities	111	131	124	131	127	125	
Total Number Injured	3,531	3,355	3,109	2,341	2,514	2,970	

Figure 2.3: Pedestrian crash summary for Maryland. Source (MDOT 2022)

Maryland Fatality Summary
2022 - 375 Total Crashes, 396 Fatalities
2021 - 524 Total Crashes, 563 Fatalities
2020 - 546 Total Crashes, 573 Fatalities

	2022**		2021**		2020	
Breakdown	Fatalities	% of Total	Fatalities	% of Total	Fatalities	% of Total
Drivers - All	249	62.9%	343	60.9%	349	60.9%
Passenger - All	46	11.6%	83	14.7%	71	12.4%
Pedestrians - walking	85	21.5%	128	22.7%	131	22.9%
Other Pedestrian Types	5	1.3%	3	0.5%	7	1.2%
Bike or Other Pedalcycle	10	2.5%	6	1.1%	15	2.6%
Unknown	1	0.3%	0	0.0%	0	0.0%
Total	396	100.0%	563	100.0%	573	100.0%

Other Pedestrians - wheelchairs, skateboards, worker etc.

Figure 2.4: Crash fatality summary for Maryland. Source (MDOT 2022)

2.4 Causes of Crashes on Roadways

There are many factors responsible for crashes on the roadway. Some of these factors are related to the motorist's behavior while others are related to the pedestrian and cyclist's behavior.

2.4.1 Motorist Behavior

Research done on crash contributory factors identified the driver’s behavior as a significant variable to the frequency of crashes. The fatality of each case is influenced by the impact of the collision between the motorist and the pedestrian or bicyclist (Salmon et al. 2022). A lot of these fatalities would have been prevented if only the drivers follow generally accepted rules. Some of these behavioral factors are further explained below.

2.4.1.1 Speeding

Speeding has been the leading cause of crashes in the US. Studies show that drivers who drive above the stated speed limit are more likely to be involved in a fatal crash (Aziz, H. A., Ukkusuri, S. V., & Hasan, S. 2013). This also increases the risk of pedestrian and bicyclist fatalities (Lee, C., & Abdel-Aty, M. 2005). The available driver reaction time before hitting an obstacle is reduced as the speed increases.

151,419 tickets for speeding were issued to motorists in Maryland in 2020 as opposed to 182,213 in 2019 and 195,649 in 2018. Though the numbers are decreasing, the issue of speeding still remains. Driver speed contributed to 8.9% of injuries and 16.5% of fatalities over the course of five years, as well as 8.2% of injuries and 19.2% of fatalities in 2020 (MDOT 2022).

2.4.1.2 Distracted driving

Some drivers believe that they can multitask while driving but driving requires the full attention of the operator. Texting or making phone calls while driving has been shown to significantly increase the frequency of crashes on roads (Salmon et al. 2022). The attention of a distracted driver is limited and the driver is likely to move toward the opposing flow of traffic or make contact with a pedestrian or bicyclist.

Between 2016 and 2020, distracted driving accidents averaged over 54,000 per year on Maryland's highways. Distracted driving contributed to an annual average of nearly half of all traffic accidents (48.1%) in Maryland, more than half of accidents resulting in injuries (53.5%), and significantly more than one-third of accidents resulting in fatalities (37.4%) (MDOT 2022).

2.4.1.3 Impaired driving

Driving under the influence whether alcohol or drugs is illegal in the US and this also contributed to the severity of crashes. Intoxicated drivers are linked to more crashes on the roadways as this affects the driving skills and visibility of the driver (Lee, C., & Abdel-Aty, M. 2005). Impaired drivers tend to drive at high speed and pay no regard to traffic control thereby increasing the risk of a fatal crash (Mohamed, M. G et al. 2013).

In 2020, 1 out of every 36 crashes involving intoxicated drivers resulted in a fatality, and alcohol and/or drugs were factors in nearly one-third (31.7%) of all fatal accidents in Maryland. Driving under the influence (DUI) has become a major area of concern for law enforcement and traffic safety experts across the state because of its relatively high frequency and association with fatal crashes and fatalities on Maryland's roads (MDOT 2022).

2.4.1.4 Aggressive driving

Drivers tend to be aggressive on the roadway by disregarding traffic control, failing to yield right of way, and involving in unsafe driving ethics. This behavior makes the roads unsafe for all users and increases the risk of fatality.

In Maryland, aggressive driving-related fatal collisions climbed by 48.6% in 2020, resulting in 56.4% more fatalities than in 2019. Aggressive driving has been a factor in 4,038 crashes on Maryland roadways annually on average over the last five years, from 2016 to 2020. Aggressive driving was responsible for an average of 8.1% of fatal incidents, 4.4% of injury crashes, and 3.6% of all traffic crashes (MDOT 2022).

2.4.2 Pedestrian Behavior

Besides the motorist's behavior as a factor in the severity of crashes, pedestrian behavior also contributes to the frequency of crashes. They include alcohol and drugs, not wearing reflective clothing, and jaywalking.

2.4.2.1 Alcohol and Drugs

Pedestrians who are intoxicated either with alcohol or drugs make improper decisions on the roadway such as walking into oncoming traffic or not paying much attention to traffic control. A fatal crash is more likely to occur when there is a pedestrian's involvement with alcohol or substance abuse (Sun, M., Sun, X., & Shan, D. 2019).

2.4.2.2 Not Wearing Reflective Clothing

Most of the crashes that occur at night are due to poor visibility (Mohamed, M. G. 2013). This poor visibility increases the risk of a fatal crash and can be prevented if pedestrians wear more reflective clothing at night. Clothing with bright and reflective materials bounces off lights and makes the pedestrians more visible to motorists.

2.4.2.3 Jaywalking

Crossing the roadway at the intersection would significantly reduce the risk of fatality but pedestrians still cross the roadway at non-intersections (Lee, C., & Abdel-Aty, M. 2005). The speed of vehicles is higher at non-intersections than at intersections because of the traffic signal control which forces motorists to slow down and resulted in lower fatalities at the intersection (Mohamed, M. G. 2013). Pedestrians who disregard traffic control and cross at midblock, which is illegal in Maryland, are at a much higher risk of being involved in a fatal crash.

2.4.3 Cyclist Behavior

Cyclists who share the roadway with other road users also contribute to the frequency of crashes on the roadway. Some of the behaviors contributing to the increased severity of crashes include the following:

2.4.3.1 Improper Training

Before motorists get driver licenses, they must first go through a series of training and tests but that is not the case for cyclists. The cyclists require little or no training before they use the roadway. This lack of training has increased the risk of crashes on the road. There is a knowledge and skill gap among cyclists (Salmon P.M., Naughton M., Hulme A., & McLean S. 2022). Some do not know the appropriate sign to display when making a turn which can be disastrous as other road users are also unfamiliar with the signs too.

2.4.3.2 Disregard to Traffic Control

It is expected that all road users follow the traffic control signs but most cyclists tend to disregard the traffic control and still enter the intersection when the light is red. This increases the risk of a possible collision (Salmon P.M., Naughton M., Hulme A., & McLean S. 2022). At intersections where "Turn On Red" is not allowed, cyclists still tend to ride through the intersection.

2.5 Road Infrastructure Influencing Crashes

Road infrastructures are those physical features on the road that can impact the frequency of crashes. They include bicycle lanes, street lighting, and medians.

2.5.1 Bicycle Lane

Studies have been conducted to identify the contributing factors to motor-bicycle crashes on the roadway. The majority of the studies have identified bicycle infrastructure as the leading cause of the collision. The majority of crashes that occurred in Australia, Canada, the United Kingdom, China, and the United States, are all linked to lack of cycling infrastructure as a significant factor (Salmon P. M. et al. 2022). Bicyclists and motorists frequently share the road. The cyclists having little or no protective gear are prone to fatal injury in an event of a crash. Roadways without bicycle lanes have recorded more fatalities than roadways with bicycle lanes (Reynolds, C.C., Harris, M.A., Teschke, K. et al. 2009).

A bicycle lane helps provide a sense of safety among cyclists and lowers the risks of a crash.

2.5.2 Street Lighting

There are no restrictions to road users from using the roads at night but proper lighting infrastructure should be available for the users. One of the major concerns for road users at night time is the inability to clearly see incoming traffic and this increases the likelihood of a fatal crash. Street lighting can help solve the problem (Mohamed, M. G. et al. 2013). Asgarzadeh et al. (2018) identified that lighting conditions were associated with the severity of crashes involving bicyclists and pedestrians. The correlations between light conditions and the severity of the cyclist's injuries as a result of a bicycle collision with a motor vehicle were investigated using log-binomial regression models with robust standard errors. The results showed that light conditions play a crucial role in determining how seriously injured a cyclist and pedestrian is in collisions involving motor vehicles. Injury severity is more likely to be higher in crashes that occur in low-light areas (Sun, M., Sun, X., & Shan, D. (2019), Aziz, H. A., Ukkusuri, S. V., & Hasan, S. (2013)).

2.5.3 Median

Medians are areas on the road that separate opposing flow of traffic. They are either depressed, closed, raised, or painted. In analyzing the impact of the median on the severity of crashes on the roadway in the state of Maryland, a safety performance function was developed using the generalized linear models over 6 years in 30 different locations. The analysis revealed that the medians significantly reduced the severity of crashes at the 16 treatment locations while the 14 controlled locations revealed an increase in the severity of crashes. The locations where medians were installed had an 86% decrease in fatal crashes and a 14% decrease in the overall frequency of crashes. The median treatment also discouraged jaywalking among pedestrians and cyclists in the treatment locations. The median treatment's success in lowering crash rates and saving lives was supported by statistical analysis, trend analysis, and survey responses (Zhang L. et al. 2017).

Various kinds of medians have different effects on collisions. There was a significant drop in the crash rate as the median width increased. The roads with high median width and shoulders had the fewest accidents, whereas the roads without curbs and painted centerlines had the worst collision records. The raised median barriers tend to increase road safety than other types of medians (Gattis, J. L., Balakumar, R., & Duncan, L. K. 2005).

2.6 Other Factors Influencing Crashes

Apart from behavior and road infrastructure, there are other significant factors influencing the frequency of crashes. They include road intersections, time of day, and population.

2.6.1 Road Intersection

As vehicles approach the intersection of a roadway, the speed is reduced. This in turn reduces the fatality of crashes. Studies have shown that the fatality of pedestrian and cyclist-related crashes tends to reduce at the intersection as the motorist is more conscious of the environment when approaching the intersection (Saad M., Abdel-Aty M., Lee J., and Cai Q. 2019). Crashes at non-intersections tend to have a higher risk of fatality mainly because the speed of the motorist is higher at the non-intersection (Islam, S., & Jones, S. L. 2014). Jaywalking by pedestrians and cyclists also influences fatalities at non-intersections.

The majority of crashes occurring at intersections, near traffic lights, and near bus stops and are less fatal. Those that occur at the non-intersections resulted in more fatality. This is due to the fact that drivers and cyclists are slowing down as they approach the crossroads. It has been demonstrated that speed worsens crashes. At non-intersections, drivers have a slower reaction time. This could increase the severity of the collision (Asgarzadeh M., Verma S., & Mekary R. A. 2017). The study done shows a relationship between speed, the severity of crashes, and intersection.

2.6.2 Time of Day

Studies have shown that the fatality of a crash also depends on the time when the crash occurred. There is more frequency of crashes at peak hours but more fatal crashes in the early hours of the day and late at night. Through the consequences of lack of sleep, early morning hours may increase the risk of fatality in an event of a crash (Asgarzadeh et al. 2018). Intoxicated drivers and pedestrians who commute at nighttime also increase the risks of fatality (Lee, C., & Abdel-Aty, M. 2005). Low visibility at night also contributes to the increased fatality of crashes (Klop, J. R., & Khattak, A. J. 1999).

2.6.3 Population

There is a linear relationship between population density and the frequency of crashes. Regions with high population density tend to have more crashes reported (Lee, C., & Abdel-Aty, M. 2005). There seems to be an inverse relation with the number of cyclists. There is a decrease in the fatality of bicycle-related crashes at intersections as more cyclists are on the roadway. This is known as safety-in-numbers. The safety-in-numbers effect became apparent when bicycle activity grew and crash rates declined (Saad M., Abdel-Aty M., Lee J., and Cai Q. 2019). The safety of cyclists is enhanced by the increased rate of cycling. Fewer injuries per bicycle occur when there are more bicyclists than motor vehicle drivers on the road (Asgarzadeh et al. 2018).

2.7 Research Gap

The factors identified by previous studies are human behaviors that can be controlled by the individuals involved, and the road infrastructures. This study however focuses on road infrastructure, environmental infrastructure, and land use as a factor influencing the severity of crashes. Other studies put the blame for crashes on either motorists or cyclists/pedestrians and on behaviors that cannot be directly influenced. This study brings in other factors that can be directly influenced.

Chapter 3: Data Collection

3.1 Vehicle Crash Data

The Open Data Portal platform is an open license database managed by the state of Maryland where Maryland statewide vehicle crash data are recorded and updated quarterly. The dataset comprises data from January 2015 to March 2022. The dataset only contains reports of approved crashes. The data file is compiled and reported by the Maryland State Police Department (MSPD) making the data to be trusted. More than 795,000 vehicle crashes were recorded during the stated time period and these crashes include those involving pedestrians, motorcyclists, cyclists, and collisions with fixed objects (Opendata Maryland 2022). The dataset also contains information about the location of the crash, time of the crash, county of crash, collision type, etc.

Table 3-1: Maryland Statewide Vehicle Crash Data (Open Data Portal 2022)

YEAR	QUAR...	LIGH...	LIGH...	COUN...	COUN...	MUNI...	MUNI...	JUNC...	JUNC...	COLL...	COLL...
2019	Q3	Daylight	1	Frederick	10		0	Intersecti...	2	Same Dir...	3
2019	Q3	Daylight	1	Montgom...	15		0	Intersecti...	2	Same Dir...	8
2018	Q2	Daylight	1	Washingt...	21		0	Intersecti...	2	Head On ...	2
2018	Q2	Daylight	1	Montgom...	15		0	Not Appli...	0	Same Dir...	3
2017	Q4	Dark Ligh...	3	Baltimore...	24		999	Intersecti...	2	Same Mo...	11
2018	Q4	Daylight	1	Baltimore	3		0	Non Inter...	1	Same Dir...	3
2015	Q1		6.02	Anne Aru...	2			Intersecti...	2	Single Ve...	17
2018	Q1	Dark Ligh...	3	Baltimore...	24		999	Intersecti...	2	Same Mo...	11
2019	Q2	Daylight	1	St. Mary's	18		0	Intersecti...	2	Angle Me...	13
2017	Q3	Dark No L...	4	Calvert	4		0	Non Inter...	1	Single Ve...	17
2016	Q1	Dark Ligh...	3	Anne Aru...	2		0	Intersecti...	2	Other	88
2017	Q2	Daylight	1	Montgom...	15		0	Intersecti...	2	Angle Me...	12
2015	Q3	Daylight	1	Prince Ge...	16		0	Non Inter...	1	Same Dir...	3
2015	Q4	Dark Ligh...	3	Montgom...	15		0	Non Inter...	1	Same Dir...	3

3.2 Population Density Data

The population data for Maryland was collected from the Maryland State Archives. The US Census Bureau conducts a national census every 10 years to record changing population characteristics, including growth rates. The Department of Planning assembles the population data and makes it available to the general public. For the state of Maryland, such data can be accessed from the state archives.

The Maryland State Archives have population data from 1790 to 2020 and estimated data for 2030 and 2040. The recorded population data for each county in Maryland range from the year 1990 to 2020 and estimates for 2030 and 2040 (MSA 2022).

The land area (in square miles) for each county was also obtained from the state archives, which were used to determine the population density for each county.

The census block geographic information for the state was obtained from the Maryland GIS data catalog (Maryland IMAP 2020) reported by the Maryland Department of Information Technology. The geospatial data was compiled from local Maryland jurisdictions. This provided the shapefile for the state and the Urban regions used in this research.

Table 3-2: Maryland Population Data (Maryland State Archives 2022)

	1990 census	2000 census	2010 census	2020 census	2030 projected*	2040 projected*
Allegany County	74,946	74,930	75,087	68,106	72,150	73,560
Anne Arundel Co.	427,239	489,656	537,656	588,261	608,990	632,200
Baltimore County	692,134	754,292	805,029	854,535	846,590	873,130
Calvert County	51,372	74,563	88,737	92,783	97,900	99,160
Caroline County	27,035	29,772	33,066	33,293	37,700	42,200
Carroll County	123,372	150,897	167,134	172,891	174,150	180,800
Cecil County	71,347	85,951	101,108	103,725	112,050	125,450
Charles County	101,154	120,546	146,551	166,617	184,470	205,290
Dorchester County	30,236	30,674	32,618	32,531	35,160	37,300
Frederick County	150,208	195,277	233,385	271,717	300,580	329,150
Garrett County	28,138	29,846	30,097	28,806	30,250	30,760
Harford County	182,132	218,590	244,826	260,924	271,860	289,220
Howard County	187,328	247,842	287,085	332,317	356,860	368,830
Kent County	17,842	19,197	20,197	19,198	20,900	21,800
Montgomery County	757,027	873,341	971,777	1,062,061	1,124,790	1,197,150
Prince George's Co.	728,553	801,515	863,420	967,201	940,960	970,770
Queen Anne's Co.	33,953	40,563	47,798	49,874	56,320	62,040
St. Mary's County	75,974	86,211	105,151	113,777	131,260	146,350

3.3 School Data

This study collected data on the number of schools and the total number of students in each county in Maryland in 2021. The school data was collected from the Maryland State Archives. The dataset contains information on the total number of elementary, middle, and high schools, and other educational buildings for technical and vocational studies for accelerated learning in the state (MSA 2022).

The Department of Education's main database for public and private elementary and secondary education in the US is called the Common Core of Data (CCD). CCD is a comprehensive database of all public elementary and secondary schools and educational districts that is updated yearly on a nationwide level. The total number of students for both public and private schools were compiled by the National Center for Education Statistics (NCES 2022). The CCD files are accessible to the general public. The students and staff data were from the official school-level data for the 2020-2021 school year.

Table 3-3: Maryland School Data (NCES 2022)

School Name	District	County Name*	Street Address	City	State	ZIP
A. Mario Loiederman Middle	Montgomery County Public Schools	Montgomery County	12701 Goodhill Rd	Silver Spring	MD	20906
AACPS Virtual Academy	Anne Arundel County Public Schools	†	241 Peninsula Farm Road	Arnold	MD	21012
Abbottston Elementary	Baltimore City Public Schools	Baltimore city	1300 Gorsuch Avenue	Baltimore	MD	21218
Aberdeen High	Harford County Public Schools	Harford County	251 Paradise Rd	Aberdeen	MD	21001
Aberdeen Middle	Harford County Public Schools	Harford County	111 Mount Royal Ave	Aberdeen	MD	21001
Abingdon Elementary	Harford County Public Schools	Harford County	399 Singer Rd	Abingdon	MD	21009
Academy for College and Career Exploration	Baltimore City Public Schools	Baltimore city	1300 W 36th Street	Baltimore	MD	21211
Academy of Health Sciences at PGCC	Schools	Prince George's County	301 Largo Rd	Largo	MD	20774
Accident Elementary	Garrett County Public Schools	Garrett County	534 Accident-Bittinger Rd	Accident	MD	21520
Accokeek Academy	Schools	Prince George's County	14400 Berry Rd	Accokeek	MD	20607
Achievement Academy at Harbor City High	Baltimore City Public Schools	Baltimore city	2201 Pinewood Avenue	Baltimore	MD	21214
Adelphi Elementary	Schools	Prince George's County	9000 25th Ave	Adelphi	MD	20783
Albert Einstein High	Montgomery County Public Schools	Montgomery County	11135 Newport Mill Rd	Kensington	MD	20895
Allegany High	Allegany County Public Schools	Allegany County	900 Seton Dr	Cumberland	MD	21502
Allenwood Elementary	Schools	Prince George's County	6300 Harley Ln	Temple Hills	MD	20748
Alternative Programs	Montgomery County Public Schools	Montgomery County	14501 Avery Road	Rockville	MD	20853
Andrew Jackson Academy	Schools	Prince George's County	3500 Regency Pkwy	Forestville	MD	20747
Annapolis Elementary	Anne Arundel County Public Schools	Anne Arundel County	180 Green Street	Annapolis	MD	21401
Annapolis High	Anne Arundel County Public Schools	Anne Arundel County	2700 Riva Rd	Annapolis	MD	21401
Annapolis Middle	Anne Arundel County Public Schools	Anne Arundel County	1399 Forest Dr	Annapolis	MD	21403

Chapter 4: Methodology

4.1 Methodological Framework

The proposed methodological framework of this study is illustrated in Figure 4-1 which include statistical analysis and model development. After all required datasets are collected, quality control activities such as cleaning the data to remove all missing and wrong entries from the dataset are conducted. Then, the data are analyzed using R programming and Excel software to understand relationships among variables in the dataset.

In the model development process, the cleaned data were used to build a regression model using R programming to determine the relationship between the dependent and independent variables.

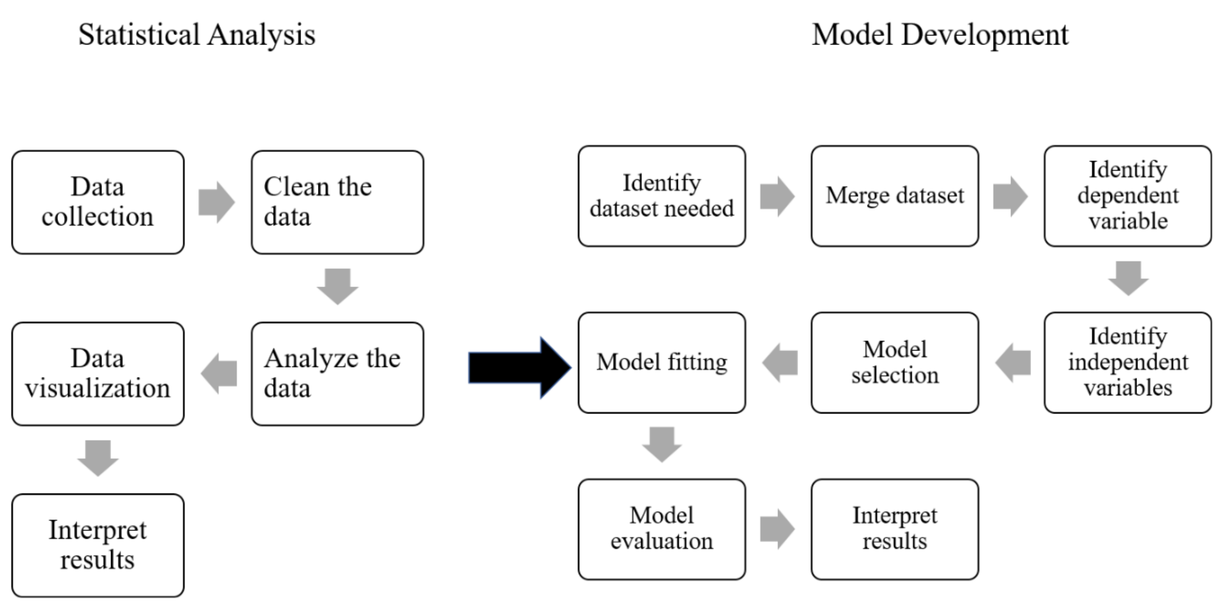


Figure 4.1: Methodological Framework

4.2 Statistical Analysis

For the purpose of this study, various datasets were collected for the analysis. The vehicle crash data having over 795,000 recorded crashes in the state of Maryland were obtained. This dataset contains the location of the crash (longitude and latitude), crash involved type (pedestrian, bicycle, pedal cycle, fixed objects, etc.), collision type (head-on or side angle), time of the crash, county of the crash, light condition (daylight or dark), road surface condition (wet or dry), weather condition (raining or clear), and road condition (defective or not defective).

The other dataset obtained is the Maryland population data, land area, and shapefile for the state. With the population and land area datasets obtained, the population density of each county was computed. With the shapefile, locations for each crash were plotted using the QGIS software for better understanding.

Finally, the school dataset was collected, which contains the total number of schools, teachers, and students enrolled in the 2020-2021 academic year for each county in Maryland. The total number of schools recorded was over 1,400 and that of students was over 985,000.

4.2.1 Data Processing

The data cleaning and data analysis were done using R programming. R is a language and environment for visual design and statistical computing. The various statistical packages include linear and nonlinear modeling, classical statistical tests, time-series analysis, classification, and clustering. R is an integrated set of tools for calculating, manipulating data, and displaying graphics. R is an implementation of the S programming language and was developed by the R Development Core Team, of which John Chambers is a member, after being founded by Ross Ihaka and Robert Gentleman at the University of Auckland in New Zealand. The “R” name was coined after the first names of the first two R authors and partly as a play on the name of S. R is a GNU project (Vikram Dayal 2015).

All missing data and incorrect entries were removed from the dataset to avoid building an imperfect model and for consistency and accuracy. A subset of crashes involving bicycles, pedal cycles, and pedestrians was created from the primary dataset. The time of the crash was categorized into 4 categories: AM (12:00 am - 05:59 am), PM Peak (06:00 am - 11:59 am), PM Peak (12:00 pm - 05:59 pm), and PM (06:00 pm - 11:59 pm). This is done to have an equal time schedule for recorded crashes each day.

The severity of the crashes was categorized into 3 levels from the crash report type. Level 1 = Property damage crash, Level 2 = Injury crash, and Level 3 = Fatal crash.

4.2.2 Data Visualization

After the data cleaning and processing, some of the output data was visualized with QGIS software and Microsoft Excel for more understanding and clarification. The QGIS is a free and open-source platform for geographic information system applications that supports viewing, editing, printing, and analysis of geospatial data (Palino G. & Sparks E. 2021).

The shapefile for the state of Maryland and the location of each crash were imported into QGIS to determine the hot zone. Figure 4-2 shows the data visualization of each bicycle, pedal cycle, and pedestrian-related crash in Maryland.

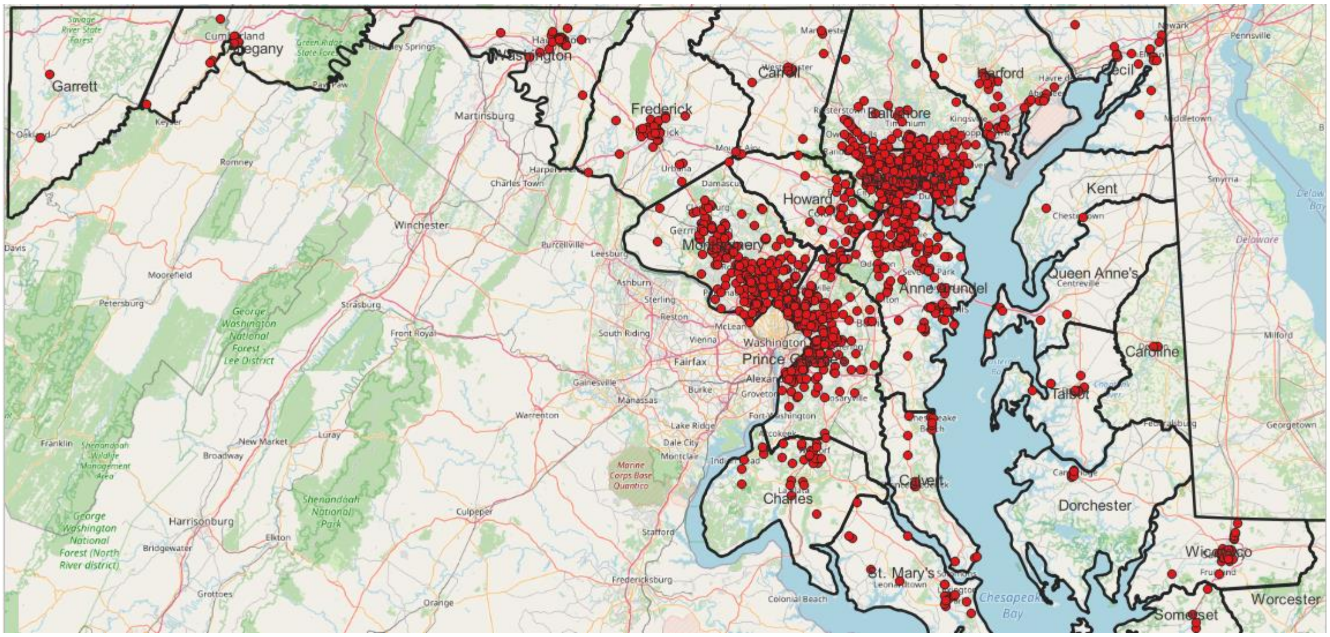


Figure 4-2: Crash location in Maryland

The recorded crashes for bicyclists, pedal cyclists, and pedestrians were for the year 2020-2021. A total of 1,825 crashes were obtained after the data cleaning. Figure 4-3 shows the percentage of the different crash types.

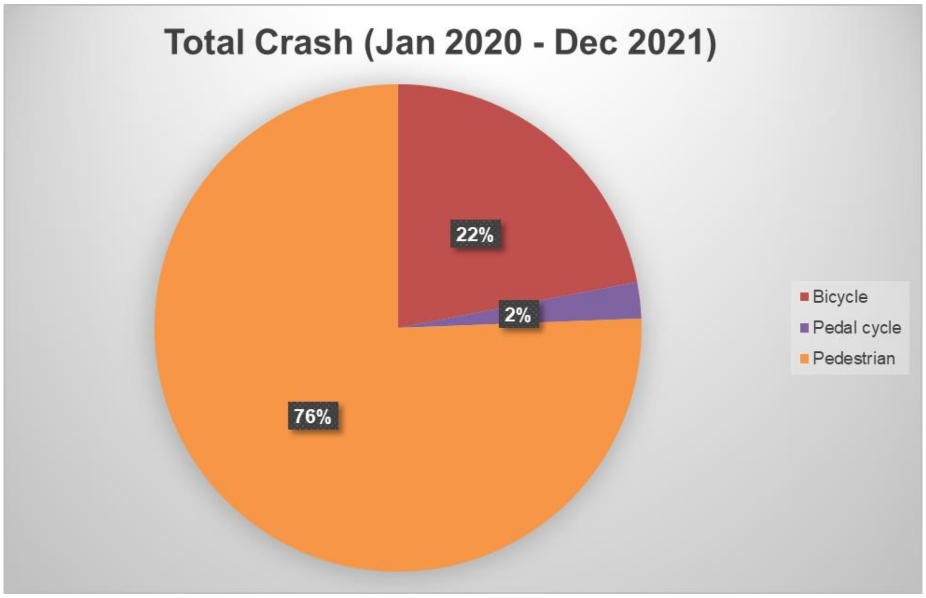


Figure 4-3: Percentage of Crash Type

4.3 Model Development

4.3.1 Ordered Logit Regression Model

The model identified for the analysis is the Ordered or Ordinal Logistic Regression (OLR) model. The ordered logit model is used when there are more than two categories for a dependent variable and in this study, the dependent variable is the severity of the crash which is categorized into property damage crash - 1, injury crash - 2, and fatal crash - 3. The values for each category are meaningfully ordered sequentially so that one value is in fact "greater" than the preceding one.

The OLR model is a statistical analysis technique used to simulate the association between an ordinal response variable and one or more explanatory variables. A categorical variable with a distinct ordering of the category levels is called an ordinal variable. The explanatory variables could be categorical or continuous. One major assumption of OLR is the assumption of proportional odds: the effect of an independent variable is constant for each increase in the level of the response. Here, the output of the model will contain an intercept for each level of the response except one, and a single slope for each explanatory variable (Stephen Parry (2020), Bilder, C. R., & Loughin, T. M. (2014)).

Let Y = ordinal outcome with j categories

$P(Y \leq j)$ = the cumulative probability of Y less than or equal to a specific category of j

j = the number of levels in the categorical response variable

j = 1, …, J - 1

p = the number of explanatory variables

$$\text{If } P\ (Y \leq j) = 1$$

The odds of being less than or equal a particular category can be defined as

$$\frac{P(Y \leq j)}{P(Y > j)}$$

The log odds will be

$$\log\frac{P(Y \leq j)}{P(Y > j)} = \text{logit}\ (P\ (Y \leq j))$$

The OLS model is defined as

$$\text{Logit}\ (P\ (Y \leq j)) = \beta_{j0} + \beta_{j1}x_1 + \ldots + \beta_{jp}x_p$$

For j = 1, …, J - 1 and p predictors

As a result of the parallel line assumption, the intercepts will be different for each category but the slopes will be constant across all categories.

The OLS model becomes

$$\text{Logit}\,(P\,(Y \leq j)) = \beta_{j0} + \beta_1 x_1 + \ldots + \beta_p x_p$$

β = parameter for each explanatory (independent) variable

4.3.2 Dependent Variable

The dependent variable used in this study is the severity of a crash obtained from the crash report type in the vehicle crash dataset. The variable was categorized into 3 ordered levels: property damage crash, injury crash, and fatal crash. Property damage crash represents crashes that involved the destruction of properties on the road such as bicycles, pedal cycles, and fixed objects on the roadway. The injury crash represents crashes that led to either minor or major injuries suffered by either the bicyclist, pedal cyclist, or pedestrian involved. Finally, the fatal crash represents crashes that led to the death of the individuals involved.

Table 4-1: Dependent Variable Used in OLR Model

	Severity of Crash	**Frequency**	**Percentage**
	1 - Property Damage Crash	177	10%
Dependent variable	2 - Injury Crash	1562	85%
	3 - Fatal crash	86	5%

4.3.3 Independent Variable

Table 4-2 shows the independent variables used in the regression model. They include light code (daylight, dark - light on, and dark - light off). This explains the lighting condition at the time of the crash. It gives insight into whether the crash occurred during the daytime or at night with or without the presence of street lighting. The junction code (non-intersection, intersection-related, and intersection) gives insight into crashes that occurred at the intersection, intersection-related (crashes that occurred close to the intersection), and midblock (non-intersection). The lane code shows crashes that occurred at the acceleration lane (when entering the ramp to a highway), deceleration lane (when leaving the ramp of a highway), left turn lane, and right turn lane. The road condition code gives information on crashes that occurred on roadways that are either defective or not. The road division code indicates crashes on the type of roadway, either one-way traffic, two-way undivided, two-way divided but unprotected, and two-way divided and protected. A roadway is protected if there is a medium barrier between opposing flows of traffic that separate the traffic moving in opposite directions. The weather conditions indicate crashes that occurred when the weather was either raining or clear. The schedule code shows the time of the crash; AM (12:00 am - 05:59 am), PM Peak (06:00 am - 11:59 am), PM Peak (12:00 pm - 05:59 pm), and PM (06:00 pm - 11:59 pm). The population density (square miles) was categorized into 3 levels. Level 1 (0 - 999), level 2 (1,000 - 2,999), and level 3 (population density above 3,000). The number of schools also has 3 levels; level 1 (0 - 99), level 2 (100 - 199), and level 3 (200 - 299). And finally, the number of students is also categorized into 3 levels; level 1 (0 - 9,999), level 2 (10,000 - 49,000), and level 3 (number of students above 50,000).

Table 4-2: Independent Variable Used in OLR Model

	Variable	**Category level**	**Frequency**	**Percentage**
	Light code	1 – Daylight	1115	61%
		2 - Dark light on	563	31%
		3 - Dark light off	147	8%
	Junction code	1 - Non-intersection	728	40%
		2 – Intersection related	194	11%
		3 - Intersection	903	49%
Independent Variables	Lane code	1 - Deceleration lane	34	2%
		2 - Left turn lane	408	22%
		3- Acceleration lane	117	6%
		4 – Right Turn Lane	1266	69%
	Road division code	1 - Two-way, not divided	865	47%

	2- one-way traffic	201	11%
	3 - Two-way, divided, unprotected	297	16%
	4- Two-way, divided, protected	462	25%
Weather code	1 – Clear	1648	90%
	2- Raining	177	10%
Schedule code	1 – AM	145	8%
	2 – AM Peak	313	17%
	3 – PM Peak	741	41%
	4 - PM	626	34%
Number of Schools	1 – 0 to 99	350	19%
	2 – 100 to 199	912	50%
	3 – 200 to 299	563	31%
Population Density	1 – 0 to 999	315	17%
	2 – 1,000 to 2,999	975	53%
	3 – 3,000 >	535	29%
Number of students	1 – 0 to 9,999	92	5%

2 – 10,000 to 49,000	223	12%
3 – 50,000 >	1510	83%

At first, a benchmark model was developed using variables in other studies to understand the relationship among variables. Then, another model was developed with more variables added and the goodness of fit was tested with the newly developed model.

Chapter 5: Results

This chapter shows the results from the methodological framework for this study. First, the statistical analysis results are examined, and then, the results and performance of the model development were examined to identify those factors having a positive significant relationship with the severity of a crash.

5.1 Results from the Statistical Analysis

5.1.1 Vehicle Crash in Maryland

The total number of vehicle crashes recorded in the state of Maryland between January 2015 and March 2022 are 795,430. These cover collisions between vehicles and bicyclists, pedal cyclists, pedestrians, fixed objects, and other vehicles.

Figure 5-1 shows the trend of the vehicle crash between January 2015 and March 2022.

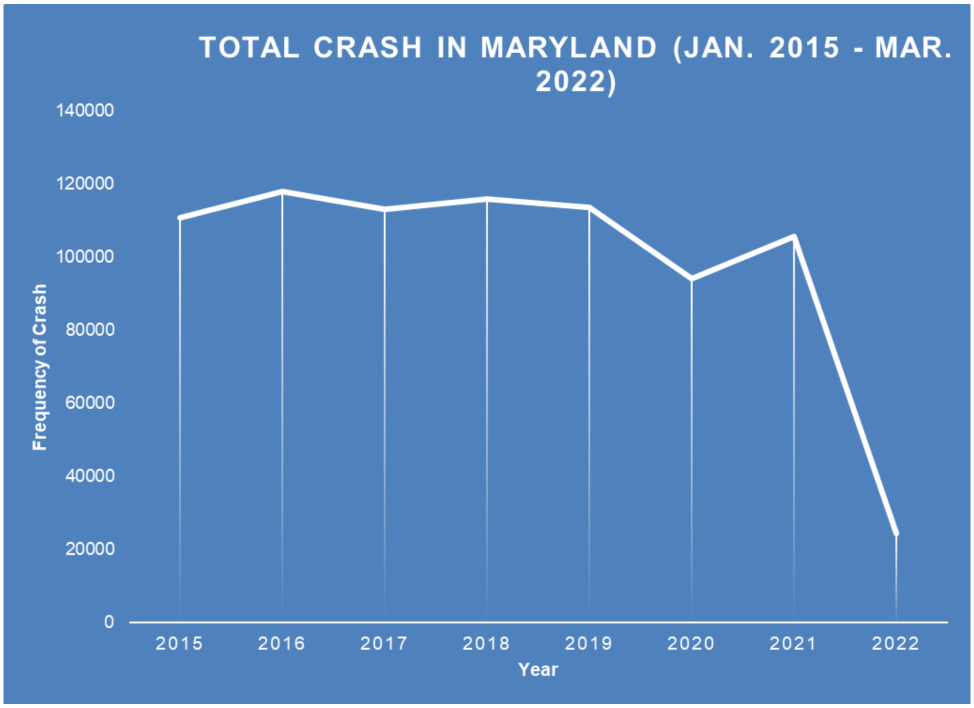


Figure 5-1: Vehicle Crash Trend in Maryland

The trend shows a major decline in the year 2020 and then an upward trend in 2021. This is a result of the Covid-19 global pandemic that made major cities around the world go into lockdown. Due to the total lockdown in Maryland, there was no vehicle on the roadway in the first quarter of 2020 and as such, no vehicle crash was recorded during that period.

The decline for the year 2022 is due to incomplete data in the dataset as crash reports are recorded quarterly by the MSPD.

5.1.2 Bicycle, Pedal Cycle, and Pedestrian Crash in Maryland

The bicycle, pedal cycle, and pedestrian-related crashes were obtained from the vehicle crash record. Table 5-1 shows the frequency of each crash.

Table 5-1: Frequency of Crash Type

Crash Type	Total Crash
Bicycle	401
Pedal cycle	44
Pedestrian	1380

The subset data of bicycle, pedal cycle, and pedestrian-related crashes are from January 2020 to December 2021.

The location for each crash is illustrated in Figure 4-2 and the location with the highest frequency of crashes was illustrated using the heatmap shown in Figure 5-2.

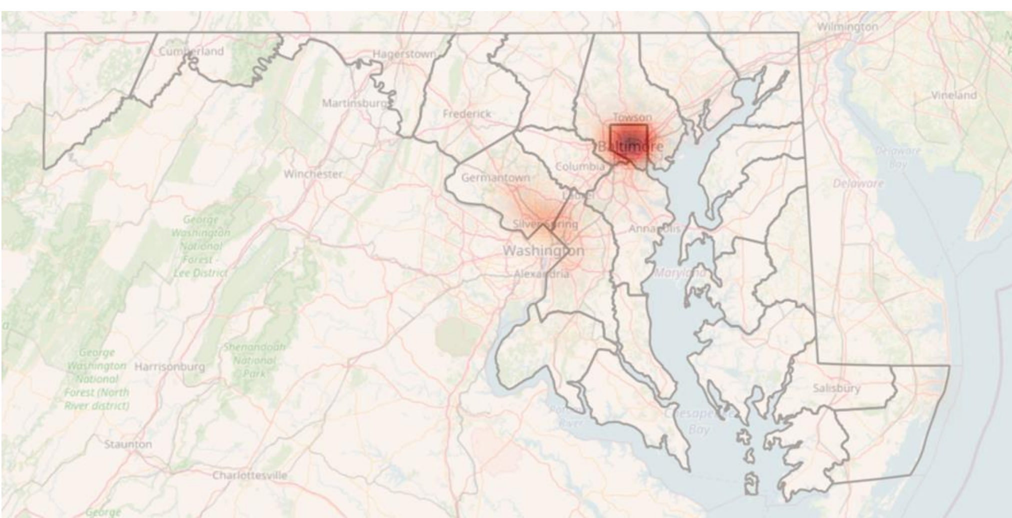
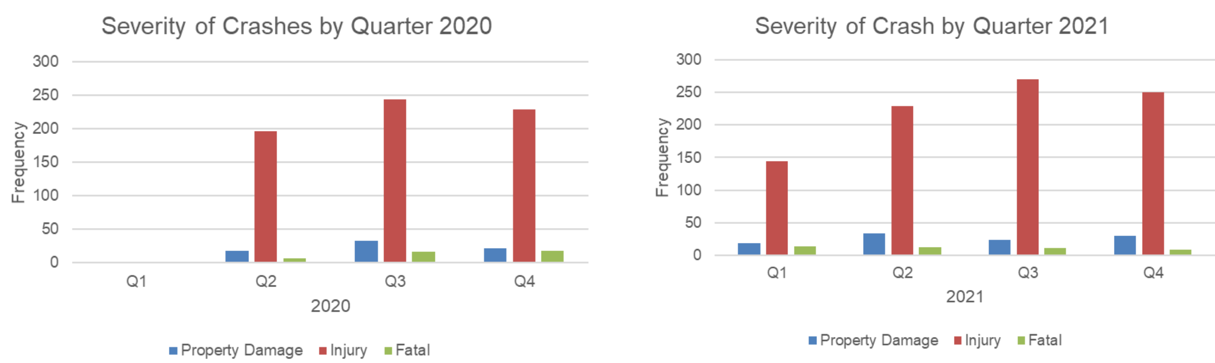


Figure 5-2: Heatmap of Crash

The heatmap shows that Baltimore City county has the highest frequency of crashes making it a hot zone for bicyclists, pedal cyclists, and pedestrians.

5.1.3 Severity of Crash by Quarter

The severity of crashes by quarter for 2020 and 2021 is illustrated below.



(a) (b)

Figure 5-3: Severity of Crash by Quarter (a) 2020, and (b) 2021

Due to the lockdown, the first quarter in 2020 did not record any crashes but the frequency of total crashes and the fatality increased throughout the year. 2020 has more fatal crashes than 2021. This is because motorists tend to drive faster as there was fewer commuters on the roadway due to the pandemic.

The third quarter has a higher frequency of crashes because, during the Summer period, more people are walking and cycling to their destination in form of exercise.

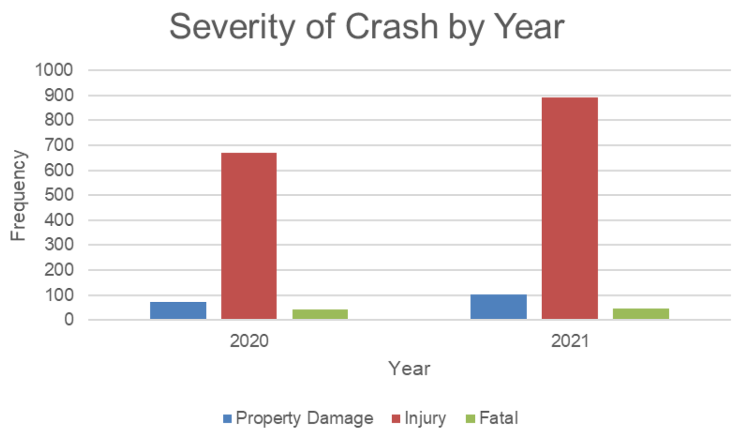


Figure 5-4: Severity of Crash by Year

As the lockdown came to an end and more commuters used the roadway, the number of crashes also increased as seen in 2021.

5.1.4 Severity of Crash by Weather Condition

The data analysis shows crashes that occurred when it was raining and when the weather was clear.

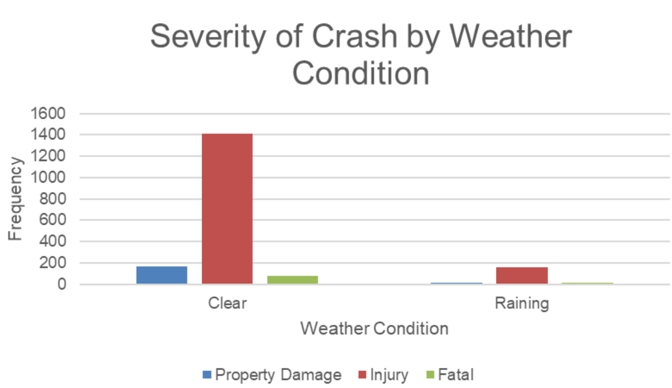


Figure 5-5: Severity of Crash by Weather Condition

More crashes were recorded when the weather was clear than when it was raining. It is assumed that fewer cyclists and pedestrians commute when it is raining and motorists tend to drive more carefully during rainy periods.

5.1.5 Severity of Crash by Surface Condition

This explains the frequency of crashes that occur when the road surface is either wet or dry. The wetness of the road may result from rain, snow, and fog.

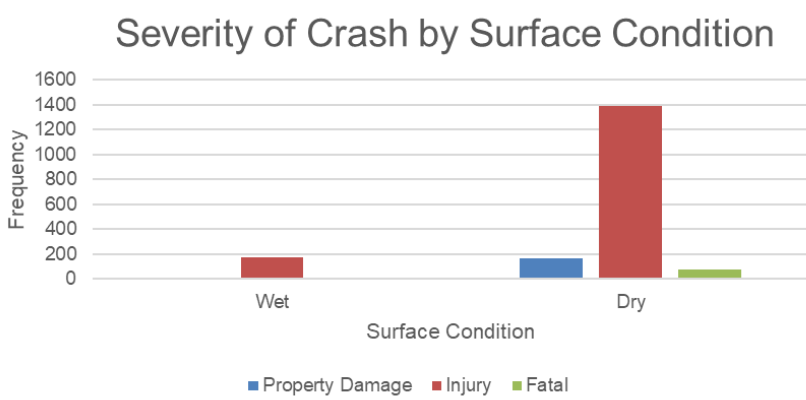


Figure 5-6: Severity of Crash by Surface Condition

More crashes are recorded when the road surface is dry than when it is wet. Motorists drive faster when the surface is dry and an impact can lead to more severity among cyclists and pedestrians.

5.1.6 Severity of Crash by Lane Type

The different types of lanes include left-turn lane, right-turn lane, and through lane. But this study only focuses on the left-turn lane, right-turn lane, acceleration lane, and deceleration lane.

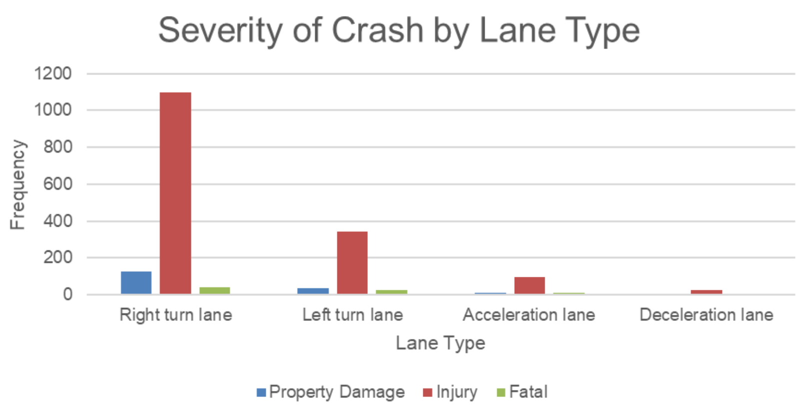


Figure 5-7: Severity of Crash by Lane Type

More crashes are recorded in the Right-turn lane. This may be due to the fact that most roadways in Maryland allow "Turn on Red" for the right-turn lane users. Motorists may not pay much attention to whether cyclists or pedestrians are trying to cross the roadway and this can lead to a collision. Motorists are more careful when entering and leaving the ramp at the acceleration and deceleration lanes, respectively.

5.1.7 Severity of Crash by Road Condition

The road condition shows crashes that occurred on defective and non-defective roadways.

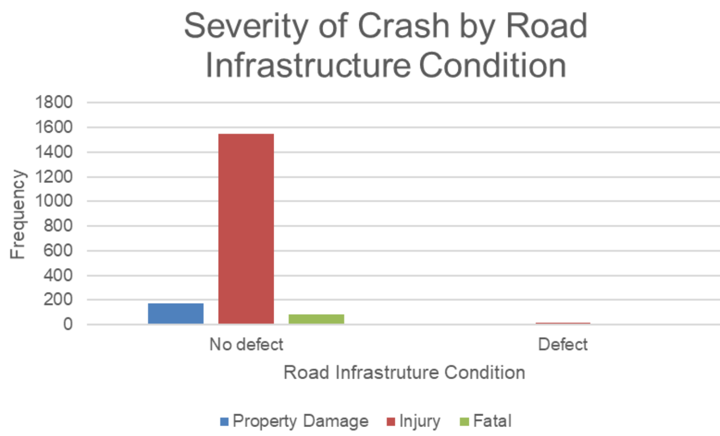


Figure 5-8: Severity of Crash by Road Condition

The data show very few crashes occurring when the road was defective and more crashes when there was no defect on the roadways. Defective roads make motorists reduce their speed and drive with care but roadways with no defects encourage motorists to drive fast. The fatality level is also higher on roadways with no defects.

5.1.8 Severity of Crash by Road Division Condition

This records crashes that occurred on a particular road type. The result shows crashes in one-way traffic, two-way undivided, two-way divided but unprotected, and two-way with a positive median barrier. The positive median barrier can either be depressed, closed, raised, or painted. The two-way with a positive median has a raised or depressed median that prevents the opposite flow of traffic from coming in contact with each other. The two-way divided but unprotected are roadways having the opposite flow of traffic separated by broken painted yellow lines. The two-way undivided is a roadway having no more than one through lane of traffic in the opposite directions with no median barrier. One-way traffic refers to roadways with traffic moving in only one direction.

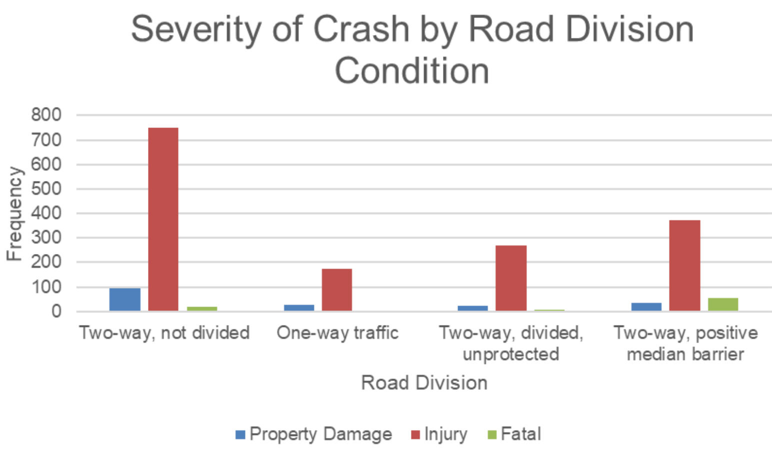


Figure 5-9: Severity of Crash by Road Division Condition

The result reveals that more crashes occurred on undivided roads with two-way. Due to the fact that the opposite flow of traffic is not separated by a positive barrier, motorists moving in opposite directions may easily come in contact with cyclists and pedestrians. However, more fatal crashes were recorded on roadways with two-way, positive median barriers.

5.1.9 Severity of Crash by Junction Type

The crashes that occurred by junction type were either at intersection, intersection-related, or at non-intersection.

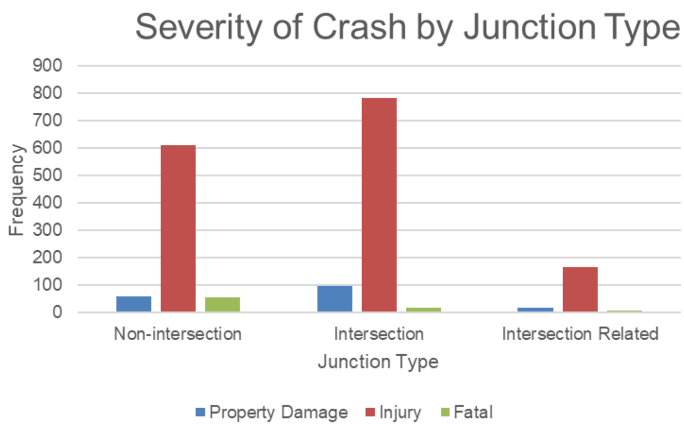


Figure 5-10: Severity of Crash by Junction Type

More crashes were recorded at intersections because more motorists, pedestrians, and cyclists are waiting to cross there. Cyclists and pedestrians who do not wait for the light to turn green may collide with motorists. Vehicles turning right at the intersection also may collide with cyclists and pedestrians if not paying attention.

The data recorded more fatal crashes at the non-intersection. This is due to the fact that motorists tend to drive at a much faster speed at the non-intersection than at the intersection and may likely collide with cyclists and pedestrians who cross at midblock instead of crossing at the intersection.

5.1.10 Severity of Crash by Time Schedule

The crash data recorded the time of each crash. The time of the crash was categorized into 4 equal hours. The AM period starts from 12 midnight to 05:59 am, the AM Peak starts from 06:00 am to 11:59 am, the PM Peak starts from 12 noon to 05:59 pm, and the PM starts from 06:00 pm to 11:59 pm.

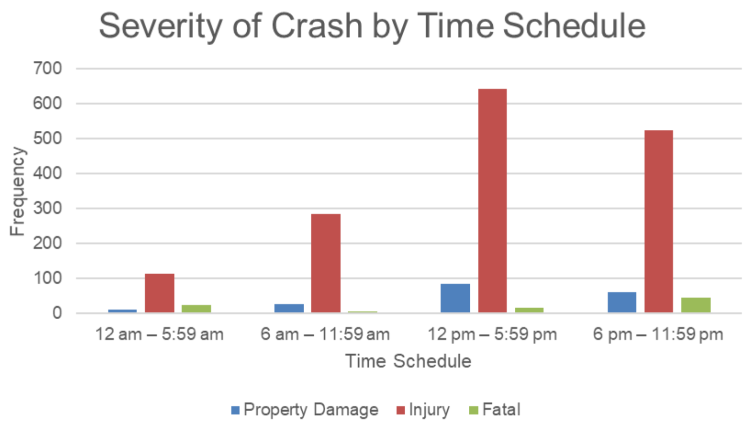


Figure 5-11: Severity of Crash by Time Schedule

The results show more crashes during the PM Peak period because there are more commuters on roads during this period, which increases the risk of a crash.

More fatal crashes were recorded during the PM and AM hours. This can be traced to the visibility of commuters during that time. Cyclists and pedestrians who do not wear reflective clothing make it difficult to be seen by motorists and increase the risk of a fatal crash. Individuals who do not have enough sleep the previous night lose concentration when driving and this also increases the risk of fatal crashes during the AM hours.

5.1.11 Severity of Crash by Light Condition

The light condition that the recorded crashes occurred were either during the day with daylight or at night when it is dark with street lighting or dark without street lighting.

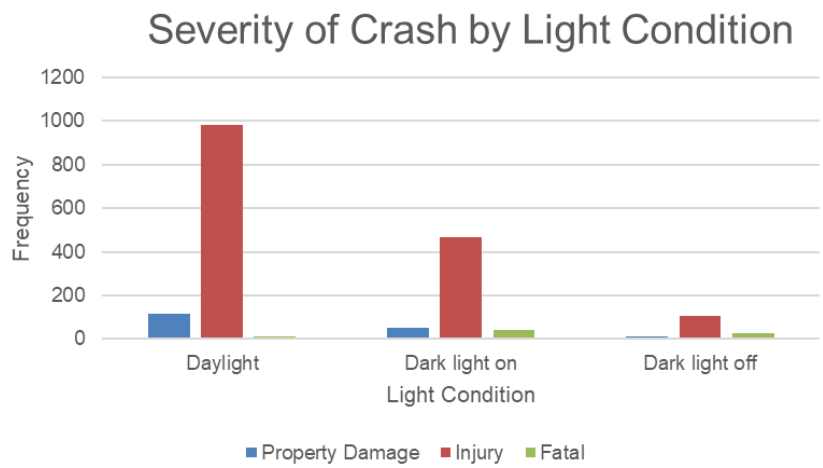


Figure 5-12: Severity of Crash by Light Condition

The results reveal that more crashes occurred during the daytime than at night time. This is because there are more users on roads during daytime. However, the data reveal that more fatal crashes were recorded on roadways at night, either with street lighting or without. This also is a result of the low visibility of cyclists or pedestrians to motorists which increases the risk of a fatal crash.

5.1.12 Analysis from Population Density

The population density shows the population per land area in square miles for each county in Maryland. The analysis was performed to determine whether there was a positive relationship between pollution density and the frequency of crashes.

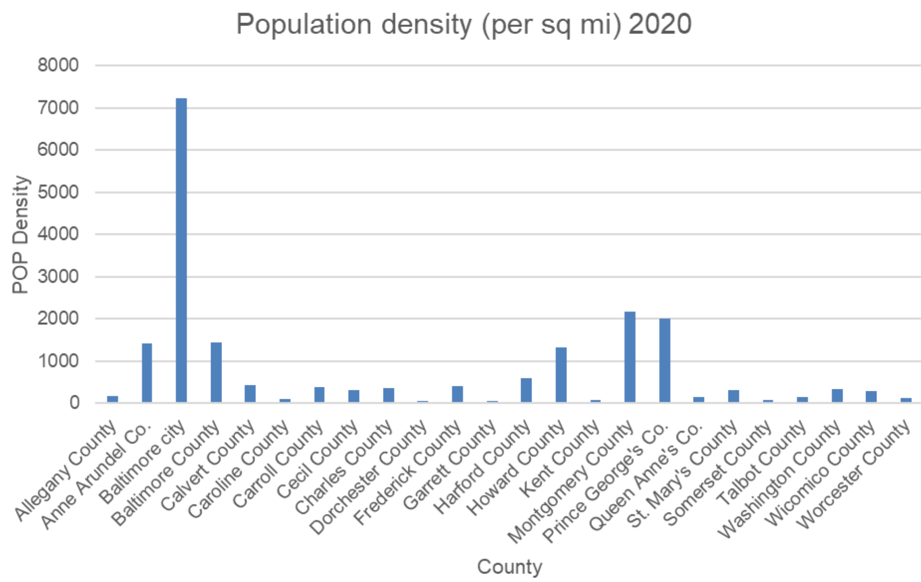


Figure 5-13: Population Density by County

The results show that Baltimore City county has the highest population density in Maryland. The others are Montgomery, Prince George's, and Baltimore Counties.

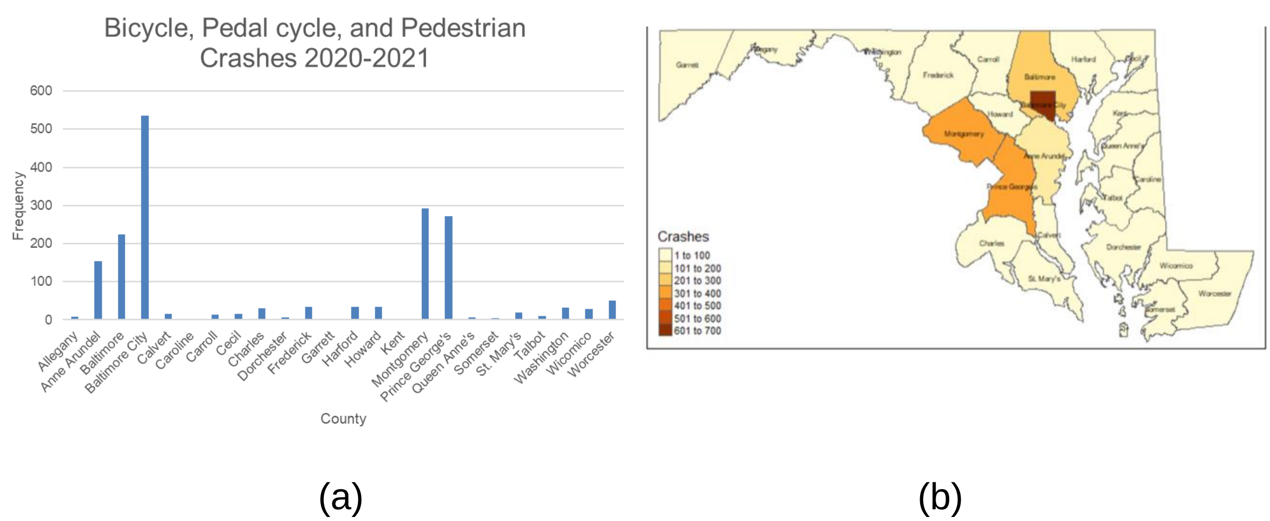


Figure 5-14: Crash Frequency by County (a) Graph representation, (b) Geospatial representation

The results show that there were more crashes recorded in Baltimore City county. The other counties that also recorded a high frequency of crashes include Montgomery, Prince George's, and Baltimore Counties.

To further clarify this hypothesis, the counties were divided into urban and rural regions. The urban regions are counties with populations between 2,500 - 49,999. The rural regions are counties with populations fewer than 2,500. The population for each county in Maryland was correlated to fit into the range.

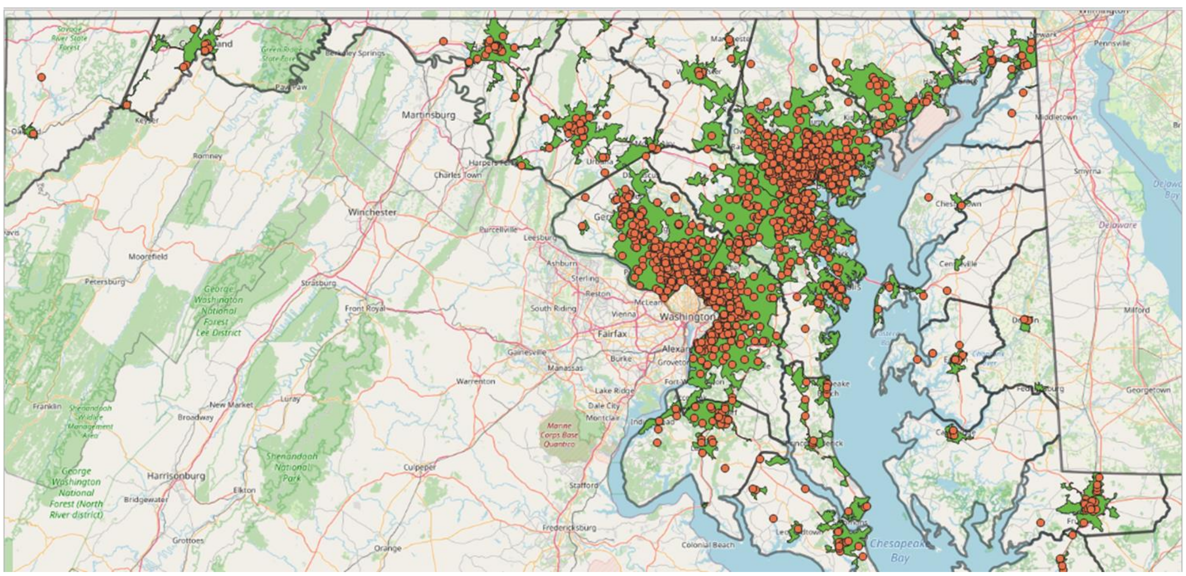


Figure 5-15: Crash Frequency in Urban Region

Figure 5-15 shows the urban regions in Maryland and reflects the crashes that occurred in the state.

This reveals that there may be a positive relationship between population density and the frequency of crashes.

5.1.13 Analysis from Presence of Schools

This study also focuses on environmental and land-use infrastructures to determine if there is a relationship with the severity of crashes. It is hypothesized that the presence of an elementary, middle, and high school in an environment may increase the likelihood of a possible crash. This is due to the population of students convening at that location.

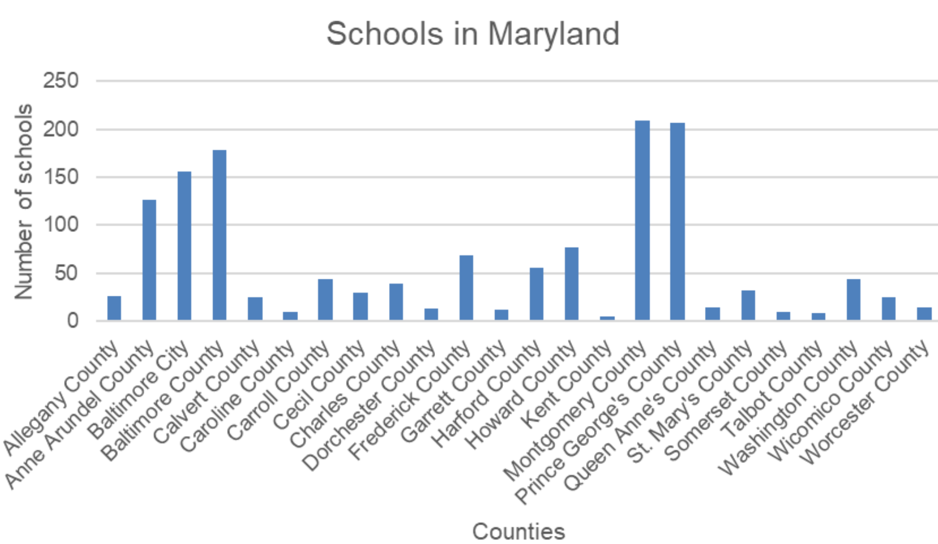


Figure 5-16: Number of Schools by County

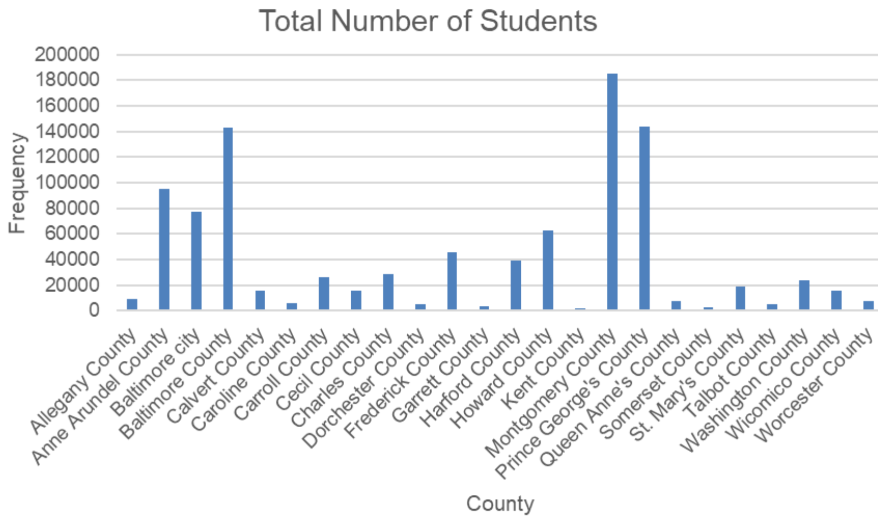


Figure 5-17: Number of Students by County

The results show that there are more schools and students in Montgomery county. Although Baltimore City county has the highest population density, it does not have the highest numbers of schools or students.

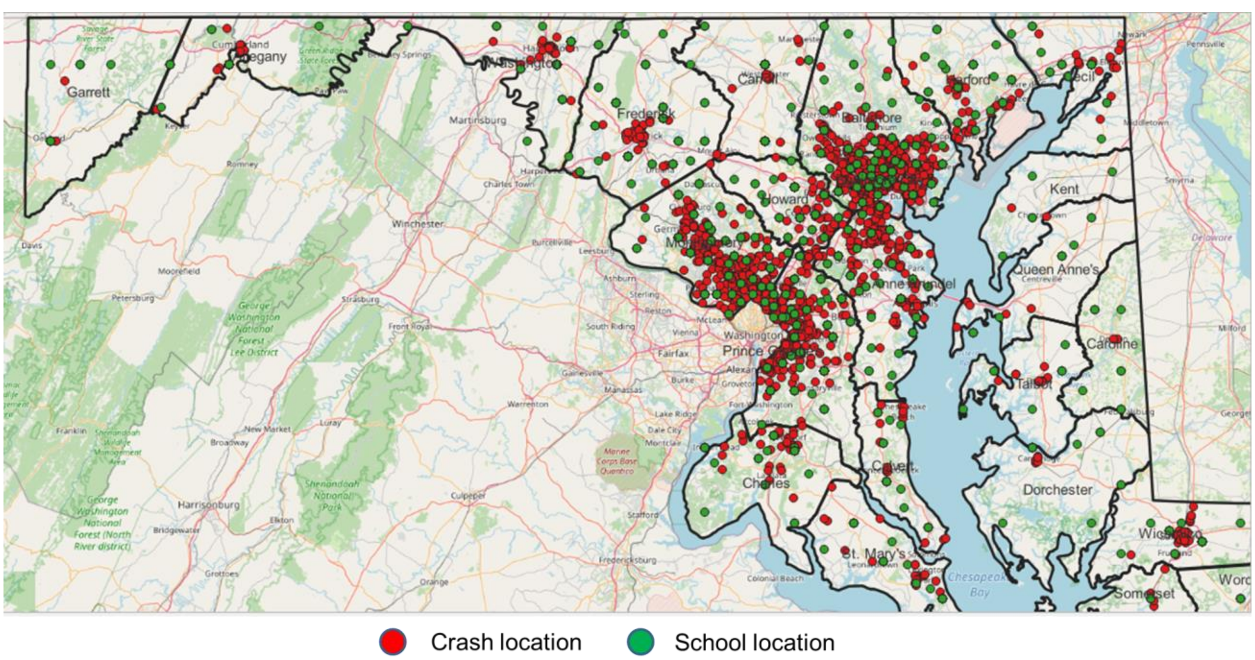


Figure 5-18: School and Crash Location by County

Figure 5-18 shows that there tend to be more crashes around the location of schools. Counties with a high number of schools and students also recorded a high number of crashes.

5.1.14 Analysis from Severity of Crashes

The data contains the various crash type in different counties in Maryland.

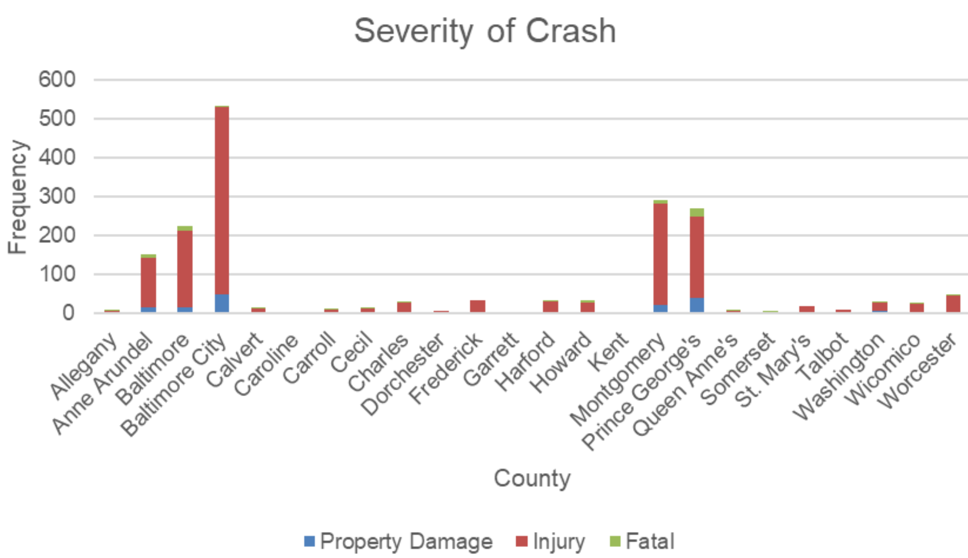


Figure 5-19: Severity of Crash by County

The results show that more crashes occurred in Baltimore City county but the more fatal crashes were observed in Prince George's county. Counties with few or no crashes include Caroline, Garrett, and Kent counties. These counties also had the least population density, number of schools, and number of students.

5.2 Results from the Model Development

The output of the model estimated the probabilistic relationship between the severity of crashes and the independent variables. This reveals what factors contribute significantly to the severity of bicycle, pedal cycle, and pedestrian-related crashes on the roadway in Maryland.

Table 5-2: Output of Benchmark Model Development

Variables	**Category**	**Value**	**T value**	**P value**	
Light Code	Dark – Light on	0.5449	2.463	0.0137	**
	Dark – Light off	1.4911	4.877	0.0000	***
Junction Code	Non-intersection	0.4926	3.291	0.0009	***
	Intersection-related	0.3104	1.344	0.1786	
Schedule Code	AM Peak	-0.3742	-1.075	0.2820	
	PM Peak	-0.6491	-1.991	0.0464	*
	PM	-0.6358	-2.326	0.0200	*

Significance codes: 0 ‘***’ 0.001 ‘**’ 0.01 ‘*’0.05 ‘.’ 0.1 ‘ ’ 1.
Lipsitz goodness of fit (p-value) = 0.5319
McFadden R^2 = 0.0388

The model output shows the relationship between the severity of crashes and the light condition, junction condition, and schedule time. Some of the variables were used as the reference variable by the model and not shown on the table.

It is seen that almost all variables are significant in the model. There was a positive significant relationship between the severity of crashes and the crashes that occurred at night whether there was street lighting or not, and at non-intersection. This reveals that more fatal crashes are prone to occur under these conditions.

There was however, a significant relationship between the severity of crashes and the time of crash. However, this is a negative relationship. It shows that more crashes tend to occur at the PM Peak and PM period.

This serves as the benchmark model in line with past studies and used to compare the output of the other model.

Table 5-3: Output of Model Development

Variables	Category	Value	T value	P value	
Light Code	Dark – Light on	0.4125	1.8386	0.0659	.
	Dark – Light off	1.1981	3.8479	0.0001	***
Junction Code	Non-intersection	0.5660	3.7353	0.0001	***
	Intersection-related	0.3256	1.3955	0.1628	
Lane Code	Left Turn Lane	0.1130	0.2214	0.8247	
	Acceleration lane	0.3506	0.6253	0.5317	
	Right Turn Lane	0.0643	0.1285	0.8977	
Road Division Code	One way	-0.0995	-0.4381	0.6612	
	Two way, divided, unprotected	0.3437	1.7123	0.0868	.
	Two-way, positive median barrier	1.0370	5.2661	0.0000	***
Weather Code	Raining	0.2651	1.1027	0.2701	
Schedule Code	AM Peak	-0.3535	-1.0096	0.3126	

	PM Peak	-0.5967	-1.8209	0.0686	.
	PM	-0.5772	-2.1015	0.0355	*
Total Number of Students	1000 - 2999	-0.0693	-0.1891	0.8500	
	>3000	0.6051	1.0095	0.3127	
Number of Schools	100 - 199	-0.9899	-1.9807	0.0476	*
	200 - 299	-1.3071	-2.6349	0.0084	**
Population Density	>3000	0.3047	1.5022	0.1330	

Significance codes: 0 '***' 0.001 '**' 0.01 '*'0.05 '.' 0.1 ' ' 1.
Lipsitz goodness of fit (p-value) = 0.01524
McFadden R^2 = 0.0665

The model output shows that there is a positive significant relationship between the severity of crashes and crashes that occurred on dark-light off, non-intersection, and two-way, positive median barrier. This result agrees with the hypothesis that low visibility and commuting at night increase the risk of a fatal crash. Also, the result is in correlation to the fact that the speed of motorists at non-intersection and cyclists and pedestrians crossing the roadway at midblock and not at the crosswalk or intersection raises the risk of a fatal crash at the non-intersection. Crashes that occurred on roadways with a median barrier recorded more fatalities. This may be a result of the type of median barrier used. If the median does not permanently discourage crossing at midblock or jaywalking, it can increase the risk of fatality in crash incidents.

The other significant variables from the model are the PM time of the crash and the presence of schools. Though the result shows a negative relationship between the severity of crashes and the PM time schedule and presence of schools, this reveals that the presence of schools and commuting at PM periods (06:00 pm - 11:59 pm) increases the risk of a crash.

The independent variables having an estimate with a positive value show a positive relationship with the severity of crash and variables having an estimate with negative values show a negative relationship with the severity of crash.

The T and P values evaluate the difference's magnitude of the variables in relation to the range of the dataset. It shows how significant each independent variable in the dataset is to the dependent variable.

The Lipsitz test and McFadden R^2 for both the benchmark and the other model development shows the goodness of fit. The benchmark model has a p-value of 0.5 which indicates that the null hypothesis is true and is not statistically significant and R^2 of 0.0388. The other improved model has a p-value of 0.015 which means that we cannot reject the null hypothesis and is greater than 5% threshold R^2 of 0.0665. This indicates that the proportional odds assumption is met by the fitted model. In other words, it is a good specification for the model and has a better goodness of fit.

In summary, there is a high likelihood that crashes involving bicyclists, pedal cyclists, and pedestrians that occurred at night from 06:00 pm - 11:59 pm with no proper lighting conditions will be more fatal. Also, crashes that occurred at the non-intersection and at regions with a positive median barrier are likely to be more fatal. The presence of schools in a location is more likely to increase the frequency of crashes at that location.

Chapter 6: Conclusion and Discussion

6.1 Research Summary

This study presents a model that identifies the variables that are likely to increase the possibility of the severity of crashes on roadways in Maryland. This study was inspired by the MDOT ZeroDeath Maryland vision (VisionZero) which is to have zero death on roads and make the road safer for everyone. Several datasets are integrated into the model after the relevant data cleaning and analytical steps have been completed to give a consistent and error-free dataset.

The first step was to collect the vehicle crash data, population data, geospatial data, and school information data. The various datasets pass the quality control activities such as cleaning and removing irrelevant data entries. A subset of the vehicle crash data was created that contains only bicycle, pedal cycle, and pedestrian-related crashes. This new dataset was then aggregated at county levels and merged with the population density and school information data using R programming.

The next step was using QGIS and Excel to visualize the dataset. This provides more illustration of what the dataset entails. The QGIS shows the exact location of crashes and the location of schools in each county in Maryland, and with Excel software, the various trend of crashes from different variables were identified. This was where the hypothesis proposed in the study was generated from. It was hypothesized that population density, time of crash, jaywalking by cyclists and pedestrians, and poor lighting would increase the possibility of a fatal crash.

Finally, the OLR model was developed using the available dataset. The severity of crash was set as the dependent variable and the collision type, time of the crash, light condition, lane type, weather condition, road condition, road division type, population density, number of schools, and number of students are identified as the independent variables.

The model output reveals the relationship between the variables and the severity of crash.

6.2 Research Contribution

While other studies focus on either the behavior of motorists or cyclists and pedestrians to increase the severity of crashes, this study focuses on road infrastructures and environmental (land-use) features as possible causes of the severity of crash. Rather than identify factors that cannot be directly controlled on a general level such as impaired driving, distracted driving, speeding, jaywalking, and lack of proper training of the individuals involved, this study identifies factors that can be directly controlled to increase the safety on the roadway. They include the road infrastructure such as street lighting conditions, road surface condition, and road division type. It also identifies land-use factors such as population density, number of schools, and number of students. With these new variables, the OLR model associates its possible relationship with the severity of crashes in Maryland.

The contribution to the transportation industry is that fatal crashes in Maryland can be prevented if the lighting condition, median barriers, and infrastructure around schools are improved.

6.3 Discussion and Future Research Directions

To achieve the ZeroDeath Maryland vision and reduce the severity of crashes on the roadway, street lights should be installed on roadways with no lighting infrastructures. Permanently discouraging crossing at non-intersection by installing raised positive median barriers. This will force cyclists and pedestrians to cross the roadway at the intersection. Infrastructures to reduce the speed of motorists around the school environment should be installed, and proper training be given to cyclists and pedestrians at a young age on how to follow traffic regulations, and what type of clothing to wear when commuting at night.

The limitation of this study is that the data available for bicycle, pedal cycle, and pedestrian-related crashes was only for 2020 - 2021. The data recorded for 2022 were incomplete and could not be added to the model. A future research step would obtain a larger dataset and test the model on it. In addition, data having more variables on the individuals involved such as age, sex, occupation, marital status, etc. would be desirable. This will provide information on the persons involved in the crash and their relationship to the severity of the crash. Also, the study will be extended on the countermeasures to understand and assess their effectiveness on roads. With the introduction of street lighting, high raised medians, and speed limit signs on the road, the effectiveness in reducing the severity of crashes would be measured and another model should be developed for effective predictions.

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